A Data-Driven Simulator for Flexible Electric Vehicle Charging: Framework, Model, and Algorithm

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***Abstract*— This paper presents a data-driven simulator under development for electric vehicle charging that emulates a high-fidelity digital environment for operations management of charging stations. We briefly introduce the key modules that frame the simulator, including data inputs, models, and algorithms, and the general goals of managing electric vehicle charging. We further highlight its potential benefits from a broader urban perspective, discussing the external connections with traffic patterns, station siting and sizing, and distribution grid upgrade. Finally, we demonstrate the development of the simulator through the design of a degradation-aware reinforcement learning algorithm that can implement vehicle-to-grid while taking into account electric vehicle battery health.**

I. Introduction

Electrification of transportation systems can effectively reduce fossil fuel over-reliance and greenhouse gas emissions, provided that electricity is generated from low-carbon renewable energy resources. The market share of electric vehicles (EV) in China is soaring, driven by carbon-neutral policies, along with the large-scale deployment of charging infrastructure and advances in battery technologies. Despite the promising EV proliferation, the daily uses of charging facilities are still limited to basic functions such as energy delivery, measurement, and monitoring, letting go of the huge charging flexibility that EVs can offer while parking.

However, harnessing such flexibility faces several key bottlenecks. First, there is a variety of sources of uncertainty in real-time decision making for charging. Second, a well-designed business model that incentivizes flexible charging is still missing. Third, it is difficult to visualize the potential connections with externalities, such as traffic patterns, station siting and sizing, and distribution grid upgrade.

To address these challenges in real-world applications, we developed a data-driven simulator framework that builds upon [1] but extends in several ways. The purpose of this abstract is to provide a brief overview of our simulator. First, multi-source data are collected as input to enrich the potential functions of flexible EV charging. Second, battery models of different levels of fidelity are equipped that allow the design, analysis and testing of novel charging algorithms. Third, interfaces with externalities are available to study and enhance the urban role of flexible EV charging. We provide slightly more details on these extensions in Section II, and demonstrate one particular example of algorithm design in Section III. In general, the simulator aims to (i) improve operations management of EV charging stations as a digital twin; (ii) provide a high-fidelity digital environment for research simulation purposes.

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II. Simulator

This section gives an overview of the key modules of our simulator; see Fig. 1. The libraries of data, models and algorithms can be readily expanded as needed.

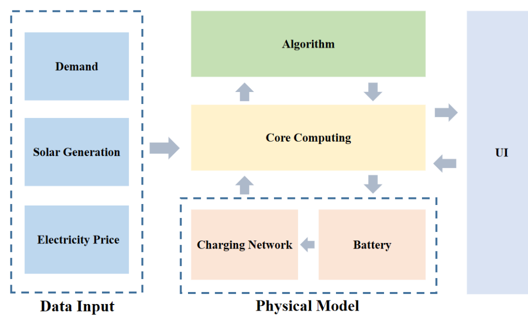

Fig. 1. Simulator Framework

A. Data

- **Demand**: The set of demand data is denoted as $\mathscr{N}$, which we will also abuse to denote the set of EVs serviced. A charging request $i \in \mathbb{N}$ takes the form of a tuple $x_i := (a_i, d_i, e_i) \in \mathbb{R}^3$, where a_i denotes the arrival time, d_i denotes the duration, and e_i denotes the total energy to be delivered in kWh. As an example, we import public real-world data from [2] and use the Gaussian Mixture Model (GMM) to approximate the underlying probability distribution of the data set; see Fig. 2. In this way, synthetic data of charging requests can be generated from this statistical model to overcome any shortfall of real-world data.
- **Solar Generation & Electricity Price**: Solar generation and (time-varying) electricity prices are examples of inputs that may drive flexible EV charging for purposes of low carbon footprints and economic incentives, respectively. We currently use data from external sources, e.g., the Australian solar PV station dataset with 1-minute granularity, and the time-of-use electricity prices from the North China Power Grid. After extensive case studies with the daily solar data, we observe that it can be well represented using a one-dimensional mixed Gaussian distribution plus white noise. Besides,

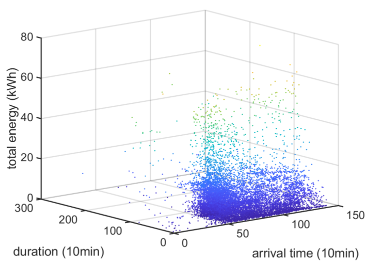

Fig. 2. Scatter Plot of Demand Data

electricity price profiles (prices and times) can also be tailored for test case studies.

