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Charge Scheduling for a Fleet of Electric Vehicles using Battery Digital Twin

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Executive Summary

The transition towards vehicle electrification presents various challenges due to uncertainties in charging behavior. This study proposes a strategy to generate a charging schedule for a fleet of Battery Electric Vehicles (BEVs) while reducing the Total Cost of Ownership (TCO). The Charge Planning Tool (CPT) is integrated with Digital Twins (DTs), which models realistic battery behaviour of aging and charging phenomenon. The DTs are adaptive, have fast prediction and low training costs. The method is tested in simulation to show the impact of different cost factors and improvements to the scheduling due to the DTs. A multi-objective optimization strategy is proposed that is suitable for adoption by the fleet operators.

Keywords: battery digital twin, battery degradation, battery charging profile, charge planning, electric vehicle logistics.

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, which could benefit from optimal scheduling for cost reduction.

Various studies have investigated charge scheduling strategies, an overview of which can be found in [5]. [6] focuses on optimal charging considering grid-capacity limitations, using a distributed optimization problem. [7] describes an algorithm to determine the size, routing and operation of an electric bus fleet. Neither approaches consider battery degradation in their strategies. In [8], a real-time optimal charging strategy is described taking into account grid constraints, dynamic energy pricing and battery degradation. But it does not consider peak shaving and the robustness of the schedules. [9] develops a comprehensive tool for charge planning taking into account electricity price, peak shaving, operational robustness and battery degradation for a non-homogeneous fleet of Electric Vehicles (EVs). However, the tool uses linear charging behaviour and lacks adaptive capabilities for the battery system.

This work presents a CPT that can be used for scheduling the charging for a large fleet of BEVs. This tool is improved by using adaptive DTs that makes realistic predictions on battery parameters and self-calibrates during the battery lifetime. The inclusion of DTs generate new opportunities for charge schedule optimization. The novel contribution of this work includes:

- Integration of adaptive DTs into a CPT whcih have self-calibrating capabilities
- Multi-objective optimization for fleet scheduling taking into account the realistic behavior of the battery

2 Charge Planning Tool

The CPT is designed to manage the smart charging of large-scale 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 estimation of energy requirements, preventing operational disruption due to underestimation, while saving time by avoiding unnecessary full charges. The CPT will generate a feasible charge schedule; the allocation of charger to vehicle, 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 ageing by controlling the charging profile and moment of charging. The tool has two components: Fast Initialization Algorithm and Genetic Algorithm.

2.1 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 (MSPs), where the similarity is drawn between available tasks and charge requests, processors and chargers, and processing speed and 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 is stored in the internal memory. Otherwise, a different charge power or charger is selected. In case the assignment fails, the priority and order is 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.

2.2 Genetic Algorithm

The Genetic Algorithm is an improvement-type algorithm; it requires a set of feasible initial schedules, which are constructed with the heuristics described in the previous section and tries to improve upon them. Iteratively, the population of feasible schedules evolves by selecting individuals (schedules) to create offspring by either crossover 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 parameter using calibration data from the EV. In this work two DTs are developed: Battery Aging and Charge Profile Prediction.

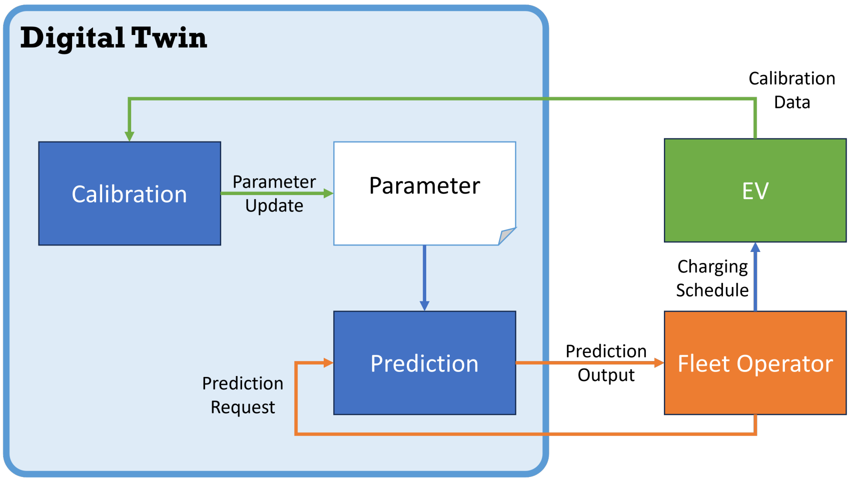

Figure 1: Architecture of a battery DT for a charge planning use-case.

