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Modelling the weekly electricity demand caused by electric cars

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HIGHLIGHTS

- Travel demand model mobiTopp extended to support electric vehicles.
- Different types of EVs: battery electric vehicles (BEV) and electric vehicles with range extender (EREVs).
- Modified travel behaviour for persons using BEVs.
- mobiTopp used to simulate electricity demand caused by charging of electric vehicles in the Greater Stuttgart Area.

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ABSTRACT

The travel demand model mobiTopp is used to analyse the effects of an increasing fleet of electric vehicles on the electricity demand. For this purpose mobiTopp has been extended to support EVs. These extensions comprise an EV ownership model, different types of EVs, namely Battery Electric Vehicles (BEVs) and Extended Range Electric Vehicles (EREVs), the charging process of EVs, and modified travel behaviour for persons using BEVs. The model is used to simulate the electricity demand for charging of EVs in the Greater Stuttgart Area over a period of one week. The daily electricity demand for EV charging contains a distinct peak around 6 p.m. for each workday and an additional morning peak around 8 a.m. when recharging at the workplace is possible. This additional electricity demand is concentrated in zones with residential use during the evening peak and in zones with office/industrial use during the morning peak.

1. Introduction

With the ratification of the Kyoto Protocol, many countries committed to reduce their emissions of carbon dioxide. In Germany, big efforts have been undertaken to start the transition from fossil fuels to renewable energies as sources of electricity production. Besides the energy sector, the transport sector is one of the major sources of carbon dioxide emissions. From this perspective, it seems logical to tackle next the second big source of carbon dioxide emissions, the transport sector. Replacing conventional combustion-engine driven cars by electric vehicles seems consequent, given the efforts made in the energy sector. The German Federal Government has set up a big funding programme to support the diffusion of electric vehicles (EV). The funding programme aims at a stock of one million EVs in the year 2020. Despite this effort, the sales of EVs are still low. It is commonly assumed that range anxiety, i.e. the fear of not reaching the destination and becoming stranded because of inadequate battery capacity, is hampering the success of battery electric vehicles (BEV) up to now. This fear is not unreasonable: Using a longitudinal perspective of car trips made, Weiss et al. [1] show that only a share of 13% of conventional cars in Germany can be replaced by BEVs with a typical battery size without a change in travel behaviour of their users. Another share of 16% could be replaced assuming minor restrictions or adaptations to their travel behaviour. As the battery accounts for a substantial share of the total cost of an electric car, increasing the battery size to a capacity that provides enough range for almost all trips would raise the costs to a level making the cars unsaleable. In consequence, a lot of funding is directed towards the development of improved battery technology.

Instead of increasing battery sizes, another solution to overcome the limited range problem is the concept of plug-in hybrid electric vehicles (PHEV) or extended-range electric vehicles (EREV). Both types of cars supplement the electric battery by a combustion-engine that is able to supply the vehicle with energy, when the battery is exhausted. As a special feature, EREVs can be customized to the owner's needs, for example trading a smaller battery for a larger combustion engine, using optimisation criteria like cost or performance [2].

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2. Related work

Research on the impact of an increased market penetration of EVs has many facets. One aspect is the identification of potential owners of EVs [3] and the estimation of its market potential [4]. Another aspect is how electric vehicles are used, and a third the energy demand of EVs and its effect on the electrical grid.

Several studies based on empirical data examine the suitability of BEVs for peoples' travel needs. Pearre et al. [5] analysed GPS data of conventional cars in order to examine the range requirements of electric vehicles assuming that potential EV drivers do not change their driving patterns. Smith et al. [6] focused on the optimisation of the battery size for a commuter sedan car. Chlond et al. [7] analysed the use of private cars from a longitudinal perspective combining data from different data sources and concluded that only a small fraction of private cars is suitable to be replaced by BEVs. Greaves et al. [8] presented an energy consumption model and a method to predict re-charge processes in addition to their analysis of the suitability of BEVs for individuals' travel needs based on GPS data. Babrowski et al. [9] estimated the temporal demand profiles for electric energy caused by charging of EVs based on travel surveys in different European countries and analysed the impact on the electric grid. Green et al. [10] concluded that combining travel demand models with power simulation systems would be a helpful option for analysing the impact of PHEVs on distribution grids.

