A Charging Scheduling System for Electric Vehicles using Vehicle-to-Grid

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***Abstract*—With the rise of sustainable energy sources, such as wind power, the energy production, and thus the energy price, fluctuates. Meanwhile, we are witnessing an increasing amount of electric vehicles, which soon will represent a substantial fraction of the electricity demand. Under this setting, the so-called *vehicle-to-grid* technology, which enables electric vehicles to sell electricity back to the power grid, appears to be an effective mean to reduce the charging costs for electric vehicles. We demonstrate a system that makes optimal scheduling for electric vehicle fleet owners using vehicle-to-grid. The principle of the scheduling is to charge electric vehicles when electricity is cheap and sell electricity back to the power grid when it is expensive, while making sure that the electric vehicles are sufficiently charged when they need to be used, e.g., 8 am in the morning. The system is integrated as part of aSTEP, a spatio-temporal data analytics platform developed at Aalborg University. In collaboration with a transportation-as-a-service company in Denmark, the system is tested through a use case that involves an electric vehicle fleet.**

I. Introduction

The European Union is very ambitious on making a shift in electricity generation from fossil fuels to sustainable energy resources such as solar and wind power. For example, in Denmark, wind power now contributes to 43% of the country's total electricity consumption and the share of electricity from wind is expected to increase to 50% by 2020 and to 84% by 2035. However, wind power depends heavily on weather and thus the electricity production may fluctuate significantly. This in turn affects the electricity prices. Meanwhile, we are witnessing more and more electric vehicles and many European countries have proposed bans on the sale of petrol and diesel cars to force the switch to electric vehicles. For example, Denmark has proposed such a ban from 2030. It is now a safe bet that electric vehicles will soon represent a substantial fraction of the electricity demand.

Under this context, the so-called *vehicle-to-grid*, which enables electric vehicles to sell electricity back to the power grid, appears to be an effective mean to reduce the charging costs for electric vehicles. This is of special interest to large electric vehicle fleet owners. We demonstrate a system that provides optimal charging schedules for electric vehicles. In collaboration with a Danish transportation-as-a-service company, we consider charging schedules for a fleet of electric vehicles. Specifically, each electric vehicle has a *booking*, which records information on when the electric vehicle will be used next time and on how much power should be charged when the electric vehicle needs to be used. For instance, if an electric vehicle is booked by a person who will make a short trip, the electric vehicle may only be charged to 50%, while a long trip may require a full charge. Based on the bookings from all vehicles in the fleet, the system makes an optimal charging plan based on the electric price such that the total charging cost is minimized and each vehicle is charged sufficiently according to its booking. We test the system using 9-month bookings from the company's electric vehicle fleet.

II. System Overview

Figure 1 gives an overview of the system. The *Input* component prepares two inputs: electricity price and a list of electric vehicle bookings. In Denmark, the electricity price in the coming 24 hours is publicly available. We use a parser to obtain such information from webpages. If the scheduling needs the electricity price that is more than the coming 24 hours, we employ an electricity price prediction function to predict future electricity price. For instance, a wide variety of time series forecasting algorithms (e.g., [1], [2]) are available to enable such prediction. This system is built based on aSTEP (aau's Spatio-TEmporal data analytics Platform where aau stands for Aalborg University) [3]. Since aSTEP already has an electricty price prediction functionality, we just call this function through an API. Next, we either use a parser to obtain booking information from a file, e.g., provided by companies, or use a booking generator to generate synthetic bookings.

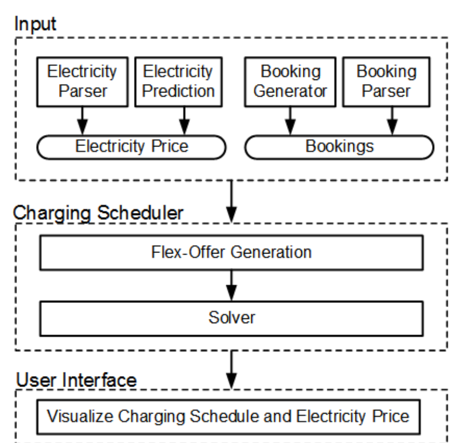

Figure 1. System Overview

The *Charging Scheduler* component first generates a *flex-offer* [4] for each electric vehicle based on its two adjacent bookings. A flex-offer is a tuple in the form of (*EST*, *LET*,

