Application of Battery Digital Twin to Charge Planning Problem for a Fleet of Electric Vehicles

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ABSTRACT: The transition towards vehicle electrification presents various challenges due to uncertainties in charging behavior and battery aging. This study proposes a strategy to generate a charging schedule for a Battery Electric Vehicles (BEVs) fleet to reduce the Total Cost of Operation (TCO). Battery Digital Twins (DTs) are used to improve the standard scheduling strategy, which provides a realistic assessment of battery aging, grid load, and charging time. The DTs are adaptive, have fast prediction and have low training costs. The method is virtually tested to show the improvements in scheduling while using the DTs.

KEY WORDS: Battery Digital Twin, Battery Aging, Battery Charging Profile, Charge Planning

1. INTRODUCTION

Greenhouse Gas Emission (GGE) are known to cause a significant negative impact on the environment and are one of the major contributors to climate change (1) due to the prevalent usage of Internal Combustion Engine (ICE) in most modern vehicles (2). This has led to the enforcement of zero-emission zones in cities where only emission-free vehicles are allowed (3). In recent years, BEV have been identified as a potential mitigation technology for this problem, as they have lower well-to-wheel GGE emissions than ICEs (4). However, the complete adoption of BEVs still faces several challenges due to uncertainties in modeling charging behavior and battery aging. These challenges are particularly relevant in commercial applications, such as delivery companies and bus operators, which require large fleets of BEVs that could benefit from optimal scheduling for cost reduction.

This work presents a Charge Planning Tool (CPT) that can be used for scheduling the charging for a large fleet of BEVs (5). This tool is improved by using adaptive DTs which can make realistic predictions on battery parameters and self-calibrate during the battery lifetime. Finally, a comparison of charging schedules with and without the DTs is shown.

2. CHARGE PLANNING TOOL

The CPT is designed to manage the smart charging of large-scale Electric Vehicle (EV) fleets, particularly heavy-duty commercial trucks and buses, at a single depot or similar facility. The objective is to create an optimal charging schedule that minimizes costs and maximizes operational efficiency, considering limitations such as limited chargers and grid capacity. The CPT is suitable for scenarios where vehicles, following a logistics schedule, return to a central hub for charging, excluding public charging during (round) trips. The logistics planning determines the constraints for the charge schedule with specific arrival (ETA) and departure times (ETD), and the required energy for the scheduled trips. Reliable scheduling requires accurate energy consumption estimation, preventing operational disruption due to underestimation, and saving time by avoiding unnecessary full charges. The CPT generates a feasible charge schedule and allocates the charger to the vehicles at a specified time with a certain charge profile. The schedule can be optimized for operational costs such as electricity price for a variable tariff, or battery aging by controlling the charging profile and moment of charging.

1.1. Problem statement

Consider a fleet of N non-homogeneous vehicles and a set of J non-homogeneous chargers, given that $N > J$, and each vehicle may drive multiple trips per day. The fleet planning software generates a set of K Charge Requests (CR), where k^{th} charge request consists of the arrival (t_k^{ETA}) and departure time (t_k^{ETD}), the expected SoC upon arrival z_k^{ETA} and a minimum SoC that is at least required for the next trip z_k^{req} for the corresponding vehicle. The problem is subject to constraints relating to a maximum grid capacity P^{grid}, maximum charging power P_j^{max} for each charger x_j and a compatibility constraint between chargers and vehicles.

The CPT maps the set of *CR's* to a set of Charge Assignments (*CA*), which contain an allocation to a specific charger x_j, a start t_k^{start} and end time t_k^{end} for charging, and a charging power profile P_k, such that the schedule is feasible – constraints are satisfied – in a heuristic fashion. Subsequently, the CPT optimizes the operational cost and efficiency of the schedule on factors such as electricity price, battery lifetime, peak shaving, and schedule flexibility (i.e., implementing slack time to account for unpredicted deviations).

2.2. Fast initialization algorithm

Evaluating the feasibility of the logistics plan on the charger allocation problem requires a computationally efficient solution. The proposed heuristic method is inspired by Multi-Processor Scheduling Problems (MSP), where the similarity is drawn between available tasks versus charge requests, processors versus chargers, and processing speed versus charging power. The charge requests are sorted and given a priority according to their laxity, deadline, arrival time, or other user-defined objectives, and the chargers are sorted on power levels, either in ascending or descending order. The algorithm then loops through each one of the charge requests, trying to assign them to chargers, according to the previously decided order of priority. In case the assignment is feasible, it will be saved in the *CA*. Otherwise, a different charge power or charger is selected. In case the assignment fails, the priority and order need to be updated, and a new attempt to generate a schedule is started.

