Optimizing Automated Mobility on-Demand Operation with Markovian Model: A Case Study of the Tel-Aviv Metropolis in 2040

Gabriel Dadashev[1] and Bat-hen Nahmias-Biran[1]

[1] The Porter School of the Environment and Earth Sciences, Tel-Aviv University, Ramat Aviv 6997801, Israel

SHORT SUMMARY

The emergence of Autonomous Mobility on Demand (AMoD) services heralds a transformative shift in urban transportation dynamics. With their potential to significantly reduce operational costs and eliminate the need for drivers, AMoD services are poised to revolutionize mobility in cities like Tel-Aviv, where they are projected to capture a substantial portion of daily trip demand. Despite their promise, comprehensive studies evaluating the full functionality of AMoD services, especially charging behavior under real-world conditions, remain scarce. Following this gap, our study delves into the core tasks of AMoD fleet management: dispatching, routing, charging, and rebalancing. Leveraging advanced simulation tools, we undertake a rigorous examination of AMoD operations to predict demand, enact daily plans, and optimize fleet activities through a sophisticated Markov decision process (MDP) model. Our findings reveal that the MDP model facilitates the derivation of optimal actions for individual AMoD vehicles, thereby maximizing future profitability while fostering substantial energy savings.

Keywords: Automated Mobility on Demand; Urban mobility; Energy constraints; Activity-based simulation; Markov decision process.

1. INTRODUCTION

Private cars in metropolitan areas mainly serve short and slow trips within dense urban areas, despite their potential for long-distance travel (Beckx et al., 2013). The high demand for vehicles for short trips leads urban transportation networks to deal with various problems of congestion and pollution (Kenworthy and Laube; 1996) and to offer complementary solutions for private vehicles (Ferreira and Liu; 2023; Mavlutova et al., 2023). Some of the proposed complementary solutions combine automation and on-demand services, utilizing automated vehicles, to provide convenient and flexible mobility solutions. Automated mobility on-demand (AmoD) services have lower operating costs, due to reduced fuel and insurance costs and have no driver (Howard and Dai, 2014; Fraedrich and Lenz, 2014), which makes it extremely attractive for future development, thus, attracted a lot of attention in the literature. AmoD services, like 'Motional' in Las Vegas and 'Waymo' in San Francisco, are already a reality, with over 10% of daily expected demand in future cities like Tel-Aviv (Nahmias-Biran et al., 2023).

Following the expected high demand for these services, a large set of simulation-based studies was dedicated to understanding the effects of such services on certain metropolitan areas, while others focused on improving the functionality of the service. For example, Bischoff and Maciejewski (2016) investigated the potential impacts if all private cars were to be replaced by AmoD services in Berlin's metropolitan area. They found that the empty trips made by the AmoD fleet would increase the total travel time by 17%. Hörl et al. (2019) employed a discrete choice model to estimate dynamic demand for AMoD system in Paris. They found that in Paris, the demand for the service can rise to 1.2 million trips per day, with the optimal fleet size identified as 25,000 vehicles. Nahmias-Biran et al. (2022) used activity-based simulation to explore the outcomes of replacing all taxis with AMoD services in the Tel-Aviv metropolis. They discovered that for the AMoD service to compete effectively with private car usage, its prices would need to be 80 percent lower than those of traditional taxis. Additionally, the study revealed that this type of service has lower demand among seniors. Zhou et al. (2021) also used agent-based simulation to assess accessibility measures to different destinations, such as employment, educational, commercial, and healthcare in the case of Singapore. They found that while the AmoD service enhances accessibility, it does so only when complementing, not replacing, private cars. Lu et al. (2023) used MATSIM model to design AmoD style service replacing students' school buses during specific hours of the day, on large rural area in Germany. However, in previous papers, electric fleet charging nature was not accounted for, given the travel distances that can be covered within a single charge.

Furthermore, all these studies formulate simulations based on information such as population, land uses, and prices, at various detail levels. However, beyond the assignment of vehicles for trip requests they do not delve into the intricacies of implementing such services. The implementation of AMoD service includes four main tasks: dispatching, routing, ridesharing, and rebalancing. Dispatching assigns vehicles to customers based on availability, proximity, and battery level. Routing optimizes routes for profitability, while ridesharing serves multiple riders with one vehicle, reducing energy use but complicating trip planning with multiple route calculations (Zardini et al., 2021). The rebalancing task involves repositioning empty vehicles to optimize responsiveness and serve future demand (Dai et al., 2021). It is especially important because AMoD systems experience imbalance when some areas have more demand than others (Pavone et al., 2012).