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 such as temperature, State-of-Charge (SoC), Depth-of-Discharge (DoD) and C-rates. The predictive capability of the DT is crucial for optimizing battery usage, enhancing charging strategies, and extending the overall lifespan of the battery. Fleet operators can also use accurate battery aging for long-term TCO optimization.

The battery aging prediction DT uses a semi-empirical model to compute battery capacity due to calendar and cyclic aging as

$$C_{cal} = \alpha_{cap} \cdot t^x \tag{1}$$
$$C_{cyc} = \beta_{cap} \cdot Q^y \tag{2}$$

Here, Q is the charge throughput in Ah and t the elapsed time during the ageing event. α_{cap} and β_{cap} are defined as

$$\alpha_{cap} = (a_1 \cdot z - a_2) \cdot 10^{-6} \cdot e^{-a_3/T_{bat}} \tag{3}$$
$$\beta_{cap} = b_1 \cdot (\varnothing z - b_2)^2 + b_3 \cdot \Delta z + b_4 \cdot Crate_{ch} + b_5 \cdot Crate_{dch} + b_6. \tag{4}$$

where, z and T_{bat} are SoC and battery pack temperature contributing to calendar ageing. $\varnothing z$ is the average SoC, Δz is the DoD, and $Crate_{ch}$ and $Crate_{dch}$ are the c-rate during a full charge and discharge cycle, respectively. a_i and b_j are several battery-specific ageing parameters. The total capacity loss is calculated as

$$C_{tot} = \alpha_{cap} \cdot t^x + \beta_{cap} \cdot Q^y \tag{5}$$

At the beginning of its life cycle, ageing parameters are identified from a cell-level aging experiment in a lab. This is used to initialize the aging model. During battery operation, the parameters are recalibrated periodically using the battery data obtained from the vehicle in the fleet.

3.2 Charge Profile Prediction

The objective of the charge profile prediction DT is to accurately predict the electrical power during a charging session. 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. Fig. 2 shows the standard charging profile that is used by the grid operators to schedule their fleets. It is seen that the predicted charging power profile from the DT has differences in peak power and charging time. This can improve the assessment of the charge time and grid load while making the charge scheduling more robust.

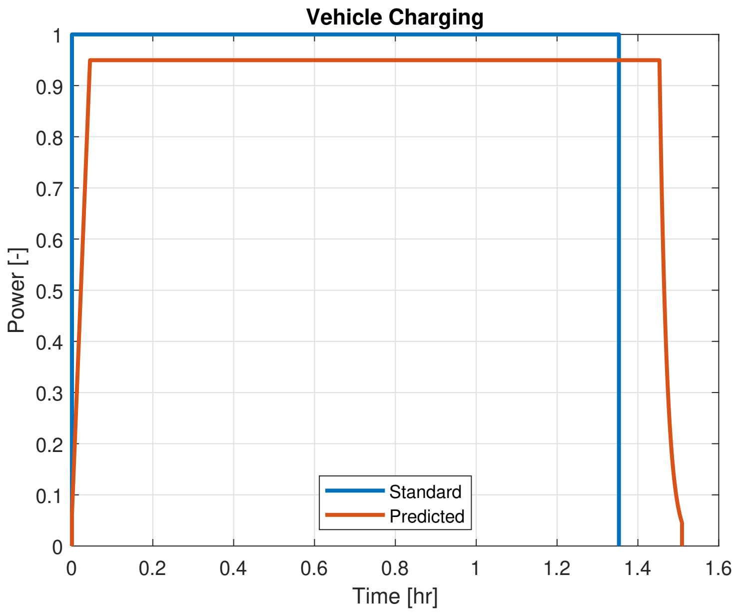

Figure 2: Charge profile prediction from Charge Profile DT.

