

Cost-optimal Fleet Management Strategies for Solar-electric Autonomous Mobility-on-Demand Systems

Citation for published version (APA):

Paparella, F., Hofman, T., & Salazar, M. (2023). Cost-optimal Fleet Management Strategies for Solar-electric Autonomous Mobility-on-Demand Systems. *arXiv*, 2023, Article 2305.18816.
<https://doi.org/10.48550/arXiv.2305.18816>

DOI:

[10.48550/arXiv.2305.18816](https://doi.org/10.48550/arXiv.2305.18816)

Document status and date:

Published: 30/05/2023

Document Version:

Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

[Link to publication](#)

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license above, please follow below link for the End User Agreement:

www.tue.nl/taverne

Take down policy

If you believe that this document breaches copyright please contact us at:

openaccess@tue.nl

providing details and we will investigate your claim.

Cost-optimal Fleet Management Strategies for Solar-electric Autonomous Mobility-on-Demand Systems

Fabio Paparella¹, Theo Hofman¹ and Mauro Salazar¹

Abstract—This paper studies mobility systems that incorporate a substantial solar energy component, generated not only on the ground, but also through solar roofs installed on vehicles, directly covering a portion of their energy consumption. In particular, we focus on Solar-electric Autonomous Mobility-on-Demand systems, whereby solar-electric autonomous vehicles provide on-demand mobility, and optimize their operation in terms of serving passenger requests, charging and vehicle-to-grid (V2G) operations. We model this fleet management problem via directed acyclic graphs and parse it as a mixed-integer linear program that can be solved using off-the-shelf solvers. We showcase our framework in a case study of Gold Coast, Australia, analyzing the fleet’s optimal operation while accounting for electricity price fluctuations resulting from a significant integration of solar power in the total energy mix. We demonstrate that using a solar-electric fleet can reduce the total cost of operation of the fleet by 10-15% compared to an electric-only counterpart. Finally, we show that for V2G operations using vehicles with a larger battery size can significantly lower the operational costs of the fleet, overcompensating its higher energy consumption by trading larger volumes of energy and even accruing profits.

I. INTRODUCTION

AS THE RISE of Mobility-as-a-Service (MaaS) paradigms has been revolutionizing transportation, this sector is one of the few where emissions are still increasing [1]. In this context, recent advances in autonomous driving, and electric powertrain and vehicle design could provide pathways to a more sustainable car-based mobility: Combining centrally controlled autonomous vehicles with powertrain electrification could enable the deployment of Electric Autonomous Mobility-on-Demand (E-AMoD) systems, whereby a fleet of electric vehicles provides on-demand mobility. The possibility of centrally controlling the fleet provides opportunities not only in optimizing the vehicles’ routes and schedules, but also in jointly optimizing their charging and vehicle-to-grid (V2G) activities, profitably trading energy in markets where electricity prices are significantly varied, for instance as a countermeasure to the so-called *duck curve* [2], typical of energy mixes with a large share of solar energy. Moreover, the deployment of such fleets allows and calls for vehicles that are tailored to the specific application. In this particular paper, we consider highly-efficient electric vehicles that can be equipped with a solar rooftop directly covering a portion of their energy demand, and study their deployment within Solar-electric Autonomous Mobility-on-Demand (S-AMoD) systems. Against this background, the paper studies

fleet operational strategies that are optimized to satisfy user demands, whilst profitably performing price-driven charging and V2G activities.

Related Literature: This paper pertains to the research streams of mobility-on-demand operation and solar-electric vehicles, which we review in the following. Multiple approaches to model and control AMoD systems are available: Two examples are the vehicle routing problem (VRP) [3]–[9] and multi-commodity network flow models [10]–[12]. Both methods are flexible and allow for the implementation of a wide range of constraints and objectives. Some examples are congestion-aware routing [13], [14], and VRP with time windows and heterogeneous fleet composition [15], [16]. When considering E-AMoD systems, vehicle coordination and charging algorithms have been studied in [17], whilst also accounting for infrastructure placement in [18], [19]. In this context, the interaction between large-fleet AMoD systems and power distribution networks has been extensively studied in [20], [21], whereas in our recent work [22] we have optimized the operations of an E-AMoD system jointly with its fleet composition in terms of number of vehicles and battery size of the individual vehicles. Nevertheless, none of these papers focuses on solar-electric systems, and their design and operations within price-varying energy markets.

Focusing on solar-electric vehicles, some studies have investigated them from a technological standpoint [23]–[25], but mostly focusing on vehicular aspects, and without exploring deployment and operational questions.

In conclusion, there are no available studies that investigate S-AMoD systems in terms of deployment and operations, optimizing their routing, charging and V2G activities.

Statement of Contributions: This paper presents a modeling framework to optimize the operations of an S-AMoD fleet, and carry out design studies by devising a directed acyclic graph (DAG) model describing the fleet routing, charging and V2G activities. Next, we leverage such a model to optimize the fleet management strategies via mixed-integer linear programming, with the objective to maximize the profit of the fleet operator. Finally, we showcase our framework on a case study of Gold Coast, Australia, where we assess the benefits of S-AMoD in terms of operational costs, and compare different vehicular designs.

