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A novel model of electric vehicle fleet aggregate battery for energy planning studies

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A R T I C L E I N F O

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The paper proposes an aggregate battery modelling approach for an (electric vehicle) EV fleet, which is aimed for energy planning studies of EV-grid integration. The proposed model improves on the existing, basic aggregate battery modelling approach by accounting for a variable structure of the aggregate battery systems, variable (state of charge) SoC constraints and specific input time-distributions such as those of average SoC at destination and number of arriving and departing vehicles. In the particular case-study presented, the input distributions are reconstructed from a large set of delivery vehicle fleet driving missions, including simulation of individual vehicle behaviours over the full set of driving cycles. The charging power input is obtained by using a dynamic programming-based optimisation algorithm aimed at finding a global optimum in terms of minimised electricity cost. For the purpose of proposed model validation and its comparison with the basic model, a distributed fleet vehicle model is developed, where a specific algorithm is proposed for distributing the optimised charging power input to charging inputs of individual vehicles.

1. Introduction

EV Electric vehicles are seen as a good alternative to conventional vehicles in terms of reduced energy consumption and emissions of air pollutants. Various traffic studies have shown that vehicles rest at parking sites for most of the time (for instance, 96% of time according to the 1995 US DOT Nationwide Personal Transportation Survey cited in Ref. [1]). Thus, EVs with their batteries represent an ample spatially-distributed energy storage convenient for providing load levelling and various ancillary services (e.g. voltage/frequency regulation and spinning reserves) to the electric power grid. The ancillary services are enabled by the EVs bidirectional energy flow possibility also known as (vehicle-to-grid) V2G [1]. From the standpoint of grid, the basic aspects of EV proliferation relate to: (i) available power and energy capacity of EV fleet storage [2], (ii) economic potential of EV-grid integration when considering different electricity markets [3], and (iii) EV impact on the grid load [4]. Furthermore, well-scheduled EV charging provides a significant potential for stronger penetration of renewable energy sources characterised by a high intermittency [5]. In order to evaluate benefits of replacing conventional vehicles with electric ones from the standpoint of EV-grid integration, the crucial step is to develop accurate and relatively simple models of EV fleets, which would be used in energy planning studies [5].

There are two basic approaches of EV fleet modelling: (i) agent-based approach, where each vehicle/battery within the fleet is modelled separately (see Ref. [6] for ancillary services-related analyses [7], for fast charging vs. smart charging analyses and [8] where this modelling approach is used as a benchmark to validate aggregate battery models); and (ii) aggregate battery modelling approach, where the EV fleet is represented by a single, “lumped” battery (see applications related to e.g. Ref. [9] a grid power fluctuation level minimization [10], two-level on-line charging control, and [11] power losses- and charging cost-related optimisations). The aggregate battery modelling approach would be a natural candidate for application in complex energy planning studies [5]. In addition, that approach is often used in hierarchical EV fleet charging management, which consists of two levels [10]: (i) optimisation of aggregate-level charging power profile (where the aggregate battery model is used), and (ii) distribution of the optimised aggregate power profile over individual vehicles. This is particularly convenient in cases when an aggregator of EVs is present as an interface to power system and electricity markets [6].

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In the basic aggregate battery modelling approach proposed in Ref. [5], the only model input distribution required is normalized transport energy demand time distribution, which is related to the number of on-road vehicles. The main drawback of this modelling approach is assumption that the aggregate battery total capacity is constant and, thus, available at all times. However, this is not the case in real scenarios where a portion of vehicles will be driving, and thus not available for charging. In the more recent reference [12], aggregate battery modelling is used for calculation of optimal investments related to distributed energy resources. In that study, the EV fleet is modelled by using four aggregate batteries submodels, where each of them represents a characteristic EV state, e.g. parked/connected at home, driving to micro-grid, driving to home, and parked/connected at micro-grid. However, the use of four aggregate battery submodels imposes a burden on model parameterisation (i.e. determination of model input time-distributions), and may complicate calculation of the (state of charge) SoC of aggregate batteries during transitions through different EV states.

This paper deals with aggregate battery modelling for energy planning as the main target application. When compared to the publication [5], dealing with the same topic, the main contribution is in proposing a more realistic (although somewhat more complex) novel aggregate battery model. As in Ref. [5], the model is based on a single, aggregate battery SoC as a state variable, but to account for the disconnected vehicle storage it has a variable structure reflected through a set of specific input time-distributions, such as the average SoC of vehicles arrived at the charging destination and the number of departing/arriving vehicles. On the other hand, the proposed model is simpler in terms of structure and the required input distributions when compared to multi-aggregate battery model from Ref. [12]. Also, the average SoC value of departing EVs is fixed to one, thus facilitating simulation-based calculation of transport demand-related input distributions. This is not the case with the approach from Ref. [12], where the SoC of EVs changing the state is set to be average of all EVs within the same state.