The predicted charging profile is divided into three segments: ramp, constant and decay. Each segment is parameterized and 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 for a use-case at these conditions [10].

4 Results and Discussion

The charge scheduling algorithm is applied to a use case with a fleet of 5 medium-duty EVs and 2 chargers as shown in Fig. 3. Each EV 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 it's stationary at the charging hub. The fleet scheduling is simulated for a single day of operation, while the DTs used are calibrated on real data.

4.1 Baseline Schedule

The standard scheduling method is used as a baseline where the vehicles are charged on a first-come first-served basis to the maximum possible SoC. This technique is commonly employed by fleet operators. Fig. 3 shows that when the DTs are not used, the fleet can be charged by using only one charger, i.e., Charger 1 can complete all change requests. However, the use of DTs enforces a longer charge time and schedules the fleet differently. The increase in SoC is 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.

4.2 Optimal Schedule

Both schedules in Fig. 3 are generated using fast initialization algorithm. The charging schedules are further improved by using Genetic Algorithm by mutating over the initial schedules. In this method, four

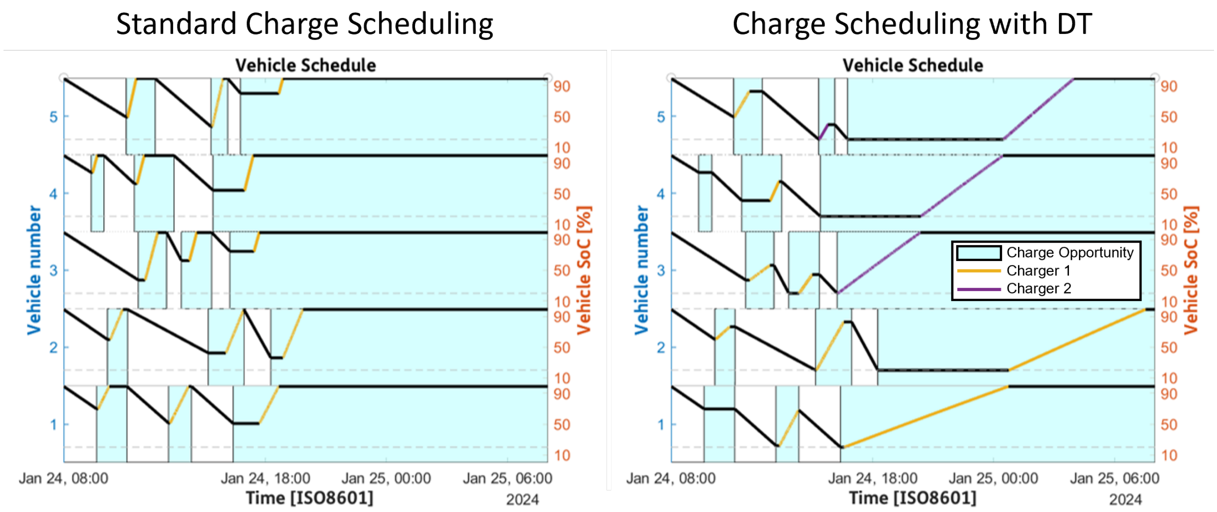

Figure 3: Charge scheduling without and with battery DTs.

types of cost factors are considered: Electricity Cost, Battery Degradation, Peak Power and Robustness.

Electricity cost is the cost of consuming power from the grid and is influenced by the varying price of electricity during the day. In this use case, the electricity tariffs are lower during the night, but the costs also have a dip during the day due to alternative renewable sources of energy (such as solar). Battery degradation is the reduction in charge capacity due to calendar and cyclic battery operations. Lower electricity cost results in short-term profit to the fleet operators while lower battery degradation gives long-term benefits by improving EV performance and saving maintenance cost.