Organization: The remainder of this paper is structured as follows: Section II introduces the S-AMoD model optimization framework, whilst Section III details our real-world case study of the city of Gold Coast, Australia, and the results obtained. Finally, Section IV draws the conclusions and provides an outlook on future research.

¹The authors are with the Control Systems Technology section, Department of Mechanical Engineering, Eindhoven University of Technology, 5600 MB Eindhoven, The Netherlands {f.paparella,t.hofman,m.r.u.salazar}@tue.nl

II. PROBLEM FORMULATION

In this section, we model the vehicle routing, charging and V2G operations problem via DAGs, extending our preliminary model [22] to fully capture V2G activities, solar-electric vehicles and time-varying electricity prices.

A. Directed Acyclic Graph Model

We define a transportation network as $\mathcal{G}' = (\mathcal{V}', \mathcal{A}')$, where the set of arcs \mathcal{A}' are roads and the set of nodes \mathcal{V}' are intersections between roads. We denote a set of charging stations $\mathcal{C} \subset \mathcal{V}'$ in the transportation network, with station $c \in \mathcal{C}$. We also define travel request $i \in \mathcal{I} := \{1, 2, \dots, I\}$ as $r_i = (o_i, d_i, t_i) \in \mathcal{V}' \times \mathcal{V}' \times \mathcal{T}$ being a travel request on network \mathcal{G}' from origin o_i to destination d_i at time $t_i \in \mathcal{T}$. First, we expand the set of travel requests to $\mathcal{I}^+ := \{0, 1, 2, \dots, I, I+1\}$ where the first and last requests represent a fixed location (deposit, parking spot), so that vehicles start and conclude their tasks at a pre-defined point. Then, we construct a DAG, $\mathcal{G} = (\mathcal{V}, \mathcal{A})$, containing deposits and transportation requests. Each arc $(i, j) \in \mathcal{A}$ represents 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 . Last, we define a set of vehicles $\mathcal{K} := \{1, 2, \dots, K\}$ with vehicle $k \in \mathcal{K}$.

B. Operational Constraints

We define a transition matrix $X \in \{0, 1\}^{(I+1) \times (I+1) \times K}$, where $X_{ij}^k = 1$ if vehicle k serves demand i and then demand j , and zero otherwise. We introduce the tensor $S \in \{0, 1\}^{(I+1) \times (I+1) \times K \times C}$ to account for charging and V2G activities. If vehicle k in-between d_i and o_j goes to charging station c , S_{ijc}^k is set to one, otherwise it is set to zero. In the same way, we quantify the amount of energy dis(charged) with element C_{ijc}^k of the corresponding charging tensor $C \in \mathcal{R}^{(I+1) \times (I+1) \times K \times C}$. If the element is positive, energy is withdrawn from the grid; if negative, energy is injected into the grid, meaning that vehicle k performs V2G.

Travel, deviation and charging times can be pre-computed via standard shortest path algorithms, thus we can directly eliminate all the unfeasible transitions from a time perspective. In particular, $t_{ij}^{\text{ava}} := t_j - t_i + t_{ii}^{\text{fp}}$ is the available time between the destination of i and the origin of request j . Thus, we can pre-compute the upper bounds of the tensors as

$$X_{ij}^k \leq \begin{cases} 1 & \text{if } t_{ij}^{\text{fp}} \leq t_{ij}^{\text{ava}} \\ 0 & \text{otherwise,} \end{cases} \quad (1)$$

$$S_{ijc}^k \leq \begin{cases} 1 & \text{if } t_{ij}^{\text{fp}} + \Delta T_{ijc}^{\text{go2S}} \leq t_{ij}^{\text{ava}} \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

$$|C_{ijc}^k| \leq \begin{cases} \hat{C}_{ijc}^k & \text{if } t_{ij}^{\text{fp}} + \Delta T_{ijc}^{\text{go2S}} \leq t_{ij}^{\text{ava}} \\ 0 & \text{otherwise,} \end{cases} \quad (3)$$

with $i, j \in \mathcal{I}^+$, $c \in \mathcal{C}$, $k \in \mathcal{K}$. The extra time needed to go to charging station c during transition ij is $\Delta T_{ijc}^{\text{go2S}}$, while the upper bound $\hat{C}_{ijc}^k = (t_{ij}^{\text{ava}} - t_{ij}^{\text{fp}} - \Delta T_{ijc}^{\text{go2S}})P_{\text{ch}}$ is

the energy (dis)charged if all the available time were used to (dis)charge at the given charging power P_{ch} . To enforce that each request can be served at most once, we define the transitions constraints

$$\sum_{i \in \mathcal{I}^+, k \in \mathcal{K}} X_{ij}^k + \sum_{k \in \mathcal{K}} f_j^k \leq 1 \quad \forall j \in \mathcal{I}^+, \quad (4)$$

$$\sum_{j \in \mathcal{I}^+, k \in \mathcal{K}} X_{ij}^k + \sum_{k \in \mathcal{K}} l_i^k \leq 1 \quad \forall i \in \mathcal{I}^+. \quad (5)$$

