OPTIMAL OPERATION OF MOBILE STORAGES BY NETWORK FLOW ALGORITHMS CONSIDERING SPATIOTEMPORAL EFFECTS

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ABSTRACT

This paper discusses the optimal operation of electric vehicle fleets, with the aim of estimating the potential value (economically) of vehicles in electrical grids. Central idea is to model the problem as a minimum-cost flow problem. The mapping of the mobility pattern is assessed via time-variable flows between the individual network nodes. The graph-theoretic problem formulation is intuitive and allows an accessible modelling of the real problem.

INTRODUCTION

The expected strong increase of electrical mobility represents a new challenge for network operators and generation companies regarding the economic, safe and reliable operation of the energy supply system. In particular, the individual and political expectations of a predominantly operation of electric vehicles with "green energy" will stimulate the further development of renewable energies but also demands for a sophisticated and intelligent control of the charging times and locations. Beside that controlled charging can also be used by network operators for possible provision of ancillary services by use of vehicle batteries. This requires modelling and observation of transport and energy flows simultaneously.

METHODOLOGY

On the subject of charging strategies for electric vehicles a large number of publications already exist. However, very few deal with the issues of the spatiotemporally coupled problem discussed in this paper. The charging and feeding back of the battery at a particular location (determined by the mobility patterns of the vehicles) and a specific time affects the operating range of later charging processes because of the battery state of charge. Interestingly the problem may be associated with hydraulically coupled pumped storage hydro-plants [1] whose crosslinking is time varying (Figure 1).

The problem is modelled by means of network-algorithms represented by the so called time-expansion of the problem graph. The charging stations as well as the vehicles are represented as nodes v and g of the graph. The edges x between the nodes carry the energy flows and accordingly represent the mobility pattern of the vehicles. The mobility/traffic pattern is directly mapped to the topology of the problem graph (Figure 1).

The mobility-related energy consumption is modelled as auxiliary nodes in the graph. As a consequence of the necessity of flow conservation in the graph some problem specific adaptions have to be made (source and sink node). The edges of the infrastructure and the mobility edges of the vehicles are limited in accordance with the technical restrictions.

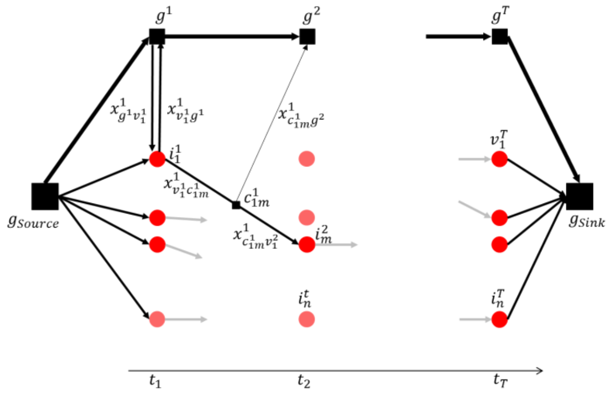

Figure 1: Problem modelling; network topology is determined by mobility pattern

Modelling

The optimal operation of electric vehicle fleets (or generally spatially variable storage) always depends on the perspective. The attempt to minimize the costs of each vehicle owner individually will lead to a different solution than the economic, total cost-minimizing approach which has been chosen in this paper. Sharing the minimum total costs to the individuals can possibly lead to a better result compared to the individual optimal solution. Following the formulation of the overall cost-minimizing approach the problem is presented as a conventional linear programming (LP) problem and as a network flow problem.

1. Conventional (LP-) approach:

The vehicle operation problem can be formulated as a linear programming minimization problem as follows:

Objective function:

$$min\left\{\sum_t \sum_v c_n^t(P_{charge}) - c_n^t(P_{feedback}) + c^t_{conv.Prod}\right\}$$

s.t.:

vehicle charging power:

$$P^t_{charge} < P_{chargeMAX}$$

vehicle feedback power:

$$P^t_{feed-in} < P_{feedbackMAX}$$

energy storage:

$$0 \le \sum_{t=1}^{T} \left(P_{charge}^{t} - P_{feed-in}^{t}\right) \le E_{MAX} \quad \forall \ times\ T$$

maximum total load at nodes:

$$\sum_{v} P_{Load,v}^{t} < P_{Load,MAX}^{n}, \forall \text{Nodes } n$$

2. Min-cost-flow approach:

The problem can also be formulated as a min-cost-flow problem as described following:

Objective function:

$$min\{z(k)\} = min\left\{\sum_{i,j\in A} costs_{ij} x_{ij}\right\}$$

s.t.:

$$lb_{ij} \le x_{ij} \le ub_{ij}$$

Energy conservation:

$$\sum x_{in} = \sum x_{out}$$

The variables used to formulate the problem are listed in the following and illustrated in Figure 2:

Nodes:

t	=	time index
g^t	=	grid node
i_k^t	=	infrastructure node k
v_i^t	=	vehicle node i
c_i^t	=	consumption node of vehicle i

Arcs:

x_{ij}^t	=	flow from node i to node j at time t
$x_{v_i^t c_i^t}^t$	=	flow from vehicle v_i to node c_i
$x_{c_i^t v_i^{t+\tau}}^t$	=	flow from node c_i to vehicle v_i
$x_{c_i^t g^{t+\tau}}^t$	=	flow from consump.-node c_i to grid node $g^{t+\tau}$ at time $(t+\tau)$
$x_{v_i^t i_i^t}^t$	=	flow from vehicle v_i to infrastr.-node i_i
$x_{i_i^t v_i^t}^t$	=	flow from infrastr.-node i_i to vehicle v_i
$x_{i_i^t g^t}^t$	=	flow from infrastr.-node i_i to grid node g
$x_{g^t i_i^t}^t$	=	flow from grid node g to infrastr.-node i_k

$costs_{ij}^t$	=	(arc-) costs for flow on arc from node i to node j
lb_{ij}^t	=	lower bound of flow from node i to node j
ub_{ij}^t	=	upper bound of flow from node i to node j

The problem graph of the min-cost-flow problem consists of grid-, infrastructure- and vehicle-nodes (g^t, i_k^t, v_i^t) which are connected by arcs. Each arc x_{ij}^t can carry a specific energy flow and is associated with flow costs as well as lower and upper bounds $(costs_{ij}^t, lb_{ij}^t, ub_{ij}^t)$ (Figure 2c). The arcs connecting grid and infrastructure nodes $x_{g^t i_i^t}^t$ represent the physical grid connection and is limited by the maximum power-flow, which is restricted by the grid-connection itself or by grid operation restrictions. Infrastructure nodes are connected to vehicles which are charging or discharging at that infrastructure-node at the specific time step $x_{i_i^t v_i^t}^t$. The arc costs represent the energy purchase/feed-in costs and the upper bound is equal to the vehicles maximum charging power. The so called *mobility*-arcs $(x_{v_i^t c_i^t}^t - x_{c_i^t v_i^{t+\tau}}^t)$ connecting the infrastructure nodes i,m via $i_i^t \to v_i^t \to c_i^t \to v_i^{t+\tau} \to i_m^{t+\tau}$ represent the energy, which is transported by the batteries of the vehicles (fig. 2c). The electrical energy consumption by mobility is defined by an additional outflow edge and consumption node c_i^t – representing the corresponding energy loss of the battery due to mobility in the considered time step.

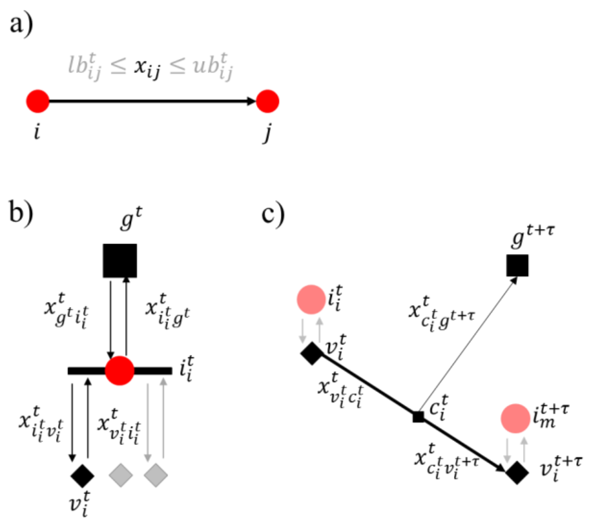

Figure 2: Modelling of: a) technical restrictions for power flow, b) vehicles at a charging station, c) movement and energy consumption of one vehicle

The lower bound flow-constraint ensures that the vehicle has to start with at least the battery level corresponding to the driving consumption. This corresponds to an implicit guarantee of mobility.