Fig. 4 shows Minimum Electricity Cost (MEC) and Minimum Battery Degradation (MBD) strategies, which optimizes electricity cost and battery degradation, respectively. It is seen that the MEC minimizes electricity cost by clustering peak charging around the lowest electricity price during the day. During the night, the charging is pushed and spread out towards the relatively lower cost periods. MBD lowers battery degradation by lowering the average charge power, thereby reducing the cyclic aging. The vehicles are also charged as late as possible to keep the average SoC low which reduces the calendar aging.

The TCO can also be reduced by minimizing peak power as energy contracts have additional costs associated with them. However, these costs are levied on a longer time horizon, such as 6 months. This work will focus on the reduction of peak power for a single day of operation. Robustness of a schedule is defined as the slack in planning that can be used to counter unforeseen circumstances and emergencies. It is an important factor for fleet operators as missing an operational schedule has the highest economic impact for them.

Fig. 5 Minimum Peak Power (MPP) and Optimal Robustness (OR) strategies, which optimizes peak power and robustness, respectively. It is seen that MPP uniformly reduces the maximum power by charging at every charge opportunity using relatively lower power. OR improves Robustness by charging in the middle of the charge opportunity. This increases the slack time both at the beginning and end of the charge opportunity. The power consumption for this optimization is also higher to reduce the charging time. Smaller charging time will also have higher slack.

4.3 Multi-factor Optimization

Amongst the cost factors, electricity cost and battery degradation have the most clear economic impacts on TCO. Analysis of optimal peak power requires a longer time horizon (outside the scope of this study). Robustness also has a high impact, but the exact cost on TCO is dependent on the fleet operator's preference while being difficult to quantify. Hence, a multi-factor optimization is simulated for electricity cost and battery degradation.

Fig. 6 shows the charge schedule with a combined optimization of electricity cost and battery degradation. This Optimal Electricity Cost and Degradation (OED) schedule resembles the MBD strategy and makes minor changes to utilize low-cost charging.