Kang and Recker [11] modelled the electric energy demand of plug-in electric vehicles (PHEV) in California for different vehicle configurations and charging strategies. Their model is based on the activity-trip chains from a household travel survey, replacing conventional combustion engine vehicles by PHEVS. Galus et al. [12] analysed the effect of PHEV usage on the power supply network with the help of a travel demand model. They coupled the agent-based transportation simulation MATSim and a power system simulation within a feedback loop. Electric energy is provided by energy hubs using a multi energy carrier system. The charging of the PHEV is optimized by a PHEV manager agent [13]. Waraich et al. [14,15] developed this approach further and analysed different charging strategies.

Knapen et al. [16] analysed the electrical power demand of EVs within the region of Flanders, Belgium, over the course of a working day using the results of the FEATHERS model [17], an activity-based travel demand model. PHEVs and, where feasible, BEVs were assigned to the schedules resulting from the FEATHERS model. Four scenarios based on different charging strategies were analysed.

Peças Lopes et al. [18] analysed the effects of EV charging on the local electricity grid. For this purpose a medium voltage distribution network of a semi-urban, mostly residential, area is modelled. They analysed the load profiles for four scenarios with different shares of EVs and three different charging strategies. As it is assumed that each EV has to be charged completely, it seems that no travel model has been used. They conclude that the local grid can handle a share of up to 10% EVs with uncontrolled charging. This share can be largely extended when using a smart charging strategy.

Mets et al. [19] analysed three different charging strategies for EV charging: an uncontrolled charging strategy, a smart charging strategy, reducing the local load variability, and a smart charging strategy where the vehicle can also provide power to the grid (vehicle-to-grid [20]). The smart charging strategies are based on an optimization model, optimizing each household's load individually. This model takes the household's load profile, the arrival time, the departure time and the state-of-charge of the car as input. Arrival time, departure time and state-of-charge are generated from random distributions. The results show that uncontrolled charging adds to the evening peek of electric power demand, while the smart charging strategy can avoid this. The smart charging strategy where the vehicle can also provide power to the grid can even reduce the evening peek of electrical demand. Keiser et al. [21] developed a charging strategy that takes the availability of renewable energy into account, charging the EV preferably when the share of renewable energy is high. This strategy allows the EVs to feed energy back to the grid, when its load is high. This charging strategy was applied in a simulation of commuters' cars. The results show that this charging strategy can reduce carbon dioxide emissions substantially.

The work presented here has some similarities with the work of Knapen et al. [16] as both approaches use a travel demand model to analyse the electric energy needed for charging of EVs. However in the current work, the EVs are explicitly represented within the model. Thus the restricted range of BEVs has influence in the mode choice and in the destination choice submodels. Moreover we consider a whole week instead of one day only. The other work, however, analyses different charging strategies while we consider only uncontrolled charging.

3. The mobiTopp model

mobiTopp [22] is a microscopic travel demand model, modelling every person, every household, and every car of the study area as an individual entity. Each person is represented as an agent. An agent is an entity that makes decisions autonomously, individually, and situation-dependent and interacts with other agents [23]. In mobiTopp, agents make decisions for destination choice and mode choice using discrete choice models. Interactions between agents occur indirectly, mediated through the availability of cars in the household context. When an agent uses a car of his household, the car is not available for other household members until the agent returns home. When the last available car is taken, the mode *car driver* will be not available for the remaining household members.

mobiTopp's simulation period is one week. The temporal resolution is one minute; the spatial resolution is based on zones. mobiTopp has been successfully applied to a study area with more than two million inhabitants and more than thousand zones [24].

mobiTopp consists of two parts, the long-term model and the short-term model. The long-term model comprises population synthesis, assignment of home zones and zones of workplace, as well as car ownership, and ownership of season ticket for public transport. The results of the long-term model are considered fixed for the following short-term model. In the short-term model the agents' behaviour (activities and trips) is simulated simultaneously and chronologically over the simulation period.

3.1. The long-term model

The first part of the long-term model is the population synthesis model. Households and persons are generated for each zone based on the total numbers of households and persons given on the level of zones and on the distributions of the households' and persons' attributes. The corresponding zone is assigned as home zone to the members of each household generated for this zone.

Population synthesis is based on aggregate statistical data on households and person for each zone and the data of a household travel survey. The population of each zone is generated by repeated random draws of households and the associated persons from the survey data. The distributions of households' and persons' attributes are taken into account by an appropriate weighting of a household's probability to be drawn.

The population synthesis model distinguishes twelve household types, which are the result of a Cartesian product between the attribute *number of persons per household* with four levels and