This algorithm can easily run in parallel to create additional schedules, by changing the priority rules and selected charge power order and running several instances in parallel.

2.3. Genetic Algorithm for CPT

The Genetic Algorithm is an improvement type algorithm; it requires a set of feasible initial schedules, that are constructed with the heuristics described in the previous section and tries to improve upon it. In an iterative manner, the population of feasible schedules evolves by selecting individuals (schedules) to create offspring by either cross-over or mutation. Only offspring with better fitness than their parents are accepted for the new generation.

The complexity of the charge scheduling problem requires an algorithm that is tailored to the needs. Due to the large scale and complexity of the optimization problem, the randomness in typical crossover and mutation operators will easily lead to either infeasible results or too little improvement per generation. Hence, a sequential mutation method and a partial crossover method are adopted. To improve computational efficiency, these operations are processed in parallel for each generation. The extent of function evaluations involved in mutation and crossover is substantial enough to offset the parallelization overhead.

3. DIGITAL TWIN

A DT is a virtual model that has a bi-directional exchange of data between physical and virtual systems. This ensures a good state of synchronization, while also guaranteeing high accuracy, real-time performance, and scalability for the prediction algorithms. Further, it can be used for process optimization, observation, prediction and maintenance. For a DT of a battery in an EV, the DT uses sensor data to calibrate itself while the Battery Management System (BMS) receives feedback to adjust its operation and control.

Fig. 1 shows the architecture of a battery DT in a charge planning use-case. The fleet operator can make a prediction request and use the output to generate a charging schedule for a fleet of EV. During the operation, the DT can update its parameters using calibration data from the EV. In this work two DTs are developed: Battery Aging and Charge Profile Prediction.

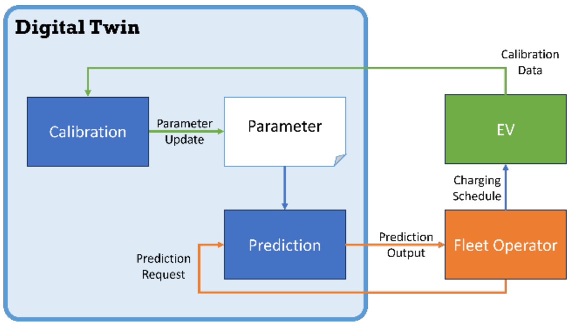

Fig. 1 Architecture of a battery DT for a charge planning use-case.

3.1. Battery Aging Prediction

Batteries degrade over time, diminishing their ability to store and deliver energy. This directly impacts the driving range, performance, and reliability of electric vehicles. The battery aging prediction DT enables prediction of the capacity degradation of the battery when subjected to varying operating conditions that include temperature, State-of-Charge (SoC), Depth-of-Discharge (DoD) and C-rates. These input conditions can be extracted from the realistic power profile from the charge profile prediction DT thereby increasing the accuracy of battery aging prediction. This predictive capability is crucial for optimizing battery usage, enhancing charging strategies, and extending the overall lifespan of the battery. Fleet operators can use accurate battery aging for long-term Total Cost of Ownership (TCO) optimization.

At the core of the battery aging prediction DT is a semi-empirical model of the battery capacity. The model distinguishes between calendar aging and cyclic aging. Eqn 1 and 2 represent the capacity loss due to calendar aging and cyclic aging respectively.

$$QL_{\mathrm{cal}} = (a_1 \cdot z - a_2) \cdot 10^6 \cdot \exp\left(\frac{-a_3}{T}\right) \cdot t^x \qquad (1)$$

$$QL_{\mathrm{cyc}} = (b_1(z - b_2)^2 + b_3 \cdot \phi z + b_4) \cdot exp - \left(\frac{b_5 \cdot C_{rate,ch} + b_6 \cdot C_{rate,dch} + b_7}{T}\right) \cdot Q^y \qquad (2)$$

The total capacity loss is the sum of the calendar and cyclic capacity loss. Considering the capacity losses of the battery due to operating conditions, the total capacity is given by

$$QL = \alpha \cdot t^x + \beta \cdot Q^y \qquad (3)$$

Initial identification of the parameters of the model is performed using data from laboratory aging experiments on the battery. Once the battery aging prediction DT is live, the parameters are re-calibrated periodically using the battery data obtained from the vehicle in the fleet.