To guarantee continuity of the schedules—meaning that if a vehicle performs transition ij , its next one will start from j —we impose

$$\sum_{i \in \mathcal{I}^+} X_{ij}^k - \sum_{l \in \mathcal{I}^+} X_{jl}^k = f_j^k + l_j^k \quad \forall j \in \mathcal{I}^+, \forall k \in \mathcal{K}. \quad (6)$$

We enforce that vehicle k can charge between demand i and j at station c , only if it serves both requests,

$$\sum_{c \in \mathcal{C}} S_{ijc}^k \leq X_{ij}^k \quad \forall i, j \in \mathcal{I}^+, \forall k \in \mathcal{K}, \quad (7)$$

and goes to station c in-between,

$$|C_{ijc}^k| \leq \hat{C}_{ijc}^k \cdot S_{ijc}^k \quad \forall i, j \in \mathcal{I}^+, \forall c \in \mathcal{C}, \forall k \in \mathcal{K}. \quad (8)$$

Last, f and l are two parameters to set the initial and final position of the vehicles in the deposit, so that $f_j^k, l_j^k = 0 \forall i, j \in \mathcal{I}, \forall k \in \mathcal{K}$ and $f_0^k = l_{I+1}^k = 1 \forall k \in \mathcal{K}$.

C. Energy Constraints

In this section we introduce the energy constraints for the vehicles. Defining the energy level of vehicle k after serving demand j as e_j^k , we formulate an energy balance at each node of the DAG as

$$e_j^k = e_i^k - E_{ij}^k + \sum_{c \in \mathcal{C}} C_{ijc}^k + C_{ijc}^{\text{sol}} \quad \forall i, j \in \mathcal{I}^+, \forall k \in \mathcal{K} | X_{ij}^k = 1, \quad (9)$$

where e_j^k is the summation of e_j^k , the energy of vehicle k at d_i , the energy required to transition from i to j and serve j E_{ij}^k , the energy charged at any charging station, and the solar energy charged from the roof during transition ij C_{ijc}^{sol} . The transition energy is defined as

$$E_{ij}^k = \begin{cases} d_{ij}^{\text{fp}} \cdot \bar{E}_{\text{con}} & \forall i, j \in \mathcal{I}^+, \forall k \in \mathcal{K} | \sum_{c \in \mathcal{C}} S_{ijc}^k = 0 \\ (d_{ij}^{\text{fp}} + \Delta d_{ijc}^{\text{go2S}}) \cdot \bar{E}_{\text{con}} & \forall i, j \in \mathcal{I}^+, \forall c \in \mathcal{C}, \forall k \in \mathcal{K} | S_{ijc}^k = 1, \end{cases} \quad (10)$$

where \bar{E}_{con} is the consumption per unit distance of the vehicles, d_{ij}^{fp} is the distance of the fastest path from d_i to o_j , and $\Delta d_{ijc}^{\text{go2S}}$ is the additional distance driven to pass by station c . Finally, we bound the state of energy of each vehicle to be within its battery capacity as

$$0 \leq e_j^k \leq E_b^{\text{max}} \quad \forall j \in \mathcal{I}^+, \forall k \in \mathcal{K}, \quad (11)$$

and set the initial and final battery level to a pre-defined value E_b^0 as

$$e_0^k = e_{I+1}^k = E_b^0 \quad \forall k \in \mathcal{K}. \quad (12)$$

D. Objective

In this paper, we set the optimization objective as the maximization of 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

$$J = \sum_{i,j \in \mathcal{I}} p_{ij}^{\text{el}} \cdot \sum_{k \in \mathcal{K}} \sum_{c \in \mathcal{C}} C_{ijc}^k - \sum_{i \in \mathcal{I}^+} b_r^i \cdot p_i, \quad (13)$$

where p_{ij}^{el} is the price of electricity during transition ij , approximated by its average between $t_i + t_{ii}^{\text{fp}}$ and t_j , the binary variable b_r^i indicates whether request i is being served, and p_i is the revenue generated from it.

Then the maximum-profit operation problem for an S-AMoD fleet is defined as follows:

Problem 1 (Optimal S-AMoD Fleet Management). *Given a set of transportation requests \mathcal{I} , the operations maximizing the total profit of the S-AMoD system result from*

$$\begin{aligned} \min J \\ \text{s.t. (1) - (13).} \end{aligned}$$

Problem 1 is a mixed integer linear program that can be solved with global optimality guarantees by off-the-shelf optimization algorithms.