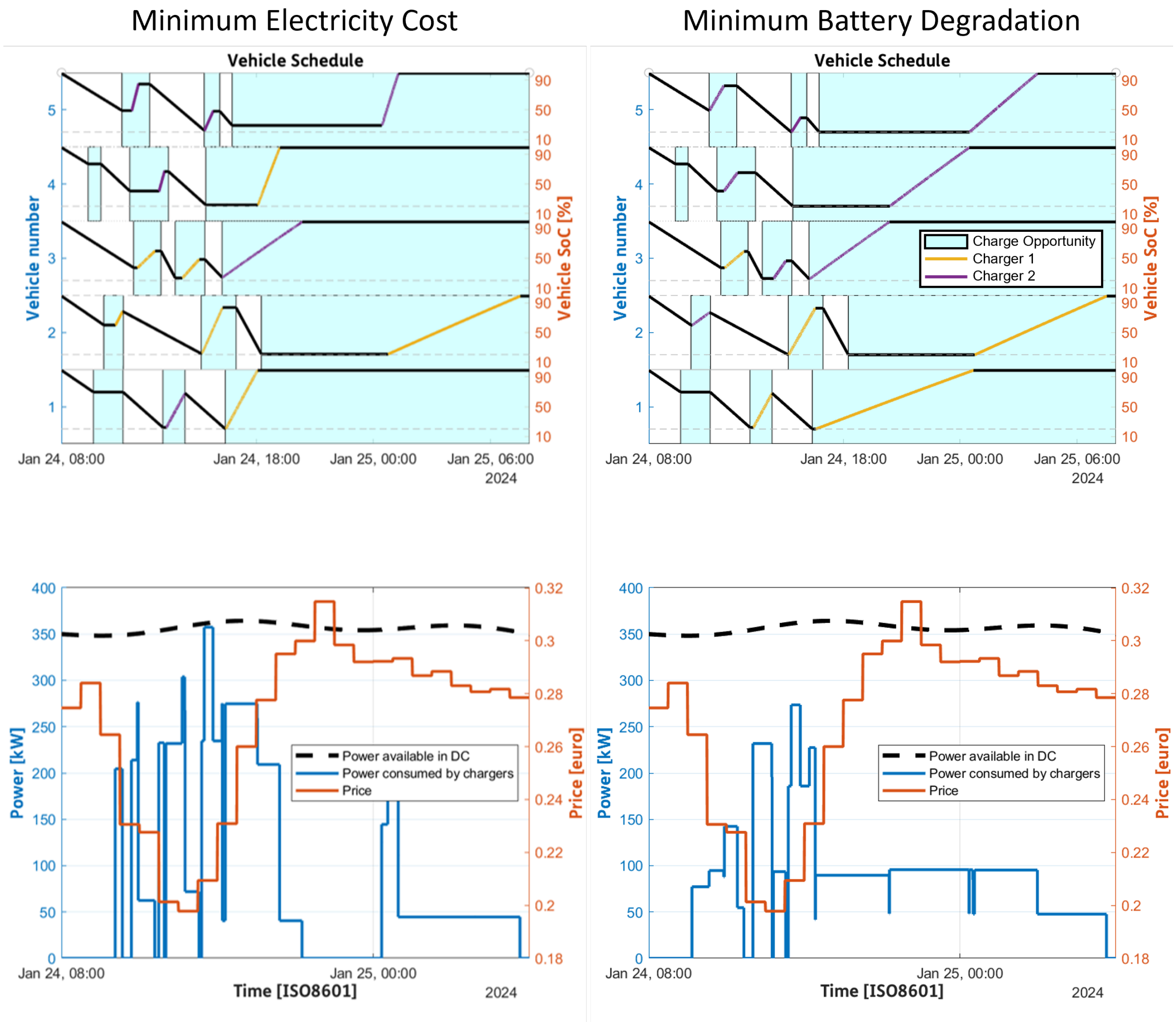

Figure 4: Charge scheduling with MEC and MBD strategies.