Many studies have tried to develop service frameworks and simulations to study and improve these tasks. For example, Tsao et al. (2019) created a system based on a linear programming problem that optimizes the price and activity times of the service and was implemented in real-time while considering predicted demand. Solovey et al. (2019) did rebalancing by using convex optimization (Frank-Wolfe Optimization) that is providing high-quality routing solutions for large-scale systems. Lin et al. (2018) relied on reinforcement learning in a multi-agent simulation platform, where each vehicle is an agent that communicates with the other cars; thus, large-scale coordination is created to assign vehicles to different activities. Wollenstein-Betech et al. (2021) proposed a quadratic program for socially optimal that interacts with exogenous private traffic. Such studies often rely on road networks that inadequately represent real cities, lacking details such as land uses, population composition, and public transportation.

Besides fulfilling the four primary tasks, the rebalancing task involves the charging policy and energy consumption of the electric fleet. Research is lacking the algorithms performing the service's main tasks and determining optimal charging locations within the metropolitan area. Advanced studies prioritize charging infrastructure within the electric grid. For example, Chen et al. (2016), conducted a preliminary simulation of AMoD wherein they determined the requisite number of charging points to meet demand. Their simulation incorporated real-time calculations of the vehicle's driving range, with charging times proportionate to this range consistently factored in. Bang and Malikopoulos (2022) established a connection between electricity consumption and the average speed of a vehicle within a given segment. Their definition of a trip necessitating charging was characterized by a battery capacity below 10%. Additionally, their model operated under the assumption of consistently available chargers at the designated charging stations. Yang et al. (2023) allocated vehicles to charging stations based on below 20% battery capacity during simulation. This allocation is designed with the consideration of maintaining balanced demand, including charging time and load in the vicinity of the station. However, these studies only partially captured urban dynamics, none of them explicitly model service demand or the interaction between demand and supply.

Studies that emphasize the integration of AmoD operation algorithms with electrical features for realistic large-scale examination hardly exist. Dean et al. (2022) employed a detailed model for each of the AMoD tasks for Austin, Texas. They concluded that a combination of charging and rebalancing of the fleet can effectively reduce the flow on main roads while resulting in 28% more passengers. This combination is especially effective during the PM rush hour. However, this analysis is done without predicting the expected demand. Demand forecasting is critical in examining network performance and operation of such future service.

In this research, we aim to bridge this gap by integrating an activity-based demand prediction model with an advanced AMoD operator. The operator manages a fleet of vehicles that perform the dispatching, routing, and rebalancing tasks, including charging. The simulation is conducted using a realistic network of the Tel-Aviv metropolis, incorporating public and private vehicle traffic. The platform is based on a Markovian decision prosses combined with an agent base SimMobility-Aimsun Ride hybrid framework.

2. METHODOLOGY

The objective of this work is to formulate an AmoD operator that advances the prediction of demand under energy constantans, while operating in a real and large-scale metropolitan area. To achieve this, we first predict the demand for AMoD services in the Tel-Aviv metropolis. This involves utilizing an advanced agent and activity-based demand simulator, SimMobility, which is integrated with the Aimsun Next simulator. Once demand generation is achieved and the trips are dynamically assigned, we analyze both private vehicle routes and demand patterns for the new service. From the demand-supply interaction results we develop and solve the Markovian decision process which provides the optimization framework for this study. This framework can make optimal adjustments at half-hour intervals and implement them within the simulation framework to achieve energy savings and enhance overall fleet performance.

The simulations of the fleet are conducted using the Aimsun Ride platform. Aimsun Ride is an API-based system built upon the Aimsun Next traffic simulator. The default operator within Aimsun Ride match each request with the nearest available vehicle at the time of the request. However, this operator was changed as part of this work to 'Semi-Event' operator that apply the optimal action from the Markovian model for optimizing the energy consumption.

