

Received 15 December 2021; revised 14 April 2022, 16 June 2022, and 9 July 2022; accepted 26 July 2022.
Date of publication 9 August 2022; date of current version 7 September 2022.

Digital Object Identifier 10.1109/OJITS.2022.3197709

Demand Exploration of Automated Mobility On-Demand Services Using an Innovative Simulation Tool

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This work was supported by the Israeli Ministry of Environmental Protection, study 192-1-1.

This article has supplementary downloadable material available at <https://doi.org/10.1109/OJITS.2022.3197709>, provided by the authors.

ABSTRACT The prospect of automated mobility on-demand (AMoD) services in urban areas has highlighted critical challenges surrounding the sustainable development of urban mobility. To address this gap, we created an improved simulation tool by combining SimMobility's demand simulator with the hybrid meso-micro supply model of Aimsun Next. A realistic and city-scale examination of AMoD using such an advanced simulation tool can address the limitations identified in the literature and significantly promote the understanding of AMoD services. In this paper, we demonstrate the use of our improved simulation tool and focus on demand exploration of AMoD services in the Tel-Aviv metropolitan area. We employ an activity- and agent-based framework, for both single and shared AMoD rides, and explore 6 service cost scenarios and its impact on demand elasticities, mode choice, travel patterns and AMoD use by population groups. Our results indicate that there is no existing latent demand in Tel-Aviv metropolitan area and the extent of mode shifts from active modes and public transportation to AMoD is neglectable. This is due to AMoD services average travel costs, which is high as compared to all other modes, even with the largest fare reduction examined. Furthermore, it was found that AMoD demand, as a single service, is more elastic than when AMoD is shared, as cost elasticities drops as fare reduction increases. Unlike other modes of transportation, the maximum number of AMoD trips is obtained for trips between 10 to 20 kilometers, while young riders and full-time students are responsible for most of AMoD trips.

INDEX TERMS Automated mobility-on-demand, agent-based simulation, scenarios, simmobility, aimsun.

I. INTRODUCTION

THE PROSPECT of Autonomous Vehicle (AV) technology has garnered significant research as well as policy and economic interest. AV technology is constantly improving, with small-scale pilot programs underway in a few urban areas. Researchers and policymakers are demonstrating that shared mobility coupled with AV technology in the form of Automated Mobility on-Demand (AMoD) service is a pathway that can deliver better levels of service while reducing environmental impacts [1]. An Automated Mobility-on-Demand (AMoD) system is a demand-responsive mobility

service, i.e., service provided to the users who have requested it, like requesting a taxi, based on a fleet of shared automated battery-electric vehicles that can be easily accessed within the operating area. However, the prognosis on AMoD availability is mixed, while its interaction with existing modes and impacts on mobility patterns and system performance are yet to be fully determined (for a comprehensive review, see [2]). Optimistic studies project that the adoption of AMoD has the potential to markedly reduce costs [3], VKT [4], [5] and parking demand [6]. Moreover, AMoD implies a new market share, as it could afford greater mobility to disadvantaged groups, such as children and low-income individuals [7]. In addition, under environmentally conscious regulation, AMoD has been shown to reduce energy use and greenhouse

The review of this article was arranged by Associate Editor Emmanouil Chaniotakis.

gas (GHG) emissions [8]. Yet the projected higher efficiency of AMoD could exacerbate the cannibalization of mass transit and even of active mobility modes such as walking and biking [9], [10]. Bleaker outlooks suggest that any energy gains from AMoD could be offset by the projected increased demand for travel that will accompany its implementation [11], [12], [13]. In some scenarios, AMoD is also expected to worsen congestion [14]. Nonetheless, AMoD systems will likely play a significant role in the future of urban mobility, and the nature of that role will depend in large part on developments today. Despite the myriad potential benefits of adopting AMoD that have been suggested, there is a large degree of uncertainty surrounding its short, medium and long-term impacts.