The connection of the infrastructure nodes over time is based on the mobility patterns.

Restrictions of vehicles and charging stations

The problem and in particular the problem constraints can be modelled intuitively with the proposed approach.

The maximum charging power of each vehicle $x_{i_i^t v_i^t}^t$ and the maximum grid connection to charging infrastructure power flow $x_{g^t i_i^t}^t$ is modelled in an intuitive way as upper bound for the specific flow.

After the problem has been modelled as a network flow problem, an appropriate solver is used to determine the optimal time and location of charging with respect to all technical constraints and especially to the mobility requirements (minimum state of charge). The problem solution allows a variety of analysis right up to the development of a single vehicle's state of charge and charging/discharging/driving cycles as show in Figure 3.

SIMULATION AND RESULTS

Solving by network simplex algorithm

The network simplex algorithm converts a *valid* solution of the network flow problem (spanning tree of the graph) into an *optimal* spanning tree of the problem-graph successively. The algorithm goes back to the adaption of the simplex-algorithm for network/graph problems and is an efficient solution method for the min-cost-flow-problem. [2].
The processing of driving data/mobility pattern and the creation of the time expanded problem graph has been done in MATLAB®. To solve the constructed network flow problem, the Library for Efficient Modelling and Optimization in Networks (LEMON) [3] has been used within an C++ implementation. The library provides efficient data structures for graphs and flexible and very fast implementations of several combinatorial algorithms.

The use of the network flow algorithm to the problem of optimal coordination of charging processes, which is the subject of many investigations like [4] and [5], will be explained with a ***didactic example:*** (see Figure 3).

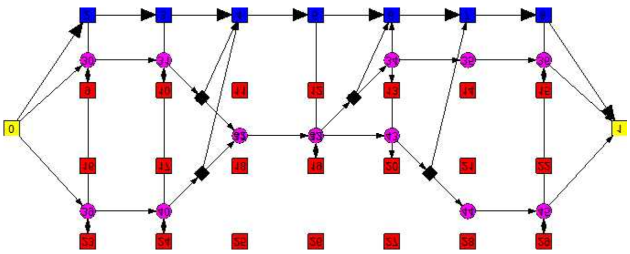

Figure 3: Exemplary time-expanded graph

This example consists of 7 time steps, whereby time steps 3 to 6 represent daytime with a high price signal level, and 3 charging locations (rectangle) where the 2 vehicles (circle) can be charged. The vehicles travel from their home location to the central node and then back again. They use energy while driving (rhombus) and charge or discharge (vertical arrows) their battery. At the beginning and at the end of the day a battery level of 80% is specified. The charging locations are connected to the power grid (top rectangles). Note that all charging locations are connected to the grid, but only connections are shown, where load-flow has occurred.

The vehicles charge their batteries in time steps 1, 2, 4 and 7 and discharge in time step 5, due to a high price signal which was specified externally. One of the vehicles charges during the high price period due to the energy demand by the following driving process.

The model has proven its capability of handling large-scale problems. Simulations have been conducted using real driving data from a German mobility study and from a field test with a large fleet of electric vehicles [6] and with high spatial and temporal extend and resolution. Figure 5 shows a reduced version (only one day and 4 nodes, due to page size limitations in this paper) of such a large-scale problem.
For instance the power consumption of all vehicles standing at two of the infrastructure nodes is shown in Figure 4 for five consecutive days. The 2 nodes are located in areas with different energy prices and many vehicles drive from the first node to the second one. This results in the power consumption which can be seen in the figure.

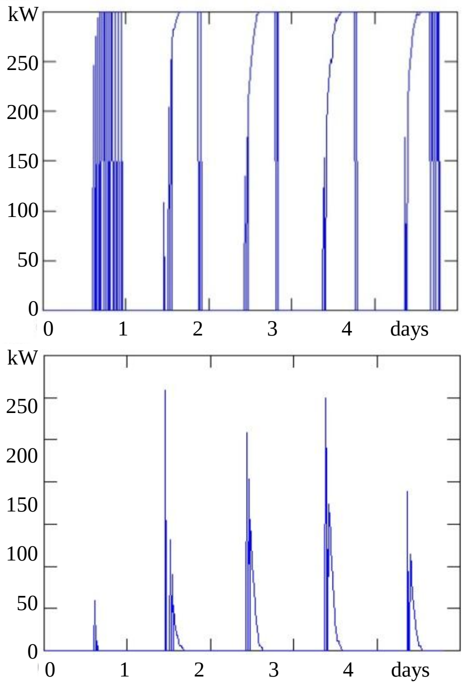

Figure 4: Charging power at 2 exemplary nodes.