The capacity equation as described in Eqn 3, evaluates the capacity of the battery with respect to the battery's capacity at beginning-of-life. However, applying the battery aging prediction to the charge planning problem requires predicting the capacity degradation of the battery during a charging session from the battery's current capacity. Hence, the differential form of Eqn 3 is applied.

3.2. Charge Profile Prediction

The objective of a charge profile prediction DT is to predict the electrical power during a charging session accurately. The input for the DT is the start and end SoC, reference charging power and ambient temperature. The output is the electrical charging power as a function of time. The primary advantage of this method is the generation of a realistic power profile as opposed to the standard profile commonly used by fleet operators (6).

Fig. 2 shows the standard and realistic charging power profile with the same energy throughput during the charging session. It is seen that a realistic profile can improve the assessment of the charge time and grid load while making the charge scheduling more robust.

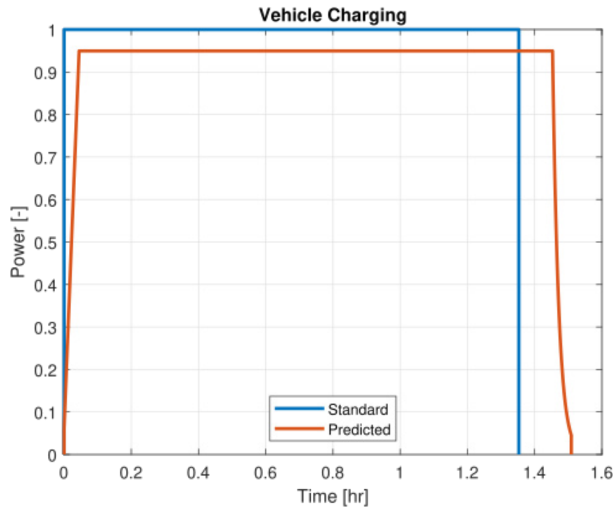

Fig. 2 Charge profile for a charging session.

The predicted charging profile is divided into three segments: ramp, constant and decay. Each segment is parameterized and the parameters are identified during the operation of the vehicle at charging conditions: Start SoC (z_s), End SoC (z_e), Reference Charging Power (P_c) and Ambient temperature (T_a). The real charge profile can be predicted in a corresponding application for these conditions (6).

4. RESULTS AND DISCUSSION

The charge scheduling technique is applied to a scenario with a fleet of 5 EVs and 2 chargers. Each vehicle is assigned 3 trips with rest periods in between (shown in blue) where the vehicle can be charged. The vehicle undergoes opportunity charging during the day and overnight charging at the end of the day when its stationary at the charging hub. The electricity prices and the total power available on the grid for charging are considered variable.

The Greedy scheduling method is used as a baseline where the vehicles are charged on a first come first serve basis to the maximum possible SoC. This technique is commonly employed by fleet operators and is shown in Fig. 3. When the DTs are not used, the fleet can be charged by using only one charger, i.e., Charger 1 for all the change requests.

However, the use of DTs enforces a longer charge time and schedules the fleet differently as shown in Fig. 4. The increase in SoC is also non-linear with slower rates of increase towards the beginning and end of charging. In this case, a second Charger 2 is also used as Charger 1 is unable to finish charging in time to move to the next charge request. Hence, using the DTs ensures correct infrastructure planning and improves the robustness of the charge schedule.