Demand and supply prediction

First, we built a representative synthetic population for the study area based on population characteristics that were analyzed using a travel habits survey (THS) conducted in 2016-2017 for the Tel-Aviv metropolitan area. This synthetic population was developed by a growth model based on government forecasts to represent the future population for 2040. In this work SimMobility demand simulator is employed to predict the demand for various modes and AmoD requests by inputting the land use and population behavior after calibrating it to match individual's behavior in Tel-Aviv metropolis. The demand prediction in this model is linked to the Aimsun Next network simulator, which updates the travel time per O-D pair to achieve sensitivity of demand to events such as traffic jams. Demand prediction results show that the demand for AMoD trips is estimated to be ~10% of the total 10 million trips predicted by the simulator for a typical day in 2040. Database of 1.2 million trips was created for the road assignment, including travel times in road segments resolution that can be analyzed to understand the dynamics of the road network (Nahmias-Biran et al., 2023; Dadashev et al., 2023).

Markov decision model design and solution

Markov decision process (MDP) is a mathematical framework taken from the worlds of reinforcement learning that enables the modeling of decision-making in situations where outcomes are partly random and partly under the control of a decision-maker. In an MDP, the decision-maker operates in a set of "states" and can take "actions" that change the current state to a new one. Each action from a specific state has a corresponding reward and result. The result represents the next state that the action can stochastically lead us to. By analyzing 1.2 million trips made by private cars and the requests for the AMOD service in the Tel-Aviv metropolis, we gain insights into the dynamics of the real world, specifically in terms of travel prices and electricity consumption on different areas at various hours. We also acquire knowledge about the probabilities of a vehicle to reach specific area with a particular state of charge (SOC) in order to design the transition from state to state as part of MDP framework. We created a set of states consisting of the location and SOC of the vehicle and designed actions for the four tasks of the AMoD service with an emphasis on rebalancing, charging, and passenger pickup as shown in Figure 1.

As shown in Fig.1, Charging is allowed only if the vehicle is in the lowest energy level. This action changes the state to the top energy level on a probability of 1 with a cost of 36.75 NIS (Figure 1b). The Trip action can take the vehicle to the Pick-Up state or stay put while the probability here depends on trip demand in the area and if vehicle's energy level is enough to finish a request (Figure 1c). Finaly, Rebalancing action is allowed travel to other zone but to lower energy levels due to energy consumption. SimMobility daily activity schedule outputs (Figure 1d).

To solve the MDP, we use dynamic programming, specifically value iterations algorithm. This algorithm creates a function between each state and the optimal action it can take to maximize its profit in the foreseeable future.