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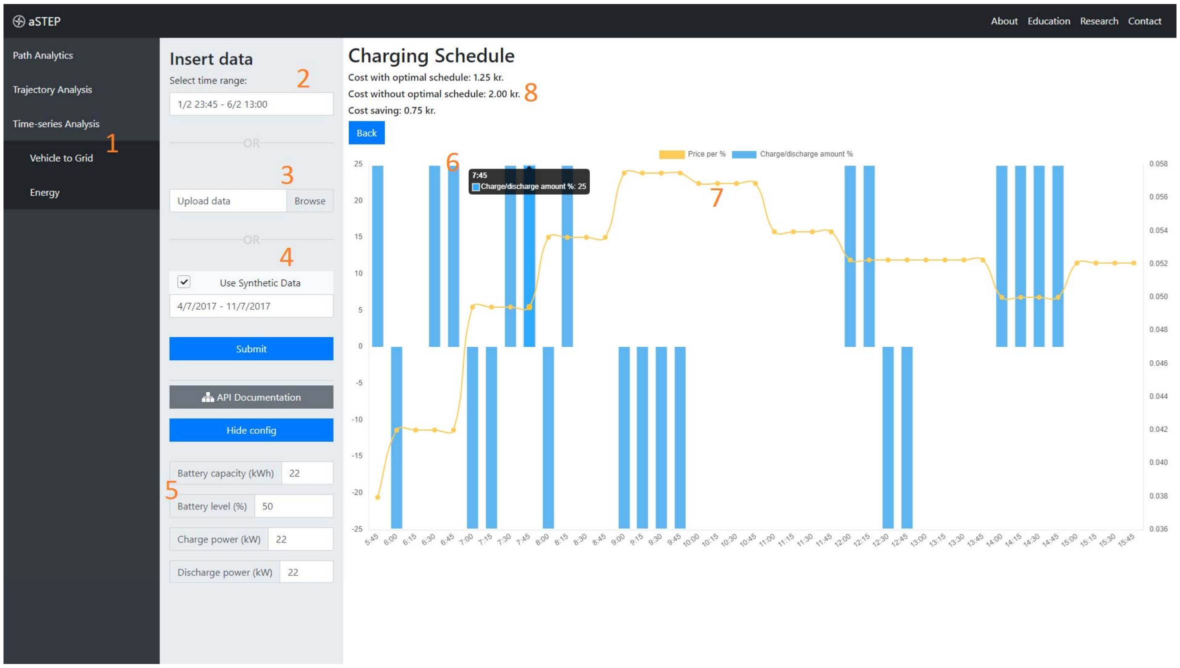

Figure 2. Demonstration Outline

LST, *CS*), where the earliest start time for charging (*EST*) is often the end time of the previous booking of the vehicle; the latest end time for charging (*LET*) is the start time of the current booking of the vehicle; the latest start time for charging (*LST*) guarantees the vehicle to be sufficiently charged before the *LET* if we keep charging. Thus, the time flexibility of the charging for the vehicle is in interval [*EST*, *LST*]. *CS* is a charging schedule which is formalized as a linear optimization problem to minimize $\sum_{i=EST}^{LST} e_i \times p_i$, where e_i is the amount of electricity needs to be charged from the grid or to be sent back to the grid at time i and p_i is the electricity price at time i. Meanwhile, we add a number of constraints to the linear optimization such as we cannot discharge/sell more than the vehicle is currently charged, and the electric vehicle should be sufficient charged at *LET* for users to use, etc.

Next, a linear programming *solver* solves the optimization problem *CS*, which gives a list of values $\langle e_1, e_2, \ldots, e_k \rangle$, where a positive/negative e_i indicates that we should buy/sell electricity and charge/discharge the vehicle e_i amount of electricty. The system uses CBC (Coin-or Branch and Cut), an open-source solver, as the default solver.

As future work, it is of interest to integrate various routing [5], [6], [7] into the system which considers time-varying uncertain traffic [8], [9], [10] to navigate electric vehicles.

Finally, the *User Interface* component visualizes the charging schedule along with electricity prices.

III. Demonstration Outline

We proceed to describe how demonstration participants can interact with the system using Figure 2. The system is built on top of aSTEP [3], which is publicly available at https://astep.cs.aau.dk/. To try the system, click "Time-series Analysis" and then "Vehicle to Grid" (Label 1). We offer three different ways to create charging schedules. First, manually choose an *EST* and a *LST* for charging (label 2). Second, upload a CSV-file that consists of bookings (label 3). Third, use the booking generator to generate bookings (label 4). We also offer participants opportunities to change the configurations of the batteries of different electric vehicles (label 5). The main interface shows the charging schedule with bars (label 6) and the electricity price with a curve (label 7). We summarize the charging costs with(out) vehicle-to-grid, making the potential charging cost saving clear (lable 8).

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