E. Discussion

A few comments are in order. First, we consider travel times to be known. This assumption is in order if the routing of the fleet does not affect travel time, i.e., traffic congestion effects are exogenous. Second, we assume the electricity prices to be known in advance during the entire day, given the predictability of the macro-trend of the price fluctuations. Third, given the offline analysis and design purpose of the work, we assume the travel requests to be known in advance. For real-time operational purposes, it would be possible to implement an online version of this framework in a receding horizon fashion. Fourth, Problem 1 is NP-hard. Hence it is not possible to solve it for large instances. However, by solving stochastically sampled scenarios, we can draw a sub-optimal, but more conservative solution of the original problem [22]. Fifth, we assume the amount of energy traded by the S-AMoD fleet not to influence the energy prices, as is the case for medium to large fleets: For instance, for the case study presented in Section III below, the considered fleet of 800 vehicles trades less than 0.2% of the overall electric energy trading volume of the region. We leave the study of the coupling between the two systems with significantly higher S-AMoD penetration rates to future research. Sixth, we assume spatially-homogeneous weather conditions, so that the solar energy harvested by each vehicle C_{ij}^{sol} depends on the time of day only. Finally, we aim at maximizing the profit generated by the operator, yet our framework can readily accommodate different cost models, which we leave to future research endeavors.

III. RESULTS

In this section, we compare an S-AMoD and E-AMoD system in terms of operational strategies and costs, and how these are influenced by the electricity price fluctuations caused by a high proportion of solar power in the energy mix, and by different vehicle design choices.

A. Case Study of Gold Coast, Australia

We present a case study conducted in the city of Gold Coast, Queensland, Australia, using data on the road network and travel requests obtained from Transportation Networks for Research [26]. Our analysis focuses on over 30,000 travel requests served by a fleet of 800 vehicles, comparing the performance of both S-AMoD and E-AMoD systems. The simulation is conducted for both winter and summer, as these periods exhibit distinct energy price and solar radiation profiles throughout the day, allowing us to observe variations in fleet operation. As a base vehicle for the S-AMoD system, we consider the highly-efficient solar-electric Lightyear 0 [27]. To ensure a fair comparison, for the E-AMoD fleet we employ the same base vehicle with disabled solar roofs. We gather data on battery size $E_b^{\text{max}} = 60$ kWh and energy consumption $\bar{E}_{\text{con}} = 0.12$ kWh/km from the website of the Dutch Car Company Lightyear [27], indicating that, over a sunny day, its rooftop produces approximately 6 kWh during summer, and 5 kWh during winter. We set the charging power to $P_{\text{ch}} = 22$ kW. Finally, we take the cost-models representing the revenues generated when serving the requests from [28]. Considering its combinatorial complexity, to solve Problem 1, we solve smaller randomly sampled scenarios multiple times, similar to [22], whereby in each sample 200 daily requests are served by 5 vehicles. We parse the problems with Yalmip [29] and solve them with Gurobi 10.1 [30].

Figs. 1 and 2 show the power withdrawn from and injected to the grid, as well as the overall energy consumed by the S-AMoD and E-AMoD fleet during one day in summer and winter, respectively. It is noteworthy that the winter and summer case studies exhibit striking similarities: Despite significant price variations, the operator can employ structurally similar strategies: Prioritize charging during midday and nighttime when electricity prices and the number of travel requests are low, and make use of V2G when electricity prices are high and the number of travel requests is low. This approach allows for the assignment of more vehicles in the fleet with discharging or charging tasks during periods of low demand, thereby increasing the operator's overall profitability. In all the four cases, the revenues generated by serving all the travel requests were the same, approximately 265 kAUD. This result highlights that, independently of every other factors, the task with the highest priority of the fleet is to serve requests, whilst charging and V2G operations are of secondary importance, given that they account for less than 10% of the objective function considered.

Considering the dis(charging) aspect, Fig. 3 reveals that trading energy is more profitable in winter compared to summer, thereby incentivizing the fleet to undertake more