In the presented case study, the required model input time-distributions are determined by using previously recorded GPS experimental data of an isolated delivery vehicle fleet [13]. The transport energy demand-related distributions are calculated by carrying out simulations of EV model over the full set of driving cycles for the target vehicle fleet. Finally, the proposed aggregate battery model is validated and compared with the basic model from Ref. [5]. The charging power input for the two aggregate battery models is obtained by using a (dynamic programming) DP-based optimisation proposed in the accompanying publication [14]. An algorithm of distributing the aggregate charging power to individual vehicles is proposed and used for the purpose of overall model assessment. The distributed charging management results, obtained by applying the DP algorithm to the agent-based EV fleet model [8], are used as an additional model assessment benchmark.

In summary, the main contributions of the paper are: (i) proposing a novel aggregate battery model for EV fleets, (ii) proposing a computationally efficient distributed charging algorithm based on aggregate-level charging optimisation results, and (iii) conducting a detailed assessment of different aggregate battery models and related charging methods including recommendations for their application.

The remaining part of the paper is organized as follows. The basic and novel aggregate battery modelling approaches are presented in Section 2. In Section 3, the required input time-distributions are calculated for both models and the case of a delivery vehicle fleet. Different optimisation- and rule-based battery charging methods are presented in Section 4. Section 5 includes the assessment results for the two aggregate models based on their comparison with the more accurate agent-based EV fleet model. Concluding remarks are given in Section 6.

2. Aggregate battery models

The aggregate battery models presented below are energy-based with the maximum energy capacity and the charging and discharging efficiencies denoted as $E_{max,agg}$, and η_{ch} and η_{dch}, respectively.

2.1. Basic aggregate battery model

The basic aggregate battery model is adopted from Ref. [5] and defined by the following discrete-time state equation:

$$\begin{aligned} SoC_{agg}(k+1) = & SoC_{agg}(k) + \eta_{ch}\frac{\left(P_{c,agg}(k) + P_{reg,agg}(k)\right)\Delta T}{E_{max,agg}} \\ & - \frac{P_{dem,agg}(k)\Delta T}{\eta_{dch}E_{max,agg}}, \quad k = 0, 1, ..., N_t - 1 \end{aligned} \tag{1}$$

where the aggregate state-of-charge (SoC_{agg}) at the next discrete time step $k+1$ is dependent on the values of $SoC_{agg} = E_{agg}/E_{\max,agg}$, charging energy $(P_{c,agg} + P_{reg,agg})\Delta T$, and discharging energy $P_{dem,agg}\Delta T$ in the current discrete time step k, with $\Delta T = t_{k+1} - t_k$ and N_t denoting the time step and the total number of time steps, respectively. The quantities $E_{max,agg}$ and E_{agg} represent the maximum energy capacity and the current energy level of the aggregate battery. The aggregate battery model (1) somewhat differs from the one defined in Ref. [5], as it separates the regenerative braking power source $P_{reg,agg}$ from the road power demand $P_{dem,agg}$. Apart from being more consistent (but, also more demanding in terms of required time-distributions), this modification makes the model compatible with the novel model proposed below in terms of the overall charging energy consumption.

Because of the limited charging power of individual vehicles/batteries ($P_{c\max,ind}$), the limit of aggregate charging power $P_{c,agg}$ is dependent on the number of vehicles connected to the grid:

$$P_{c,agg}(k) \le n_{dc}(k)P_{cmax,ind}, \quad k = 0, 1, ..., N_t - 1 \tag{2}$$

Also, the aggregate SoC variable needs to satisfy the upper and lower constraints:

$$0 \le SoC_{agg,min} \le SoC_{agg}(k) \le SoC_{agg,max} \le 1, \quad k = 0, 1, ..., N_t - 1 \tag{3}$$

The above model requires the following input time-distributions:

1) Transport power demand distribution $P_{dem,agg}(k)$,
2) Transport regenerative braking power distribution $P_{reg,agg}(k)$,
3) Distribution of number of vehicles connected to the grid, $n_{dc}(k)$.

This simple modelling approach, which requires the basic transport-related time-distributions, is convenient in cases where no details on vehicles arrivals, departures, and driving cycles are known. Namely, the total transport energy consumption over a considered period of time is usually known (or can be estimated), and using that information and the known vehicle on-road activity distribution the energy/power time distribution can be estimated [5]. When inverted, the vehicle on-road activity also gives the distribution of vehicles available for charging, $n_{dc}(k)$.

The simplicity of basic model is paid for by a certain inaccuracy due to the unrealistic assumption that the full capacity of aggregate battery is available at all times. In reality, some vehicles get disconnected from the grid thus abruptly reducing the aggregate battery charge, and at the same time other vehicles get connected to the grid contributing to the increase of the aggregate battery