Despite the large body of work on the impacts of AVs and AMoD, the literature has several critical limitations. First, many studies exploit simplified abstractions of the urban region and network, including grid-type cities [15], Euclidean planes [16], quasi-dynamic grid-based networks/roads [17], [18], synthetic grids [19], and synthetic cities [7], [20]. As noted [21], this may be restrictive and thus insufficient to capture the complex spatio-temporal characteristics of real transport demand. Second, almost all studies (with the exception of [20] and [21]) assume fixed network travel times [4], [16], [18], [21], [22], [23], [24] and do not explicitly model network congestion effects. Furthermore, most efforts considered simplified fleet deployment strategies (usually rule-based) [2]. Modeling the real effects of service use, travel times and network congestion is crucial to accurately determine the impacts on network performance and the interactions with demand. Third, most studies do not explicitly capture behavioral responses to AMoD and assume that existing private vehicle demand is completely or partially substituted by AMoD [21], [22], [23], [25], [26], [27], [28]. Fourth, only a few studies have been done on large-scale cities using advanced activity-based simulation tools such as SimMobility [7], [29], [30] or MATSim [21], [25], [26], [28]. Finally, to the best of our knowledge only one study explicitly captured the demand-supply interactions of a full city (using SimMobility) by taking into account the complex relationship between travel times and waiting times, demand for AMoD, and fleet supply and operations [29]. Despite all its advantages, SimMobility lacks a friendly interface. Therefore, we decided to combine SimMobility's activity-based demand simulator with the powerful multi-resolution supply engine of Aimsun Next. Aimsun Next is a single integrated platform for macroscopic, mesoscopic, and microscopic modeling. Furthermore, it offers a hybrid meso-micro (and macro-meso) model for large-scale networks with specific areas that require a microscopic level of detail but with a global network evaluation and without impacting adversely on the runtime (Aimsun, 2018). Its advantage over research software is its intuitive and friendly interface, however, it generates the demand using a four-step model. Activity Based Models, the state of the art in travel demand models today, provide better understanding

of travel behavior, compared to traditional modeling and are able to account for trade-offs among various activities and new travel alternatives in one's daily activity, thus are better suited for AMoD modeling. By combining SimMobility's demand simulator with the hybrid meso-micro supply model, we can capitalize on the best of both worlds in the form of an improved simulation framework. A realistic and city-scale examination of AMoD using such an advanced simulation tool can address the above limitations and significantly promote the understanding of AMoD services.

In this paper, we summarize the development and calibration of a new simulation framework for the Tel-Aviv metropolitan area. We then demonstrate the use of our improved simulation tool and focus on demand exploration of AMoD services in Tel-Aviv. Our study was conducted using a representative synthetic population and network of Tel-Aviv metropolitan area, which is the largest metropolitan area and economic center of Israel.

Our paper, thus, makes significant contributions to the existing literature in the following areas: (a) We introduce a new and improved simulation framework by combining SimMobility's activity-based demand simulator with the hybrid meso-micro supply simulator of Aimsun Next; (b) We implement and calibrate the demand and supply models for Tel-Aviv metropolitan area using multiple Big Data sources; and (c) We conduct a large-scale demand exploration of AMoD services given various fare strategies in the study area using the new simulation framework.

The organization of the remainder of this paper is as follows. First, we describe in Section II our experimental framework and methodology. This begins with an introduction of the new simulation tool. We go on to discuss the demand and supply generation and calibration approach (Section II-A and II-B), including model calibration results. We then present the scenarios simulated in this study (Section II-C). Data sources are also indicated throughout this section where relevant. Simulation results of the AMoD scenarios for the Tel-Aviv metropolitan area are presented and discussed in Section III. We conclude with a summary of key findings and contributions, outlining steps for further work in Section IV.

II. DATA AND METHODS

The new simulation framework presented in this study is a hybridization of SimMobility's agent-based and activity-based demand simulator with Aimsun's multi-scale dynamic traffic assignment model. SimMobility's demand simulator is capable of simulating daily travel at both the household and individual levels, while the traffic dynamics are simulated using a micro-meso (or macro-meso) approach. Fig. 1 presents the modeling framework of the new simulator. A detailed description of SimMobility's activity-based demand models along with its components can be found in [30]. A detailed description of Aimsun's multi-scale supply simulator including its components and models can be found in [31].