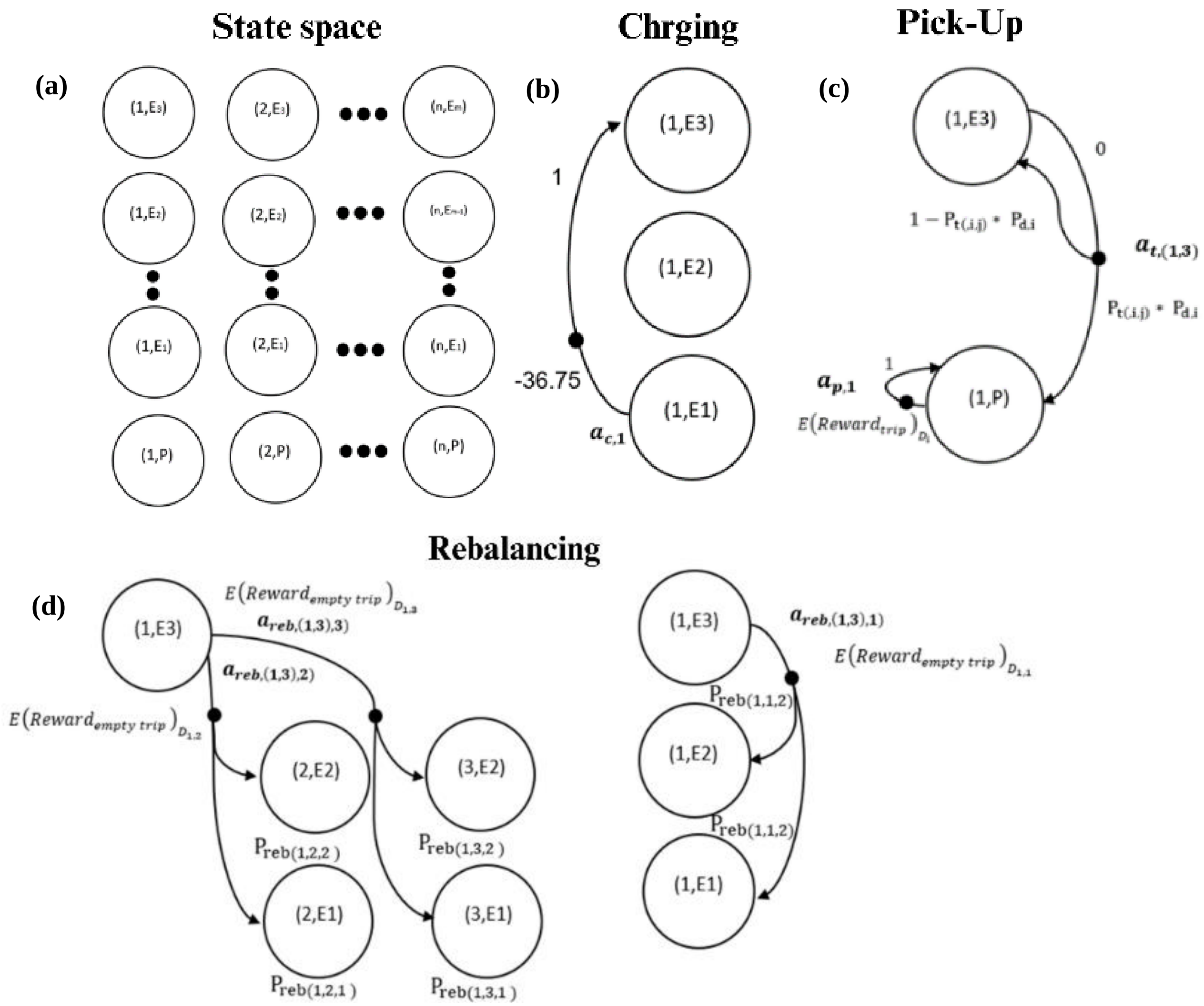

Figure 1: Markov decision prosses designed for AmoD main tasks.

Semi-event AmoD operator

To simulate the optimal policy on Tel-Aviv 2040 network, we design an operator that can effectively navigate the outcomes of a MDP, taking into consideration the location and energy level of the vehicle. To achieve this functionality, it is necessary to redesign the Ride operator in order to seamlessly integrate it into the current simulation framework. In this simulation, an empty AmoD vehicle "asks" for instructions from the MDP model to maximize its future profit in terms of operation costs. A flow chart of operator's commands is described in Figure 2.

According to Figure 2 each vehicle can be in one of 3 statuses: charge, rebalance or trip search. If the vehicle is "idle" it asks the MDP for recommendation regarding its next action (charge, rebalance or search a trip) and follow the recommendation. If the vehicle finished rebalancing or charging, it is open to trips requests for a defined time. After this period the vehicle "asks" the MDP for optimal action and follow it. The SOC of the vehicle is being updated in each trip to identify the correct MDP state and to accept only offers that the vehicle can complete due to SOC.