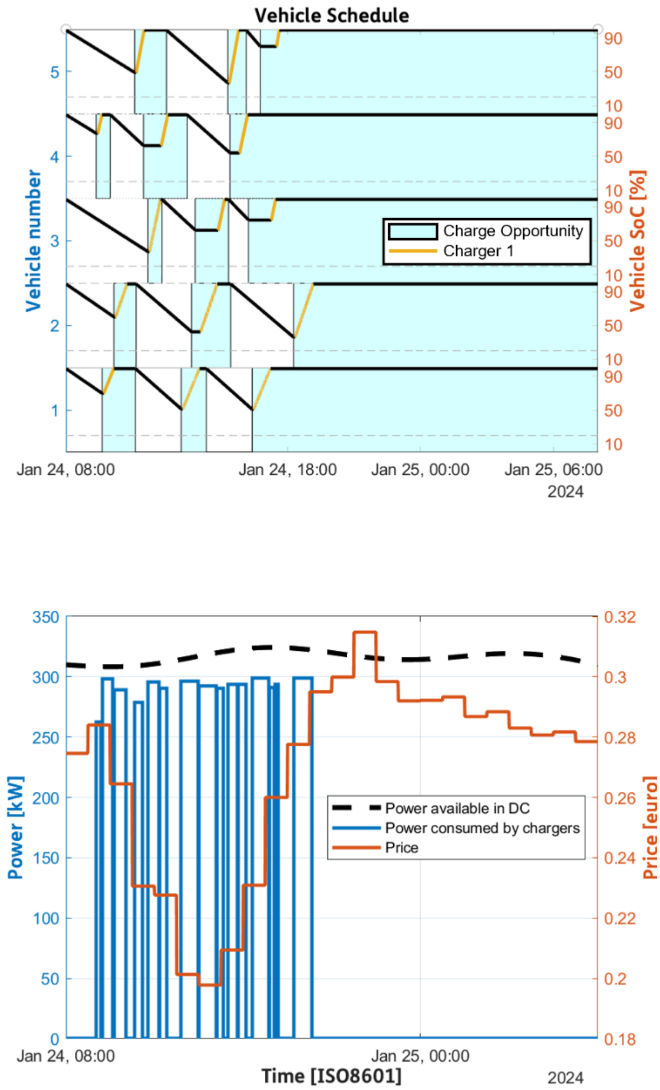

Fig. 3 Charge scheduling without battery DTs.

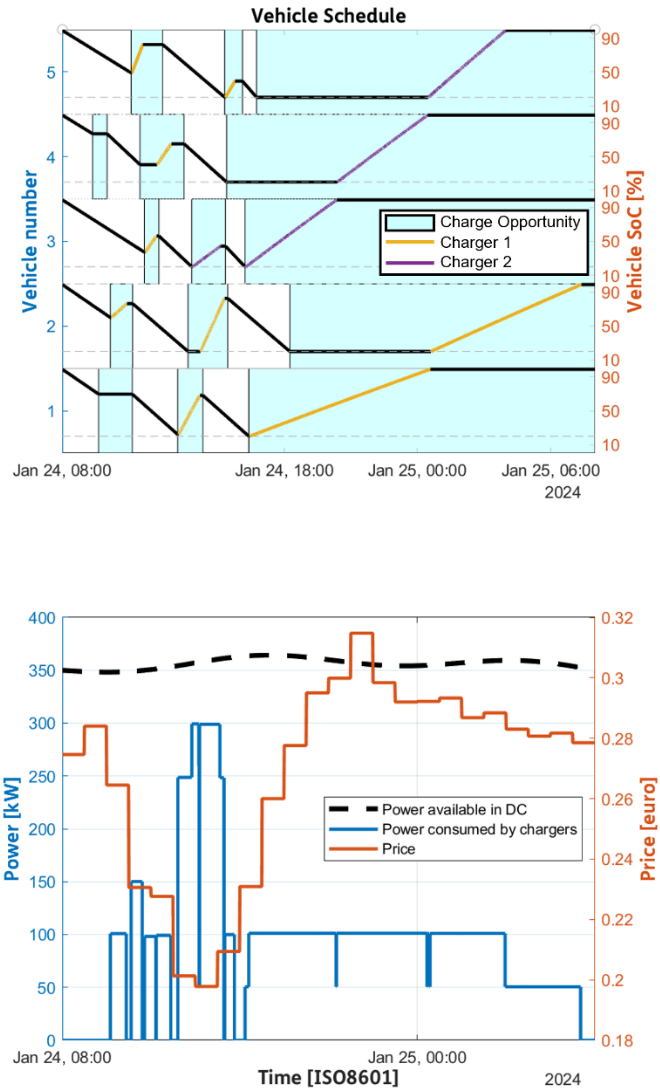

Fig. 4 Charge scheduling with battery DTs.

The use of DTs within the CPT also optimizes the schedule by charging the majority of the time when the electricity price is lower. The optimized schedule saves € 18.8 per vehicle per day compared to the baseline.

Additionally, during overnight charging, the vehicles are charged as late as possible with lower power. This is better for reducing the degradation of the battery due to aging and maintaining battery performance [7]. Hence, using DTs can achieve a realistic charging schedule that has a clear improvement over the standard method while reducing the TCO.

5. CONCLUSION

In this work, two battery DTs (Battery Aging and Charge Profile Prediction) were implemented to a CPT to achieve a realistic charging schedule for a fleet of EVs.

The DTs were calibrated on real data while the CPT implementation was simulated. The implementation generates a realistic schedule that is robust and reduces TCO by charging when electricity prices are lower and late charging during overnight periods.

Future work will focus on analyzing different objective functions and applying the method to a larger fleet. Improving the algorithm for faster implementation will also be analyzed.

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