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Stochastic expansion planning of the electric-drive vehicle charging infrastructure

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ABSTRACT

This paper presents a stochastic optimisation model for the long-term expansion planning of the electric vehicle charging infrastructure based on the minimisation of the charging station overall costs subjected to the charging reliability and the requested Quality of Service. In fact, an earlier deterministic optimisation model is upgraded to a stochastic model due to the stochastic nature of the mobility behaviour of electric vehicle drivers, driving range, disposable charging time and the overall costs for different charging technology types. A probabilistic approach is used to generate numerous stochastic trajectories for electric vehicles followed by the newly proposed scenario reduction procedure that employs the new Trajectory Similarity Index to obtain representative trajectories of the stochastic mobility behaviour of electric vehicle drivers. The K-MEANS reduction procedure is also used to derive stochastic scenarios of the electric vehicle driving range, Quality of Service and overall (installation, maintenance, operation) costs, which are subsequently executed by applying an optimisation algorithm together with representative trajectories. The proposed model is verified on a test road network. Results show the optimal charging locations and their placement probability, which exposes their importance to charging infrastructure planners in terms of prioritisation and robust decision-making.

1. Introduction

In the near future, an increased deployment of electric-drive vehicles (EDVs) is envisioned due to the rapid development of battery charging technologies, lower transportation costs and environment conservation benefits, Ref. [1]. When considering the EDV driving range limitation, there is a growing transportation demand that calls for finding a solution for the optimal charging stations placement.

EDVs follow a certain spatial and temporal pattern of movement. For example, EDV drivers going to work on workdays would go from A to B at the precisely known time instances of the day, however, some deviation of the trajectory between A and B is to be expected in reality. In order to capture the stochastic nature of EDV drivers' mobility behaviour, some representative trajectories of various EDV fleets or individual EDVs have to be derived. Thus, the importance of a similarity analysis of trajectory data (e.g. EDVs' trajectories) is widely recognised, Ref. [2]. Raw EDV drivers' mobility data include a combination of all sequential spatial-temporal EDV movement-driving locations. However, they must henceforth be analysed, since the data alone does not give any information. This complicated task is also handled in other research areas, such as traffic estimation, movement behaviour, traffic pattern finding etc. In Ref. [3], the current tracking technologies are used to collect movement data from vehicles. By applying aggregation methods, the gathered data are processed to represent the results of aggregations and enable comprehensive exploration of the data which is hence used in the domain of city traffic management. Similarly, in Ref. [4], a clustering approach is proposed to extract meaningful clusters from large databases of spatial-temporal movement data by combining clustering and classification. An interesting approach is presented in Ref. [5], where an area of interest can be determined based on the movement behaviour and given a spatial-temporal movement data. In addition, in Ref. [6], an approach is presented to analyse the movement behaviour, gain additional insights into the data, and cope with the inherent geospatial and behavioural uncertainty. Alternatively, in Ref. [7], a method is shown which can be used to determine the vehicles' activity from recorded trajectory movement data, which

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can be used to find patterns for the designation of roads, maximum allowed speed and even the urban or rural structure along the roads. In addition, in Ref. [8], an interactive visual analytics system is demonstrated that can be used to effectively find both regular and abnormal traffic flow patterns.

So far, the literature has recognised a categorisation of discrete location models that can be used for the charging station (CS) placement. The coverage discrete location problem is slightly related to the discrete set-covering problem, as noted in Refs. [9,10], where by its very definition, the optimisation problem is to find the minimum number of facilities to cover the demand represented by the passing flows of users. One of the first optimisation models that considered the discrete set modelling is introduced in Ref. [11], where the presented model is used to find the optimal locations for allocating emergency vehicles. The constraints are set on covering the area by minimal traveling time or distance to demand points with equal costs in the objective function. Similarly, in Ref. [12], an integer programming method is used to optimise the location and the number of battery exchange stations. The optimisation model determines optimal locations and the number of stations, while considering batteries' maximum range, EDV trajectories, size of the EDV fleets, location capacity and costs. Moreover, in Ref. [13], a set covering concept is proposed for refuelling-station-location using a mixed-integer programming method based on the vehicle-routing logic. As shown in Ref. [14], the set covering location modelling can be used in combination with the existing traditional gas station network having the role of candidate locations, to determine both the charging locations, as well as the battery swap stations. The objective function in Ref. [14] minimises the total cost of deployment of charging stations by including the transformation cost of the gas station into a grade-noted charging station, as well as by using the constraints on the number of charging points that should cover the charging demand and the capacity of the CSs. Ref. [15] incorporates an optimisation model based on EDV travel patterns with a view of capturing public charging demand and selecting the locations of public charging stations to maximise the amount of vehicle-miles-travelled being electrified. In addition, the CS placement is combined with the provision of EDV ancillary services, as partly shown in Ref. [16], where EDVs are used to improve the power network reliability.