B. Model and Algorithm

Models are intended for the characterization of physical battery charging processes and operational constraints, such as maximum allowable charging rates, capacity, etc. We currently maintain approximate models of Level-2 charging networks on the Caltech and JPL campuses. Given a particular model, charging algorithms can be designed to pursue various goals. We retain some standard online algorithms, e.g., First-Come First-Served (FCFS), Earliest Deadline First (EDF), and Least-Laxity-First (LLF), but also allow customizing algorithm designs, leading to an MPC-based peek-shaving algorithm and a battery degradation-aware charging algorithm (in Section III). The performance of different algorithms can be visualized for comparison.

C. Connection with Externalities

The current version of the simulator mainly focuses on the operations management of EV charging stations. However, we recognize the important role that such a simulator may play in an urban perspective. Our simulator is expected to interact with many externalities that will have a broader socio-economic impact, e.g., traffic patterns, station siting and sizing, distribution grid upgrade. We plan to pursue collaborations with relevant research teams on these topics.

Traffic Patterns & Station Siting and Sizing: Through analyzing traffic patterns that are directly related to EV charging demand, we can have a better sense of what the demand profile looks like. This extra knowledge can assist the charging algorithms in improving the service quality and lowering operational costs. The siting and sizing of EV charging stations in turn affects traffic patterns and forms a closed loop. Addressing such problems contributes to efficient access to charging facilities and, to some extent, relieves traffic/station congestion.

Distribution Grid Upgrade: One significant benefit of flexible EV charging is the shiftable charging demand that allows a lowered peak. This immediately implies reduced transformer capacity and line rating, and consequently delayed distribution grid upgrade. Additionally, the well managed EV charging and the forthcoming vehicle-to-grid (V2G) technologies can help accommodate the uncertainty and variability of renewables, which enhances the stability and reliability of urban power distribution systems.

III. Example: Battery Degradation Aware Charging Algorithm

V2G is a promising battery technology that plays a key role in reducing EV station operational costs, integrating renewables, and relieving overloading on the grid. However, it unavoidably causes battery degradation that is often difficult to quantify. Therefore, we propose a battery degradation aware charging algorithm based on the Rainflow-counting algorithm that allows us to trade the benefits of V2G off against the potential cost of battery degradation in real time.

The Rainflow algorithm is widely used to count battery charge-discharge cycles, as shown in Fig. 3, the depth of which is the dominant factor in degradation. However, here are two major challenges: (i) the Rainflow algorithm is easy to describe but there is no analytical form of its input-output relations; (ii) the Rainflow algorithm works on a full State-of-Charge (SoC) profile that spans a whole time horizon, making it inapplicable to online implementation.

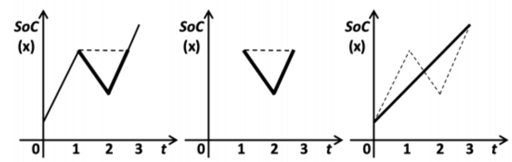

Fig. 3. Rainflow Cycle Counting: Extraction of Full Cycles

Our Solution: First, we adopt a piecewise linear cost model with increasing marginal cost per unit cycle depth. This is a discretized version of the Rainflow cost function. In this way, the energy in the battery, up to its capacity, is also discretized and each segment has its cost if charged or discharged. We show that if we always charge and discharge the cheapest energy segment in the battery, the accumulative cost equals the (discretized) Rainflow cost.

Second, based on the above property, we formulate the charging scheduling problem on a Markov Decision Process (MDP) with proper definition of state/action/reward spaces. The state includes not only the EV SOC but also the exact available energy segments. Actions are charging decisions and rewards include the corresponding costs of charging/discharging energy segments. In this way, degradation information is decoupled across time and embedded in action feedback.

Last, note that a well-defined MDP optimization problem can be solved through sequential interaction with the environment, using any standard reinforcement learning algorithms. Therefore, an optimal online charging strategy will become available whenever it is learnt (almost surely).

References

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