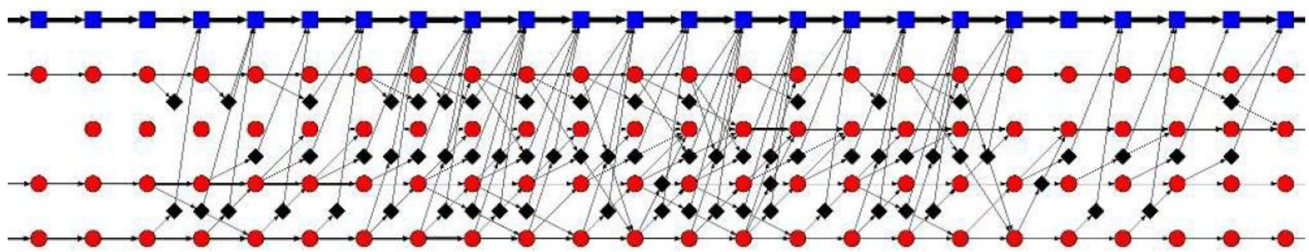

Figure 5: Large-Scale Problem with Real Driving Patterns

With the proposed method it is also possible to model restrictions of the power grid by limiting the power flow of the edge from the grid to the charging location. Even flow-dependent costs can be approximated, by replacing one edge by multiple parallel edges, each with a respective (max flow / costs)-pair as shown in Figure 6.

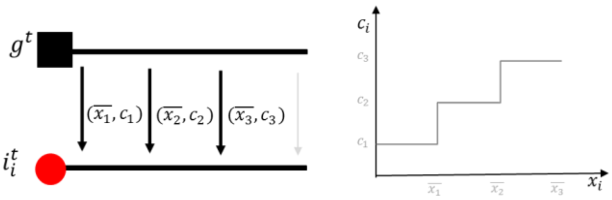

Figure 6: Approximation of flow-dependent costs

A way to adapt the network flow formulation to consider flow dependent costs directly are under current investigation. This adaption would make the approach of multiple parallel edges obsolete.
Also the sensitivity of the system with regard to the availability of charging locations can be investigated, by setting the maximum power flow in some locations to zero (setting a price close to infinite for the corresponding edge has proven to be more advantageous, because convergence problems are avoided).

The presented approach is capable to model both an individual as well as an aggregated formulation of the vehicles. The aggregated formulation groups vehicles moving at a certain time step from and to the same location. The differences of an aggregated and individual formulation have been investigated. Up to now no clear statement can be given to the usefulness or accuracy of either of these approaches.

CONCLUSIONS & OUTLOOK

The proposed method, allows determining the optimal (cost-minimizing) operation of electric vehicle fleets. Also the potential value (economically) of electrical vehicles in electrical grids can be estimated. The graph-theoretic problem formulation is intuitive and allows an easy modelling of 'real-world' problems regarding number of vehicles, time-steps and spatial interdependencies.
Already in this simple version the proposed method is capable to analyse charging infrastructure utilization rate.
In addition to the investigation of charging strategies also charging station siting and sizing analysis can be conducted, up to studies about provision of ancillary services by the vehicles.

Currently investigations of charging station´s siting and sizing are employed. The proposed method can play an promising role in solving the so called operation-problem efficiently (thinking about decomposition approaches of the classical facility location problem). The dual variables of the flow-problem can easily be used to feed back indications to the master/investment-problem about consequences of the investment for the operation-side.

To reduce the complexity of the model it might be beneficial to aggregate the vehicles at each charging place to one entity. The permissibility and model error of such an approach has to be further investigated.

Another targeted model expansion is the integration of the electric power-flow for representing network restrictions endogenously by replacing the current exogenous setting of upper and lower bound grid-charging infrastructure-flows (e.g. $x^{t}_{g^t i_i^t}$). Integrated approaches are equally investigated as iterative processes between the proposed network flow algorithm and e.g. optimal power flow calculations.

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