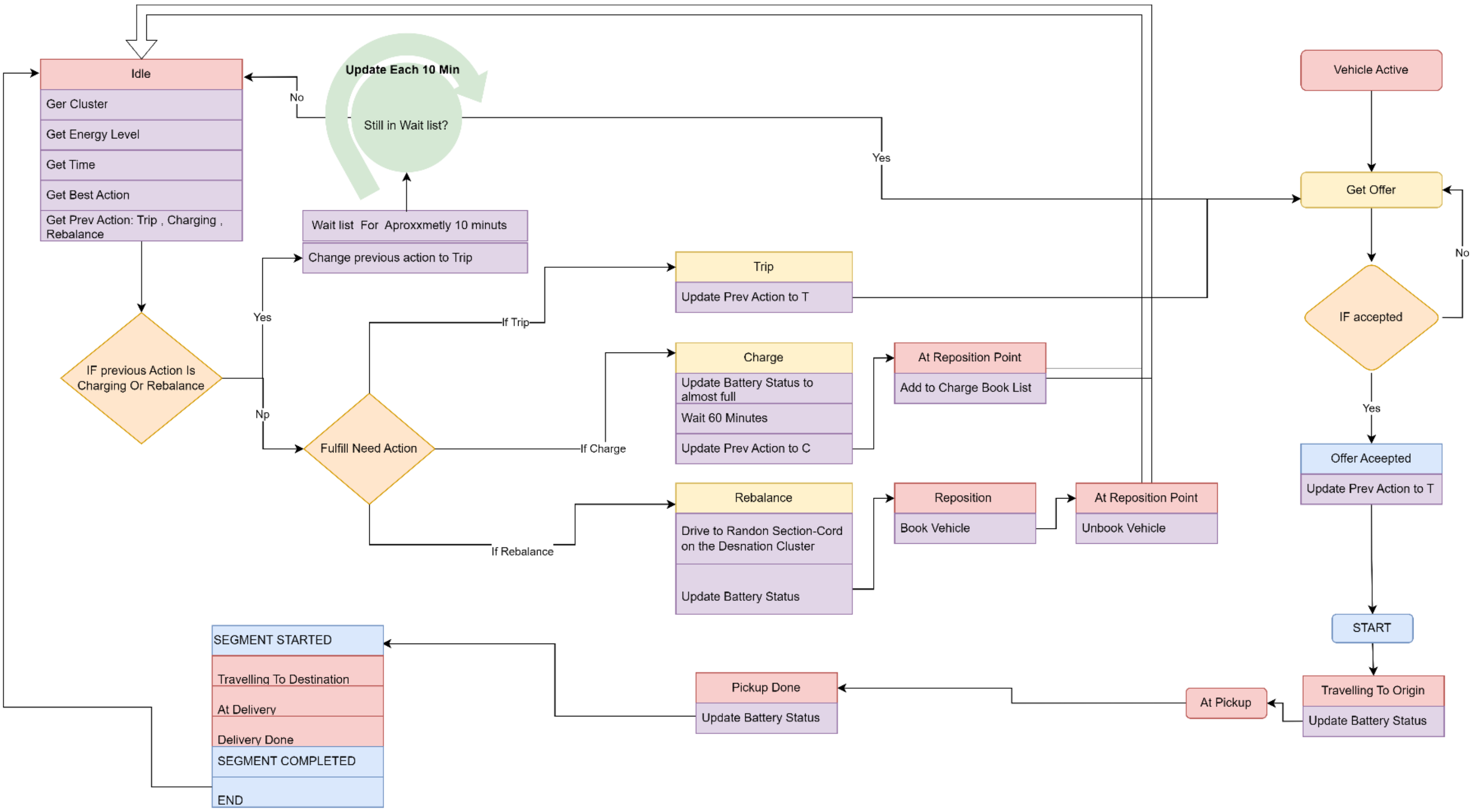

Figure 2: Semi-event AmoD operator flow chart

3. RESULTS AND DISCUSSION

The input for the Markovian model is the number of clusters by which the user wants to split the AmoD demand using geospatial Hard K-means. The second aspect is the sensitivity of the model to SOC changes. The user splits the 58-kWh battery capacity into equal intervals (Energy level), so vehicle state is tuple consists of area clustering, energy level. A large number of clustering areas and energy levels make the MDP more detailed, but it comes with the price of the runtime of the optimization algorithm. We use three main cases in this simulation experiment: (1) the MDP model case with different energy sensitivity (2) demand-oriented solution while rebalancing to areas with high demand, and (3) the random action case that represents chaos in the system. The results presented here are partial and part of an ongoing study demonstrating the potential of such a model.

In our experiment we split the Tel-Aviv metropolis into 5 clusters (the optimal number of clustering of Tel-Aviv metropolis following the Elbow method is eleven areas). We defined the number of energy levels to 5, 16, and 32, to see the initial sensitivity of the model. In Fig. 3, we see the map of Tel-Aviv metropolis after applying the k-mean analysis and the MDP model result when each state receives the optimal action.

