Profitability of Vehicle-to-grid in Mobility-as-a-service: A Case Study of Eindhoven

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SHORT SUMMARY

This paper presents a directed acyclic graph model to study the profitability of a fleet of electric robo-taxis, whereby the vehicles do not only serve travel requests, but they also perform vehicle-to-grid as a secondary activity to increase the revenues generated by the fleet. Then, when including operational costs, we also account for the battery degradation induced by charging and discharging activities. We present a real world case study of Eindhoven, The Netherlands, where we quantify the advantages and disadvantages of allowing V2G activities and show the difference in terms of operational costs, and revenues. The results show that allowing for V2G activities can be counterproductive for the profitability of the fleet. Even if it is possible to generate revenues by trading energy, the additional costs in term of battery degradation cannot be neglected and should be accounted for.
Keywords: Mobility-as-a-service, Optimization, Vehicle-to-grid.

1 INTRODUCTION

Mobility-as-a-Service (MaaS) is revolutionizing transportation, however this sector is one of the few where emissions are still increasing (EPA, 2018). In this environment, advances in autonomous driving and electric powertrain can provide a more sustainable car-based mobility: combining centrally controlled electric autonomous vehicles can allow the deployment of Electric Autonomous Mobility-on-Demand (E-AMoD) systems, whereby these vehicles provide on-demand mobility. Controlling such a fleet can, not only allow efficient traffic management by real time route optimization, but also enables optimizing fleets' charging time and location. This will maximize the opportunity for the operator to trade energy in markets via vehicle-to-grid (V2G) activities. This is the case especially in markets where electricity prices are volatile, due to energy mixed with a large share of solar energy. This paper studies fleet operational strategies that are optimized to satisfy user demands, whilst profitably performing price-driven charging and V2G activities. In particular, we perform a real-world case study where we analyze the advantages and disadvantages of performing V2G taking into account battery degradation.
Related Literature: This paper pertains to the research streams of mobility-on-demand operation. Multiple approaches to model and control AMoD systems have been proposed: Two examples are the vehicle routing problem (VRP), see Yao et al. (2021) and multi-commodity network flow models (Iglesias et al., 2018; Paparella, Pedroso, et al., 2024). Both methods are flexible and allow for the implementation of a wide range of constraints and objectives. When considering E-AMoD systems, vehicle coordination and charging algorithms have been extensively studied, for example by Rossi et al. (2020).
This paper presents a modeling framework to optimize the operations of an E-AMoD fleet to maximize the profitability, and a case study of the city of Eindhoven, the Netherlands.
Organization: The remainder of this paper is structured as follows: Section 2 briefly introduces the E-AMoD model optimization framework, whilst Section 3 details our real-world case study of the city of Eindhoven, The Netherlands, and the results obtained. Finally, Section 4 draws the conclusions and provides an outlook on future research.

2 PROBLEM FORMULATION

In this section, we briefly recall the optimization problem of the vehicle routing, charging and V2G operations via directed acyclic graphs (DAGs), an extension of the vehicle routing problem. We refer the reader to our previous work, Paparella, Hofman, & Salazar (2024), for a detailed explanation.

Directed Acyclic Graph Model

First, we define travel request $i \in \mathcal{I} := \{1, 2..., I\}$ is defined as $r_i = (o_i, d_i, t_i)$ being a travel request from origin o_i to destination d_i at time t_i. Then, we construct a DAG, $\mathcal{G} = (\mathcal{V}, \mathcal{A})$, where the nodes $\mathcal{V}$ are travel requests and the arcs $\mathcal{A}$ are the fastest path from the destination of r_i, d_i, to the origin of r_j, o_j and it is characterized by travel time t_{ij}^{fp} and distance d_{ij}^{fp}, respectively. If $i = j$, we denote with t_{ii}^{fp} the time of the fastest path to serve request i. To consider depots of vehicles, we extend $\mathcal{I}^+ := \{0, 1, 2..., I, I+1\}$, where the first and last requests represent a fixed location (depot, parking spot), so that vehicles start and conclude their tasks at a pre-defined point. Finally, we define a set of vehicles $\mathcal{K} := \{1, 2..., K\}$ with vehicle $k \in \mathcal{K}$.

Problem Formulation

In this paper, the objective is to maximize the profit accrued by the fleet. The two terms that influence it are the cost of operation and the revenues generated by serving requests. Formulated as a cost-minimization function, the objective is then

$$J = \sum_{i,j \in \mathcal{I}} p_{ij}^{\mathrm{el}} \cdot \sum_{k \in \mathcal{K}} C_{ij}^{k} - \sum_{i \in \mathcal{I}^+} b_{\mathrm{r}}^{i} \cdot p_i, \tag{1}$$

where p_{ij}^{el} is the average price of electricity in between the drop off of requests i and the pick up of request j, C_{ij}^{k} is the amount of energy withdrawn from or injected to the grid, b_{r}^{i} is a binary variable indicating whether request i is being served, and p_i is the revenue generated by serving it.
Then, the maximum-profit operation problem for an E-AMoD fleet is defined as follows:

Problem 1 (Optimal E-AMoD Fleet Management) *Given a road network $\mathcal{G}'$, a set of transportation requests $\mathcal{I}$, the operations in terms of serving requests, charging and V2G that maximize the total profit of the E-AMoD system result from*

$$\begin{aligned} &\min\ J \\ &\text{s.t. Operational Constraints} \\ &\quad\ \ \text{Energy Constraints} \\ &\quad\ \ \text{Time Constraints} \end{aligned}$$

Problem 1 is a mixed integer linear program that can be solved with optimality guaranteed by commercial optimization algorithms. The constraints ensure continuity of battery State of Charge (SoC), that a vehicle can charge only if it goes to a charging station, and that there is sufficient time to go from the destination of a request to the origin of the next request that has to be served. Given that the objective of the operator is to maximize profit, the fleet will try to serve as many users as possible. However it might not be possible to serve all of them, so, to indicate whether a user i is served or not, we define binary variable b_{r}^{i}.
A few comments are in order. First, we consider travel times on the road digraph to be given. This assumption is in order for a small fleet as the one under consideration, whose routing strategies do not significantly impact travel time and hence overall traffic. This way, also varying levels of exogenous traffic during the course of the day can be captured by simply including time-dependent traffic data and adjusting fastest path time and distance accordingly. Second, we assume the charging stations to always be available. We leave the inclusion of constraints to avoid potentially conflicting charging activities by multiple vehicles to future research. Third, the solution of Problem 1 is deterministic and assumes perfect knowledge of travel requests. In fact, Problem 1 should be interpreted as a design problem (not suitable for online implementation), where the result is an upper bound on the performance that such AMoD system can achieve in an online fashion. Last, we assume the electricity prices to be known in advance, given the presence of the day-ahead market and that the fleet size is small enough to not influence the energy prices.

Battery Degradation

During the lifetime of a vehicle, its battery deteriorates due to irreversible electro-chemical reactions, known as battery aging. This phenomenon is called "cyclic ageing", and occurs during the charging and discharging of the battery. It is predominant in mobility system such as the one considered in this study because of the intensive use of the vehicles. The normalized battery charge capacity degradation, according to Rath et al. (2023), is defined as

$$\Delta \tilde{E}_{\mathrm{b}} = \kappa \cdot \sqrt{Q}, \tag{2}$$

where, Q is the charge throughput in Ah, and the constant κ is

$$\kappa = b_1 \cdot (\phi_z - b_2)^2 + b_3 \cdot \Delta z + b_4 \cdot C_{\mathrm{rate}}^{\mathrm{ch}} + b_5 \cdot C_{\mathrm{rate}}^{\mathrm{dch}} + b_6. \tag{3}$$

The average SoC is ϕ_z, while Δz is the Depth of Discharge (DoD), $C^{\text{ch}}_{\text{rate}}$ and $C^{\text{dch}}_{\text{rate}}$ are the c-rates during a full charge and discharge cycle, respectively. The battery-specific values of the battery are $b_{1,2..,6}$. We refer the reader to Rath et al. (2023) for a detailed explanation of the model and of the meaning of the parameters. Note that the operation of the E-AMoD fleet does not aim to minimize cyclic aging, but merely to estimate the number of cycles before End of Life (EoL). In particular, after solving Problem 1, we post-process the results to compute the relative battery degradation cost. This allows to show the potential effects that V2G activities can have on battery degradation and on the relative operational costs. In the future, the authors would like to include a tractable model of battery degradation in the objective function so that the cost related to degradation can be jointly optimized.

3 Results

In this section, we compare an E-AMoD system in terms of operational strategies and costs, and compare it based on allowing or not V2G capabilities. We present a case study conducted in the city of Eindhoven, The Netherlands, using data generated by Albatross, A Learning BAsed Transportation Oriented Simulation System, (Arentze & Timmermans, 2004; Rasouli et al., 2018). Albatross is a state-of-the-art activity-based model from the computational process model family, employing a series of CHAID decision trees at its core, to simulate activity-travel schedules. Albatross is household-based meaning that up to two household heads are included in the household. Initially, a synthetic population is simulated for Eindhoven using the iterative proportional fitting method. Subsequently, the synthetic population is used as input for the activity-travel model. Albatross simulates the activity-travel schedules for this population for a complete day, down to the minute. The model simulates leave times, travel times, start times of the activity, end times of the activity, origin and destination (at Postal Code level 4, i.e., the first 4 digits of the Dutch postal code), activity type, and mode choice as most important information for the remainder of this study. Due to the high level of detail in the output data and the ability to simulate a complete city, we are able to provide insights whether V2G could be profitable for Dutch cities such as Eindhoven. Fig. 1 shows the number of demands batched every 5 minutes and the registered electricity prices on the 1st of November 2023.