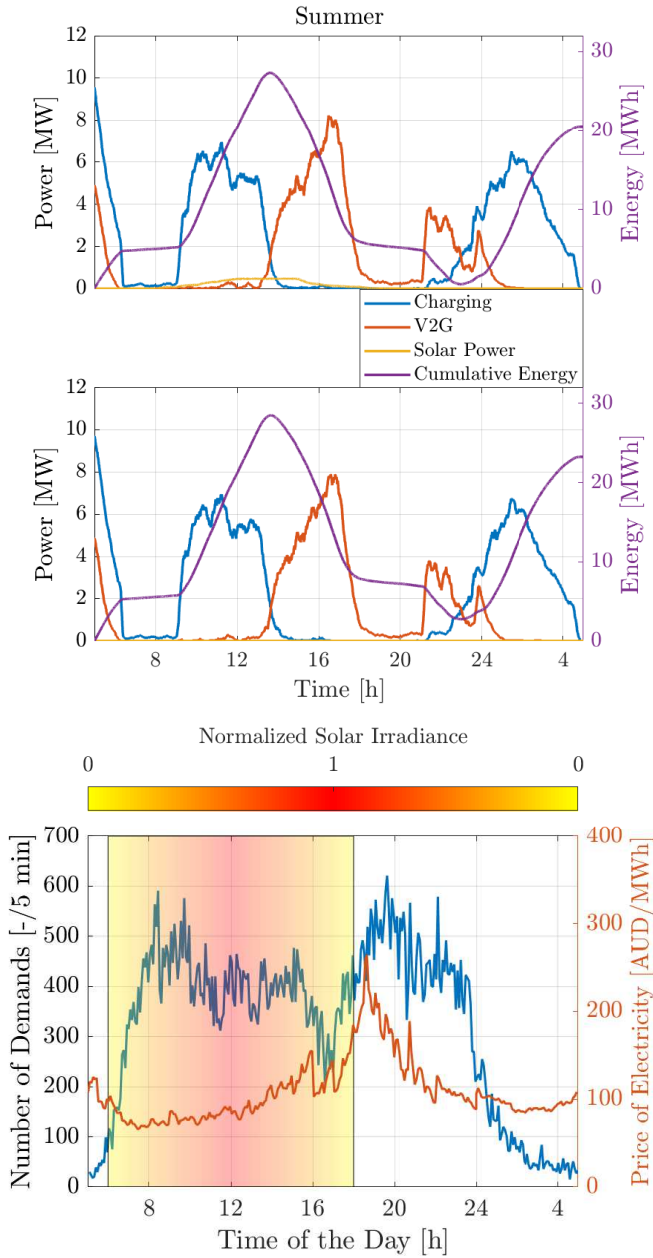


Fig. 1. The top two figures show the results during summer for an S-AMoD and E-AMoD fleet, respectively, in terms of charging power (blue), V2G power (red), solar power generated by the roof (yellow), and overall cumulative energy consumption (purple). Interestingly, the bottom figure shows the average electricity price in summer 2022 in Queensland (Courtesy of Australian Energy Market Operator) and the number of demands every 5 minutes. The colored area denotes the solar irradiance.

trips for charging and discharging purposes, which, in turn, results in a higher energy consumption. Then, comparing S-AMoD with E-AMoD, we note that, on the one hand, the operational strategies are very much the same: Indeed, with an average daily solar panel production of 5-6 kWh, each vehicle saves approximately 10-15 min of charging time. However, this time-saving is not significant since the fleet has ample daily time-windows available for charging. Furthermore, it is crucial to observe that the surplus energy from the solar roofs coincides with periods of abundant solar

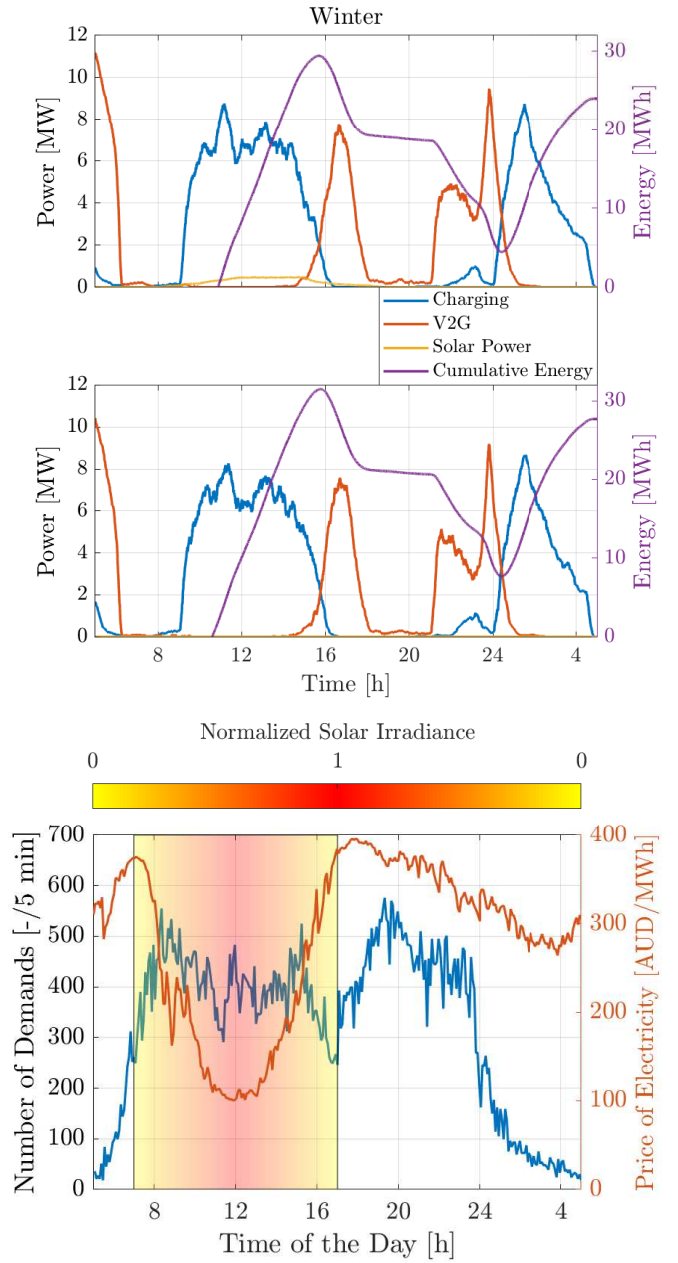


Fig. 2. The figures show a simulation during winter for an S-AMoD and E-AMoD systems. During winter, the operator fully recharges the fleet during midday and during night, and conveniently discharges during the two peaks at 7:00 and 18:00.

production in the energy mix, resulting in lower electricity prices. Consequently, the fleet operator does not benefit significantly from the additional driving range provided by the solar roofs, as it aligns with the fleet's natural recharging periods. On the other hand, the energy profitability, excluding the part related to the travel requests that coincides in all scenarios, is approximately 10% higher due to the energy generated by the solar roof.