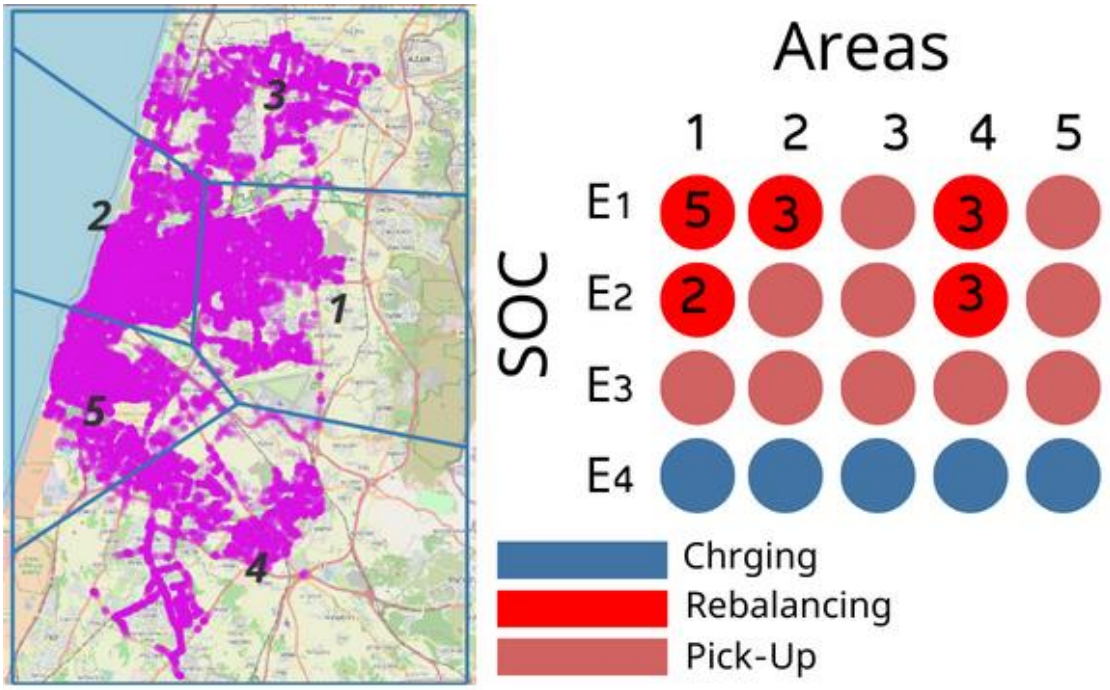

Figure 3: MDP best policy using 5 areas, 4 energy levels model.

In Fig. 3, we see five clusters – two in the Tel-Aviv center (2,5) and three in the outer ring of the metropolis (3,4,1). The MDP results show that the most profitable areas are five, in the Tel-Aviv center, and three in the north outer ring. In these areas, the best policy that the AmoD vehicle can adopt is to pick up customers, regardless of its battery status. For cars in zone two, which are located in the center, it is recommended to go to the nearest zone, zone three, if their energy level is very high. If AMoD's energy level is medium or below, the model suggests picking up people inside their area. This is apparently because people in the center of the metropolis make shorter trips and pay less for the service. zone four, in the south of the outer ring, is the least profitable for picking up passengers, and the model recommends picking people up there only when the battery is at its lowest level. Otherwise, it recommends going to the northern part of the metropolis, apparently due to the good connectivity of main roads connecting the zones, bypassing congestions in the center of the metropolis in zones five and two. Zone one, located in the center of the outer ring, is also less profitable. AMoD vehicles will perform pick-ups there according to the model only when the battery is relatively weak. Otherwise, it is recommended rebalancing to area five when the battery is strong to maximize gains. Additionally, when the battery is lower, it is advisable to focus the search for customers on the area closest to the center of the metropolis. As the energy level of the model increase, the exact battery level at which the policy should shift can be determined. Fig. 4 provides a visual representation of the energy consumption based on random selection of 100 vehicles in the AmoD Fleet.