Recently, the optimisation models for CS placement are upgraded by a stochastic component, which reflects the uncertainty of the renewable generation integration into the power system and simultaneous generation/charging, electricity market pricing, EDV battery charge, EDV mobility, etc. For example, in Ref. [17], a practical solution to deal with the challenges of integrating the renewable generation and EDVs in the electric grid, considering the renewable generation source intermittency, energy usage inconsistency and the proper location of CSs to embed vehicle-to-grid functionality. However, the paper is more focused on siting and sizing of renewable generation in combination with the power network connection functionalities of on-board battery of the EDVs, rather than on finding the optimal location of the CSs considering the mobility behaviour, connection costs, charging service, etc. Another example where the EDVs can be used to mitigate the renewable generation intermittency through vehicle-to-grid technology is shown in Ref. [18]. Furthermore, in Ref. [19], a multi-year expansion planning method is shown for enabling distribution systems to support growing penetrations of EDVs. The proposed method considers the capacity reinforcement of distribution systems in conjunction with their operation decisions to minimise the total system costs for accommodating the EDVs. Multiple probabilistic scenarios are used to represent the uncertainties associated with renewable energy generation, charging behaviours and conventional load demand. Similarly, in Ref. [20], an uncertainty component into the optimisation model is incorporated, thus giving the stochastic characteristic to the load growth, electricity price and the EDV access to a charging station location. Furthermore, the uncertainty of the initial battery state-of-charge is also included. Ref. [21] addresses a novel framework for the economic operation of EDVs parking docks integrated with an on-site renewable energy generation. The stochastic approach includes the consideration of forecasting errors related to the variable solar power output and users' charging demand. However, in Refs. [20,21] significant entities are neglected such as the stochastic mobility behaviour and trajectories of movement, the disposable charging times of EDV drivers and Quality of Service (QoS) of the charging infrastructure (CI), as well as the types of charging technology and the overall (installation, maintenance, operation) costs of candidate locations.

Ref. [22], which reviewed recent trends in optimisation techniques for EDV CIs, highlights the fact that there is a need to apply stochastic approaches in the optimisation of the CS placement in order to reflect the uncertainty and randomness of the EDV trajectory movement. These facts, which were analysed in Ref. [22], are the main motivation to improve and upgrade the earlier deterministic model for CSs placement, (Ref. [23]), to a stochastic optimisation model, which would approximate and reflect the stochastic occurrences and EDV needs. Ref. [23] presents an optimisation model for CS placement in order to minimise the overall cost by satisfying the charging reliability and QoS expected by EDV owners/drivers. The model employs a charging reliability criterion to exceed the mobility limitation of EDVs and employs a charging service index that considers the disposable charging time duration of EDV users when going on longer trips.

The main contribution of this paper is to incorporate all uncertainties in reality concerning the EDV drivers' mobility behaviour, EDV's driving range, QoS and related costs into the deterministic optimisation procedure for CS placement presented earlier in Ref. [23]. Certainly, the CSs should be placed at the most often used mobility trajectory paths of EDVs, which is why all the uncertainties related to the deviation from the most frequently driven paths must be included in the optimisation placement procedure. Uncertain factors, such as the driving speed, acceleration, angle or road grade, vehicle mass, aerodynamic rolling and grade resistance can affect the driving range, which are considered in the stochastic scenario generation of the driving range presented in this paper, and thus its scenarios included in the concept for the charging reliability to enable unlimited EDV mobility. This paper also contributes towards the improvement of the deterministic QoS presented in Ref. [23] by upgrading it to a stochastic QoS, which undertakes the real-time stochastic occurrences that have an effect on the EDV drivers' disposable charging time, such as partial charging, traffic and road conditions, time delays due to charging constraints on the capacity of a CS in the event of excessive charging demand, etc. Moreover, this paper introduces the stochastic EDV mobility behaviour, which includes all deviations from the usual trajectory patterns of EDVs movement. It is convincing that the improvement arising from a shift from a deterministic to stochastic module may provide beneficial gains to CI planners, such as CSs importance prioritisation based on the placement probability, scenarios' occurrence probabilities, scenario overall CS placement costs, number of CSs and the optimal CS layout.

The remaining part of the paper is organised as follows: the optimisation procedure is presented in Section 2. Section 3 presents the stochastic optimisation model for the CS placement, while Section 4 presents numerical results. The conclusion is provided in Section 5.