B. Comparing Fleets with Different Battery Size

In this section, we examine the impact of the solar roof for fleets with smaller battery sizes, where the surplus energy

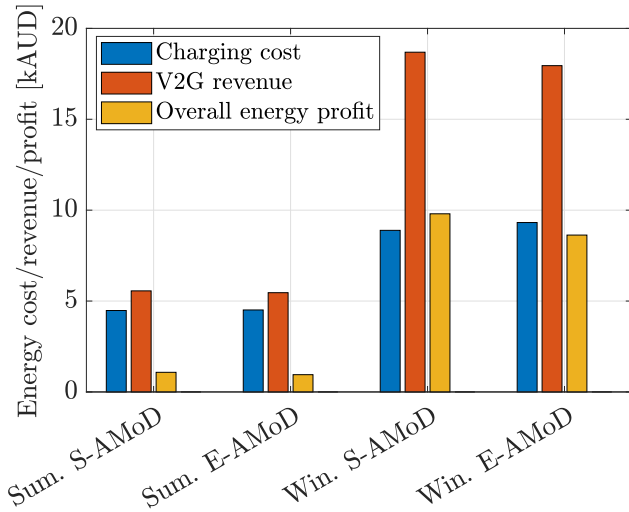


Fig. 3. Charging cost, V2G revenue, and overall profit generated by trading energy during summer and winter for S-AMoD and E-AMoD systems. The revenue generated by serving travel requests is 265 kAUD in all four cases.

can potentially have a more pronounced effect. We conduct a similar case study as the previous section, focusing on summer, and compare S-AMoD and E-AMoD fleets with battery sizes of 20 kWh and 40 kWh, respectively. We capture the lower energy consumption per unit distance caused by the smaller battery sizes, by accounting for the lower weight of the vehicles in their energy consumption models as shown in [22] and [31, Ch. 2]. Furthermore, considering charging-levels standards, we set the charging powers to $P_{ch} = 8$ kW and 12 kW, respectively, ensuring a similar C-rate between the different types of vehicles [31].

Fig. 4 illustrates the discharging and charging operations in the four cases from which we learn that the lower the battery capacity, the lower the overall amount of energy exchanged. The E-AMoD fleets equipped with 20 and 40 kWh batteries achieve revenues from serving travel requests equal to 240 kAUD, 9% lower compared to the 60 kWh case study. This is due to the longer time spent charging due to the lower charging power. Notably, for solar-electric fleets, this gap goes down to 6% (245 kAUD), showing that, for smaller vehicles, the solar-energy surplus not only positively benefit the energy costs shown in Fig. 5, but also the overall number of requests that can be served.

Overall, in terms of battery size, this case study shows that when V2G is possible, it is financially more advantageous to employ a fleet with a larger battery size, albeit its higher energy consumption, due to higher trading volumes and the ability to use a stronger charging power. Moreover, the convenience of having a solar rooftop increases for smaller battery sizes, whereby it can increasingly counter-balance the lower power of the charging stations, and allow a higher number of requests to be served. Finally, we recall that it would be also important to consider the amortized fixed costs to purchase the fleet, which may be higher for larger batteries, and battery lifetime. Whilst the present paper is focused on operational costs only, we leave such a comprehensive

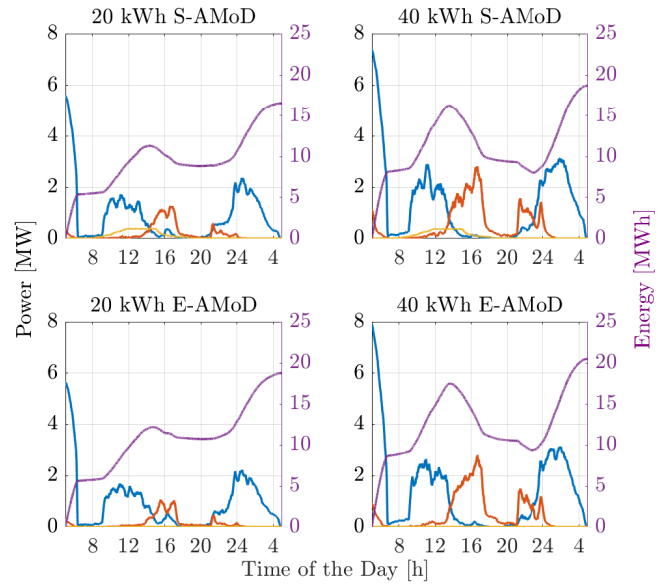


Fig. 4. Charging and discharging operations during summer. The four cases are: S-AMoD and E-AMoD, both with 20 and 40 kWh battery pack. The meaning of the lines-color is the same as in Figs. 1 and 2.