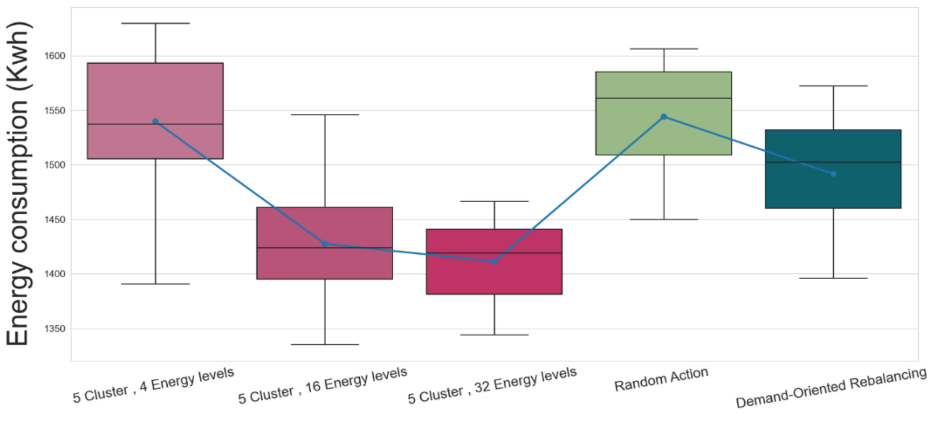

Fig 4: Energy consumption in different scenarios

Results show that in the Random Action case, energy consumption is 1544 kWh, while in the Demand-Oriented case, it is 1492 kWh. The MDP model requires 1551 kWh for 4 energy levels, 1443.6 kWh for 16 energy levels, and 1411 kWh for 32 energy levels. This data indicates a diminishing trend in consumption as more energy levels are added. In Fig .5, the number of trips lasting less than 10 minutes and those lasting longer than 10 minutes can be observed.

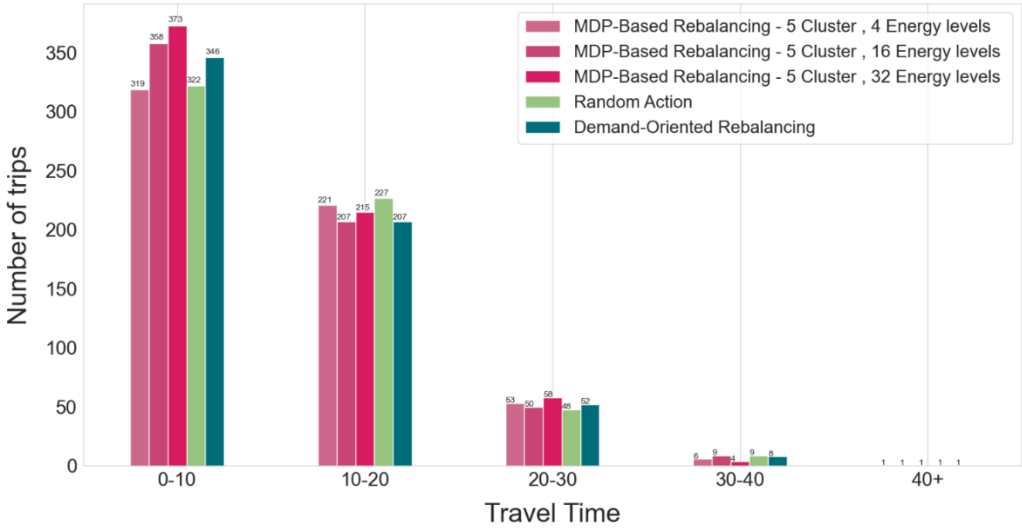

Figure 5: Travel time in different scenarios

The increase in number of energy levels leading to heightened sensitivity to battery conditions; there is also a noticeable increase in the frequency of short trips, those lasting under 10 minutes, as compared to longer trips. With 4 energy levels, there are 319 trips under 10 minutes. When sensitivity is increased to 16 energy levels, the number of trips rises to 356, and at 32 energy levels, it further increases to 373 trips. This upsurge in short trips is attributed to the model's growing emphasis on optimizing battery preservation as energy levels increase, causing the vehicle to reroute to areas with a higher occurrence of short trips and reduce costs. In the two scenarios, the number of short trips remains similar, with 322 trips in the Random Action case and 346 trips in the Demand-Oriented case.

CONCLUSION

In conclusion, we have designed and demonstrated the operation of an AmoD controller framework based on mathematical MDP model. This effort was made to create realistic simulation conditions that mimic as much as possible the operation of such fleet in Tel-Aviv’s urban environment. On top of this simulation framework, an innovative fleet controller was created using Ride tool which can monitor the electric battery status, complete self-charging, and initiating empty trips for fleet rebalancing. After accurately representing the current road network conditions, we forecast future demand in the large metropolis of Tel-Aviv of 2040. Our findings reveal substantial potential for energy savings. Furthermore, our results underscore the model's sensitivity to variations in energy parameters, indicating that higher numbers of energy levels correspond to greater energy savings and consumption efficiency. The insights gleaned from our study carry substantial implications for the advancement of sustainable and efficient mobility solutions in metropolitan environments.