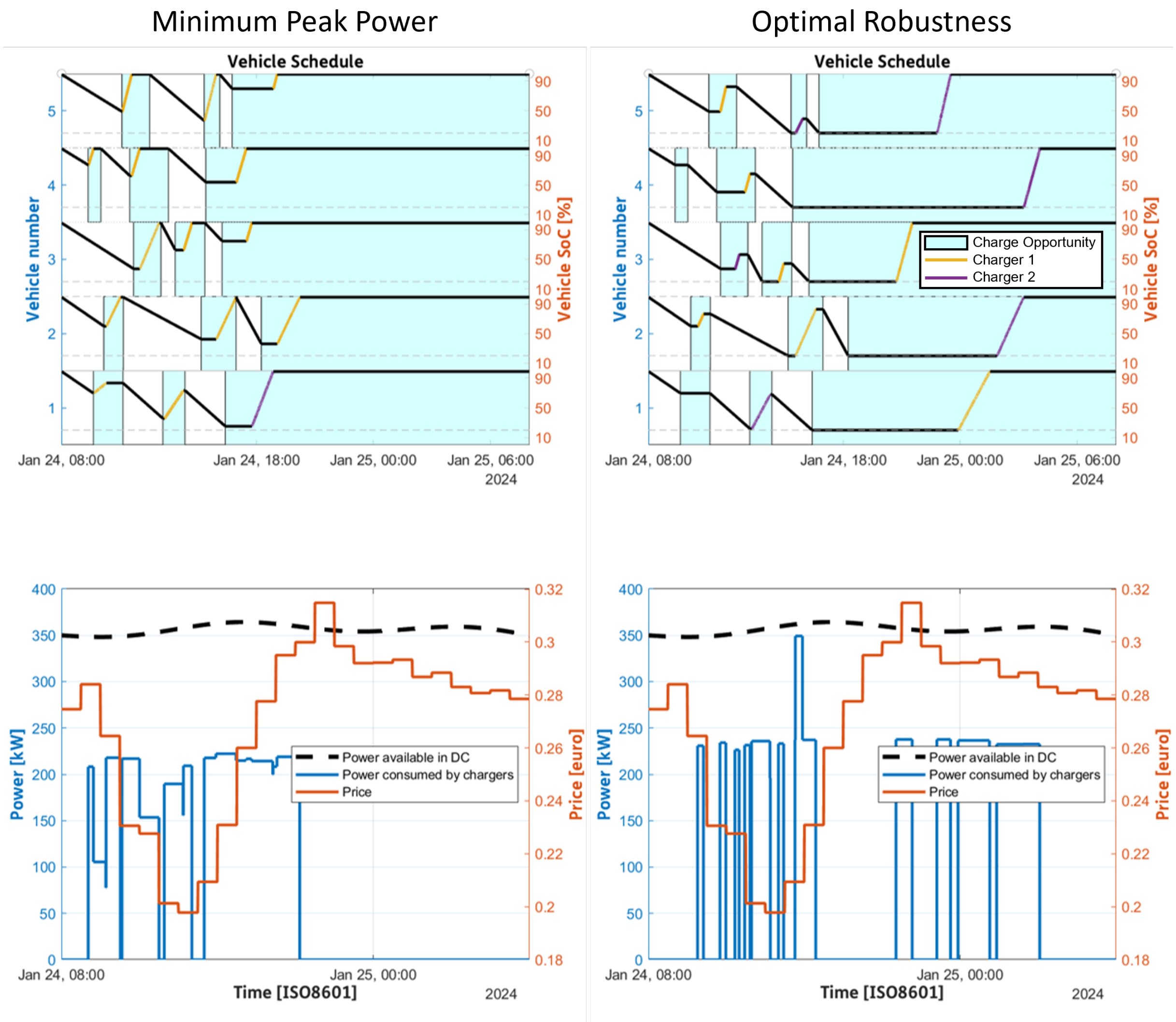

Figure 5: Charge scheduling with MPP and OR strategies.

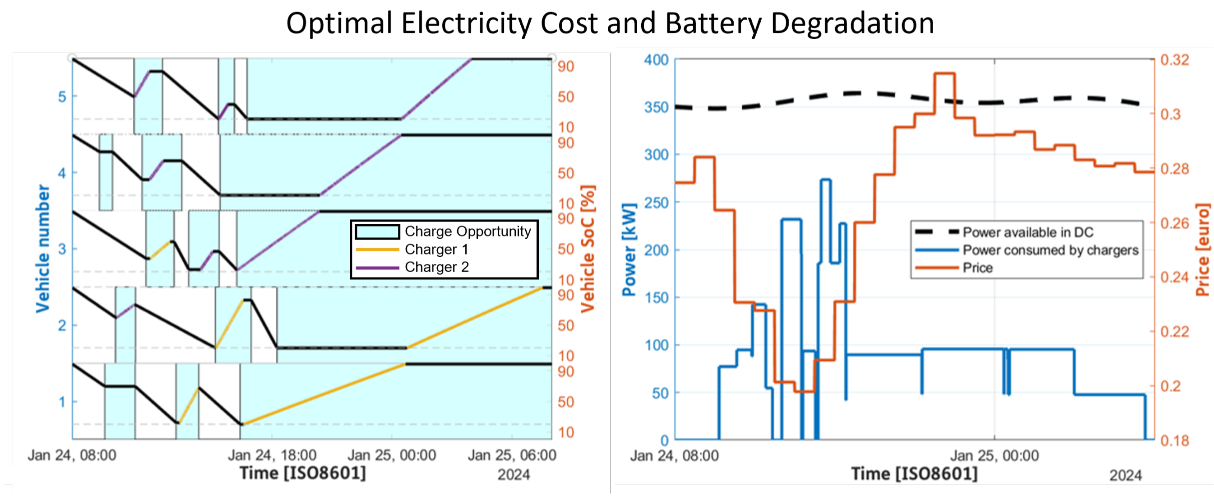

Figure 6: Charge scheduling with OED strategy.

Fig. 7 shows the comparison between the 5 optimal strategies and their relative impacts on the cost factors Electricity Cost, Battery Degradation and Peak Power. The greedy algorithm is taken as the baseline for comparison. It is seen that the strategies focused on reducing a singular cost factor have the optimal for it; MEC for electricity cost, MBD for battery degradation and MPP for peak power, while the OED schedule presents a good score for all cost factors.