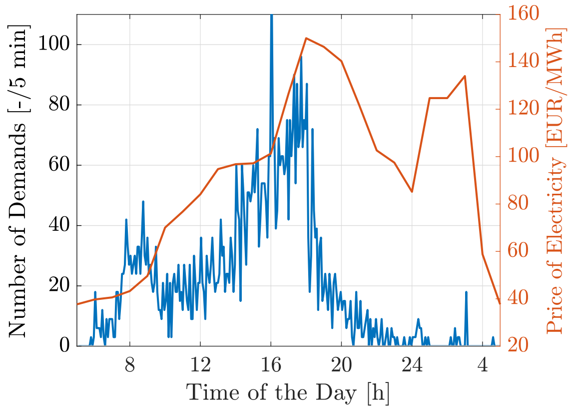

Figure 1: The figure shows the number of demands during a day, and the recorded energy price in the Netherlands during November 1st, 2023 (courtesy of nordpoolgroup.com).

Comparison of Operational Costs With and Without V2G

In this section, we examine the impact of V2G activities on the overall profitability of an E-AMoD fleet. In particular, we take into account the battery degradation that is caused by higher dis(charging) activities, which, however, is not included in the objective function. Moreover, we assume that every time a battery reaches EoL, it is sold, and replaced in the vehicle with a new one. We consider a fleet of 70 Nissan Leafs 2022. The charging infrastructure is composed of 10 chargers of 22 kW uniformly spread in the urban area of Eindhoven. The net cost of a Nissan Leaf's battery, accounting for the EoL value, is set to 5300 €. Fig. 2 shows two case studies with a fleet of 70 Nissan Leafs during a day of operation. The two case studies are with (left) and without (right) V2G capabilities. In particular, the figure shows the power withdrawn from and injected to the grid, and the net energy usage. Table 1 shows the operational revenues and costs of the fleet for the two cases. The results show that revenues generated by travel requests are not influenced by the V2G activities. In fact, given that serving travel requests is more profitable than trading

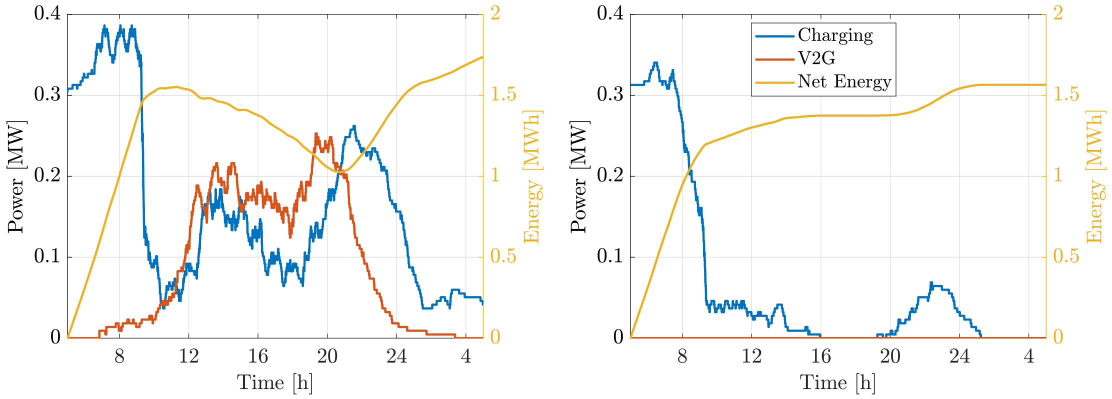

Figure 2: Charging, discharging activities and net energy withdrawn from the grid during the day. In the left figure the fleet is allowed to perform V2G, while in the right figure the fleet can only charge. Fleet composed of 70 Nissan Leafs. Power of the chargers of 22 kW.

Table 1: Daily Operational Costs and Revenues to operate a fleet of 70 Nissan Leafs.

-	V2G	No V2G	Unit
Travel Requests Revenue	21900	21900	[€/day]
Charging Cost	610	165	[€/day]
Discharging Revenue	750	0	[€/day]
Battery Degradation Cost	730	290	[€/day]
Profit	21310	21445	[€/day]
Battery Life Time	510	1290	[day]

energy, the fleet gives strong priority to serve travel requests. Second, we highlight that performing V2G strongly influences the degradation of the battery, and as a consequence, it leads to a significant increase in the costs per day. Due to strong V2G activities, degradation is so accelerated that battery life is in the order of six months. From this result, we can conclude that performing V2G activities can be counter-productive for the profitability of a fleet of electric vehicles for mobility-as-a-service, because of the strong battery degradation induced, which should be jointly optimized with the operation of the fleet.

4 Conclusions

In this paper we presented a directed acyclic graph formulation to optimize the activities of a fleet of electric vehicles for mobility-as-a-service purpose. We conducted a real-world case study of Eindhoven, The Netherlands, where we showed that allowing for V2G activities can be counter-productive for the profitability of a fleet mainly due to the increase in costs due to battery degradation. Moving forward, several extensions to this work are worth exploring. First, incorporating battery degradation inside the objective function will allow to draw the trade-off between V2G intensity of activities and battery degradation. Second, we would like to include ride-pooling and intermodal settings where transportation requests are served jointly with public transit and active modes. Third, we would like to study the solutions stemming from different cost-functions, such as environmental impact, accessiblity and fairness. Finally, it would be worthwhile developing tailored solution algorithms to solve the optimization problems presented, as well as deriving implementable online control schemes.

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