REFERENCES

Bang, H., & Malikopoulos, A. A. (2022, June). Congestion-aware routing, rebalancing, and charging scheduling for electric autonomous mobility-on-demand system. In 2022 American Control Conference (ACC) (pp. 3152-3157). IEEE.

Beckx, C., Broekx, S., Degraeuwe, B., Beusen, B., & Panis, L. I. (2013). Limits to active transport substitution of short car trips. Transportation Research Part D: Transport and Environment, 22, 10-13.

Bischoff, J., & Maciejewski, M. (2016). Simulation of city-wide replacement of private cars with autonomous taxis in Berlin. Procedia computer science, 83, 237-244.

Chen, T. D., Kockelman, K. M., & Hanna, J. P. (2016). Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. Transportation Research Part A: Policy and Practice, 94, 243-254.

Dadashev, G., Levi, Y., & Nahmias-Biran, B. H. (2023). Implications of de-carbonization policies using an innovative urban transport simulator. Transportation Research Part D: Transport and Environment, 119, 103754.

Dean, M. D., Gurumurthy, K. M., de Souza, F., Auld, J., & Kockelman, K. M. (2022). Synergies between repositioning and charging strategies for shared autonomous electric vehicle fleets. Transportation Research Part D: Transport and Environment, 108, 103314.

Ferreira, L. J., & Liu, J. (2023). Social Determinants, Motivation, and Communication: How People Perceive and Choose Sustainable Mobility at a Local Level in Portugal. Sustainability, 15(18), 13294.

Hörl, S., Balac, M., & Axhausen, K. W. (2019, June). Dynamic demand estimation for an AMoD system in Paris. In 2019 IEEE Intelligent Vehicles Symposium (IV) (pp. 260-266). IEEE.

Kenworthy, J. R., & Laube, F. B. (1996). Automobile dependence in cities: an international comparison of urban transport and land use patterns with implications for sustainability. Environmental impact assessment review, 16(4-6), 279-308.

Lin K, Zhao R, Xu Z, Zhou J. 2018. Efficient large-scaliest management via multi-agent deep rein-forcement learning. InKDD '18: Proceedings of the 24th ACM SIGKDD International Conference on Know-edge Discovery & Data Mining,pp.1774–83.NewYork:ACM

Lu, C., Maciejewski, M., Wu, H., & Nagel, K. (2023). Demand-responsive transport for students in rural areas: A case study in vulkaneifel, germany. Transportation Research Part A: Policy and Practice, 178, 103837.

Mavlutova, I., Atstaja, D., Grasis, J., Kuzmina, J., Uvarova, I., & Roga, D. (2023). Urban Transportation Concept and Sustainable Urban Mobility in Smart Cities: A Review. Energies, 16(8), 3585.

Nahmias-Biran, B. H., Dadashev, G., & Levi, Y. (2022). Demand exploration of automated mobility on-demand services using an innovative simulation tool. IEEE Open Journal of Intelligent Transportation Systems, 3, 580-591.

Solovey K,Salazar M,Pavone M.2019.Scalable and congestion-aware routing for autonomous mobility-on-demand via Frank-Wolfe optimization. InRobotics: Science and Systems XV, ed. A Bicchi, H Kress-Gazit, S Hutchinson, pap. 66. N.p.: Robot. Sci. Syst. Found.

Tsao M, Milojevic D, Ruch C, Salazar M, Frazzoli E, Pavone M. 2019. Model predictive control ofride-sharing autonomous mobility-on-demand systems. In2019 International Conference on Robotics andAutomation (ICRA), pp.6665–71.Piscataway,NJ:IEEE

Wollenstein-Betech, S., Salazar, M., Houshmand, A., Pavone, M., Paschalidis, I. C., & Cassandras, C. G. (2021). Routing and rebalancing intermodal autonomous mobility-on-demand systems in mixed traffic. IEEE Transactions on Intelligent Transportation Systems, 23(8), 12263-12275.

Yang, J., Levin, M. W., Hu, L., Li, H., & Jiang, Y. (2023). Fleet sizing and charging infrastructure design for electric autonomous mobility-on-demand systems with endogenous congestion and limited link space. Transportation Research Part C: Emerging Technologies, 152, 104172.

Zhou, M., Le, D. T., Nguyen-Phuoc, D. Q., Zegras, P. C., & Ferreira Jr, J. (2021). Simulating impacts of Automated Mobility-on-Demand on accessibility and residential relocation. Cities, 118, 103345.