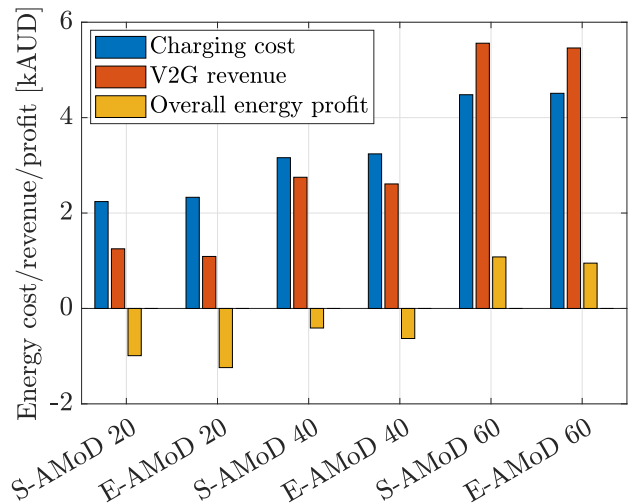


Fig. 5. Charging cost, V2G revenue, and overall profit generated by trading energy during summer for S-AMoD and E-AMoD systems with vehicles equipped with a 20, 40 and 60 kWh battery. Note that the last two groups of bars correspond to the first two of Fig. 3.

investigation of the fleet's total cost of ownership to future research.

IV. CONCLUSIONS

In this paper, we introduced a framework for optimizing the operation of a Solar-electric Autonomous Mobility-on-Demand (S-AMoD) fleet with vehicle-to-grid capabilities. To this end, we leveraged directed acyclic graphs and mixed-integer linear programming to solve the maximum-profit fleet management problem w.r.t. the fleet operator point of view. We showcased our framework through real-world case studies conducted in Gold Coast, Australia, during summer and winter, showing that actively trading energy could lower

operational costs for the fleet. Furthermore, we found that whilst there were no significant operational differences in terms of strategy between a standard electric fleet and a solar-electric fleet, the S-AMoD system exhibited a 10-15% improvement in operational costs due to a reduction in energy consumption, resulting in additional reductions in CO₂ emissions and overall environmental impact. Finally, we demonstrated that deploying a fleet with a larger battery size is more profitable when V2G operations are considered, even when accounting for the resulting higher energy consumption of the vehicles.

Moving forward, several extensions to this work are worth exploring. First, incorporating ride-sharing into the framework would be a natural progression [12], as well as studying intermodal settings where transportation requests are served jointly with public transit and active modes [32]. Second, we would like to study the solutions stemming from different cost-functions, such as environmental impact and battery-lifetime-aware total cost of ownership. Finally, it would be worthwhile developing tailored solution algorithms to solve the optimization problems presented, as well as deriving implementable online control schemes.

V. ACKNOWLEDGMENTS

We thank Dr. I. New, L. Pedroso and J.P. Bertucci for proofreading this paper. This publication is part of the project NEON with project number 17628 of the research program Crossover which is (partly) financed by the Dutch Research Council (NWO).