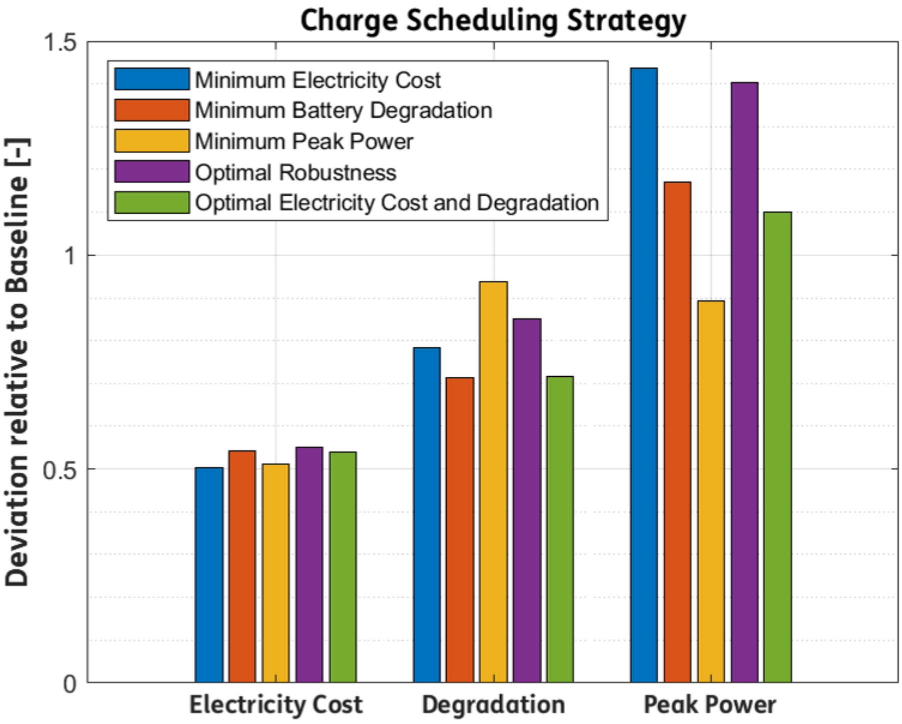

Figure 7: Charge scheduling without and with battery DTs.

Commonly, when fleet operators are looking to improve their charge scheduling, their focus is on the reduction of electricity costs, with battery degradation not being a priority. However, it is seen that OED gives lower electricity cost than MBD, lower battery degradation than MEC and lower peak power than both of them. Hence, this strategy can be used by fleet operators as an improvement to their current charge scheduling.

5 Conclusion

In this work, two battery DTs (Battery Aging and Charge Profile Prediction) were implemented into a CPT to achieve a realistic charging schedule for a fleet of EVs. The DTs were calibrated on real data while the fleet scheduling with CPT was simulated. The implementation generates a realistic schedule that is robust and reduces TCO by applying various optimization strategies. A combined optimal electricity cost and battery degradation strategy (OED) was found to be most suitable for fleet operators' adoption due to its multi-objective minimization.

Future work will focus on the integration of peak power and robustness to the TCO analysis. The impact of other cost factors such as alternate energy sources, peak shaving via stationary storage, micro-grid stabilization and imbalance market will be analyzed. Analysis will be done on the real-time implementation by leveraging the fast and slow algorithms in different scenarios. The tool will be extended to integrate more DTs such as energy estimation and traffic prediction. This will provide further avenues for cost factor optimization. Lastly, the algorithm will incorporate the generation of suboptimal solutions in case of infeasibility for the required charging conditions.

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Presenter Biography

Subhajeet Rath is a scientist in the Powertrains Department at TNO (Netherlands Organisation for Applied Scientific Research), specializing in battery modeling, state estimation and controls. His work focuses on the development of BMS algorithms, battery digital twins and optimization of EV fleet charging. Additionally, he leads research into making battery systems compliant with EU Battery Passport regulations.