REFERENCES

- [1] EPA, "Inventory of us greenhouse gas emissions and sinks: 1990-2016," *United States Environmental Protection Agency*, 2018.
- [2] P. Denholm, M. O'Connell, G. Brinkman, and J. Jorgenson, "Overgeneration from solar energy in california. a field guide to the duck chart," National Renewable Energy Lab (NREL), Tech. Rep. NREL/TP-6A20-65023, 2015.
- [3] C. Yao, S. Chen, and Y. Zaiyue, "Joint routing and charging problem of multiple electric vehicles: A fast optimization algorithm," *IEEE Transactions on Intelligent Transportation Systems*, 2021.
- [4] M. Pavone and E. Frazzoli, "Dynamic vehicle routing with stochastic time constraints," in *Proc. IEEE Conf. on Robotics and Automation*, 2010.
- [5] M. Pavone, N. Bisnik, E. Frazzoli, and V. Isler, "Decentralized vehicle routing in a stochastic and dynamic environment with customer impatience," in *Int. Conf. on Robot Communication and Coordination*, 2007.
- [6] P. Toth and D. Vigo, *Vehicle Routing – Problems, Methods, and Applications*, 2nd ed., K. Scheinberg, Ed. SIAM, 2014.
- [7] G. Laporte, "The vehicle routing problem: An overview of exact and approximate algorithms," *European Journal of Operational Research*, vol. 59, no. 3, pp. 345–358, 1992.
- [8] H. N. Psaraftis, M. Wen, and C. A. Kontovas, "Dynamic vehicle routing problems: Three decades and counting," *Networks*, vol. 67, no. 1, pp. 3–31, 2016.
- [9] V. Pillac, M. Gendreau, C. Guéret, and A. L. Medaglia, "A review of dynamic vehicle routing problems," *European Journal of Operational Research*, vol. 225, no. 1, pp. 1–11, 2013.
- [10] K. Spieser, K. Treleaven, R. Zhang, E. Frazzoli, D. Morton, and M. Pavone, "Toward a systematic approach to the design and evaluation of Autonomous Mobility-on-Demand systems: A case study in Singapore," in *Road Vehicle Automation*. Springer, 2014.
- [11] R. Iglesias, F. Rossi, K. Wang, D. Hallac, J. Leskovec, and M. Pavone, "Data-driven model predictive control of autonomous mobility-on-demand systems," in *Proc. IEEE Conf. on Robotics and Automation*, 2018.
- [12] F. Paparella, L. Pedroso, T. Hofman, and M. Salazar, "A time-invariant network flow model for two-person ride-pooling mobility-on-demand," *IEEE Control Systems Letters*, 2023, under Review.
- [13] F. Rossi, R. Zhang, Y. Hindy, and M. Pavone, "Routing autonomous vehicles in congested transportation networks: Structural properties and coordination algorithms," *Autonomous Robots*, vol. 42, no. 7, pp. 1427–1442, 2018.
- [14] S. Wollenstein-Betech, A. Houshmand, M. Salazar, M. Pavone, C. G. Cassandras, and I. C. Paschalidis, "Congestion-aware routing and rebalancing of autonomous mobility-on-demand systems in mixed traffic," in *Proc. IEEE Int. Conf. on Intelligent Transportation Systems*, 2020.
- [15] A. Hoff, H. Andersson, M. Christiansen, G. Hasle, and A. Løkketangen, "Industrial aspects and literature survey: Fleet composition and routing," *Computers & Operations Research*, vol. 37, no. 12, pp. 2041–2061, 2010. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0305054810000699>
- [16] T. M. J. T. Baltussen, M. Goutham, M. Menon, S. G. Garrow, M. Santillo, and S. Stockar, "A parallel monte-carlo tree search-based metaheuristic for optimal fleet composition considering vehicle routing using branch & bound," *arXiv*, 2023.
- [17] F. Boewing, M. Schiffer, M. Salazar, and M. Pavone, "A vehicle coordination and charge scheduling algorithm for electric autonomous mobility-on-demand systems," in *American Control Conference*, 2020.
- [18] J. Luke, M. Salazar, R. Rajagopal, and M. Pavone, "Joint optimization of electric vehicle fleet operations and charging station siting," in *Proc. IEEE Int. Conf. on Intelligent Transportation Systems*, 2021.
- [19] F. Paparella, K. Chauhan, T. Hofman, and M. Salazar, "Electric autonomous mobility-on-demand: Joint optimization of routing and charging infrastructure siting," in *IFAC World Congress*, 2023, in Press.
- [20] F. Rossi, R. Iglesias, M. Alizadeh, and M. Pavone, "On the interaction between Autonomous Mobility-on-Demand systems and the power network: Models and coordination algorithms," *IEEE Transactions on Control of Network Systems*, vol. 7, no. 1, pp. 384–397, 2020.
- [21] A. Estandia, M. Schiffer, F. Rossi, J. Luke, E. C. Kara, R. Rajagopal, and M. Pavone, "On the interaction between autonomous mobility on demand systems and power distribution networks—an optimal power flow approach," *IEEE Transactions on Control of Network Systems*, vol. 8, no. 3, pp. 1163–1176, 2021.
- [22] F. Paparella, T. Hofman, and M. Salazar, "Joint optimization of number of vehicles, battery capacity and operations of an electric autonomous mobility-on-demand fleet," in *Proc. IEEE Conf. on Decision and Control*, 2022, pp. 6284–6291.
- [23] J. Connors, "On the subject of solar vehicles and the benefits of the technology," in *2007 International Conference on Clean Electrical Power*, 2007, pp. 700–705.
- [24] Y. S. Wamborikar and A. Sinha, "Solar powered vehicle," in *proceedings of the World Congress on Engineering and Computer Science*, vol. 2. Citeseer, 2010, pp. 20–22.
- [25] M. Waseem, A. F. Sherwani, and M. Suhaib, "Integration of solar energy in electrical, hybrid, autonomous vehicles: a technological review," *SN Applied Sciences*, vol. 1, 2019.
- [26] T. N. for Research Core Team. Transportation networks for research. <https://github.com/bstabler/transportationnetworks>. Accessed January, 05, 2023.
- [27] Lightyear. (2016) Available online at <https://lightyear.one/> Accessed: 26/09/2022.
- [28] (2018) Updating a payment method on your account. Uber Technologies Inc. Available at <https://help.uber.com/h/8f78dca4-9d75-44f1-bdc1-e90ca3da0319>.
- [29] J. Löfberg, "YALMIP : A toolbox for modeling and optimization in MATLAB," in *IEEE Int. Symp. on Computer Aided Control Systems Design*, 2004.
- [30] Gurobi Optimization, LLC. (2021) Gurobi optimizer reference manual. Available at <http://www.gurobi.com>.
- [31] L. Guzzella and A. Sciarretta, *Vehicle propulsion systems: Introduction to Modeling and Optimization*, 2nd ed. Springer Berlin Heidelberg, 2007.
- [32] S. Wollenstein-Betech, M. Salazar, A. Houshmand, M. Pavone, C. G. Cassandras, and I. C. Paschalidis, "Routing and rebalancing intermodal autonomous mobility-on-demand systems in mixed traffic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 12 263–12 275, 2021.