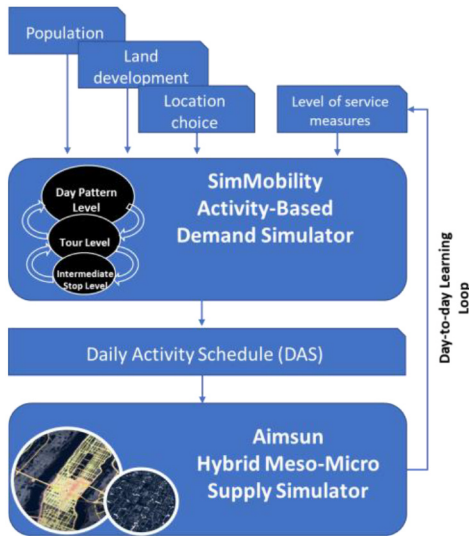


FIGURE 1. A hybrid activity-based and micro-meso simulation framework.

The demand simulator follows an enhanced version of the econometric Day Activity Schedule (DAS) approach to decide an initial overall daily activity schedule of the agent, particularly its activity sequence (including tours and sub-tours), with preferred modes, departure times by half-hour slots, and destinations. This is based on sequential application of hierarchical discrete choice models using a Monte-Carlo simulation approach (For a thorough explanation of demand simulator structure and components see Section II-A. *Demand generation and calibration*). This DAS is translated into a series of mode-based time-dependent OD matrixes, which is then used as an input by Aimsun’s supply simulator.

The supply simulator is a fully integrated application that fuses simultaneous micro-meso or macro-meso simulation, allowing to scope large-scale models while applying detailed simulation in a well-defined area. This results in fast run times, low calibration effort and accurate detail. In combination with either mesoscopic or microscopic modeling, dynamic user equilibrium techniques and stochastic/discrete route choice models can be applied [31]. Network performance, in the form of travel times and costs, are fed back to the demand simulator to update the agent’s knowledge and enable a day-to-day learning process. In this study, we built a hybrid activity based and micro-meso simulation tool for simulating AMoD services in the Tel-Aviv metropolitan area. To realize such a system, we first generated and calibrated the demand and supply models separately and then integrated them into a single system as shown in Fig. 1.

A. DEMAND GENERATION AND CALIBRATION

A main tool utilized to generate the demand in this research is the SimMobility activity/travel simulation tool. SimMobility is an open source, multi-scale simulator to design and test mobility portfolios [30]. It comprises three

primary time-frame-oriented models, each incorporating numerous sub-models to interactively simulate the behaviors in an urban system. In this study, we utilized SimMobility’s demand simulator (pre-day) which generates travel demand in the form of Daily Activity Schedules for each individual in the population. The overall model structure, overview of models of different levels, accessibility measures and the data used for development and calibration of the demand for Tel-Aviv will be covered in this section.

Synthetic population with known socio-demographic characteristics is an input to the system. We synthesized 3.78 million individuals as part of the Tel-Aviv metropolitan population, mainly based on the synthetic population of Ayalon Highways’ (AH) model, while synthesizing all necessary information on individuals, including their characteristics and households that is used by the Pre-day model. Other inputs taken by the demand model include network skims, land use characteristics, etc.

The Israel Central Bureau of Statistics (ICBS) divides the Tel Aviv metropolitan area into four areas: Core, Inner, Middle and Outer rings (see Fig. 2a). In the Tel-Aviv metropolitan area, passengers make over 14 million trips on a daily basis with an average stop rate of 3.7 per individual. Fig. 2 shows selected synthetic population outputs - population and employment density and income distribution by TAZ.

We used Pre-day’s behavioral models which were originally estimated for the greater Boston area and calibrated them to Tel-Aviv using multiple data sources, most of them big data sources. The main data sets were the latest Tel-Aviv metropolitan area travel survey (THS) and Ayalon Highways’ synthetic population, as well as the Central Bureau of Statistics’ (CBS) information and geographical data. The travel survey (THS) is a smartphone-based travel survey conducted by Future Mobility Sensing’s (FMS) survey system in the years 2016-2017 in the Tel Aviv metropolitan area: 13,500 households were sampled with a total population of 39,090 individuals. The survey contains two days of data for most households, while the data sampled from the early stage were surveyed for only one day. The THS dataset is composed from information on household characteristics, household vehicles, individual characteristics, and day activity diaries.

In general, the calibration process of the behavioral models in pre-day consists of four steps: (1) estimating the accessibility measures (logsums) of the entire pre-day structure; (2) changing the alternative constant of each model from the higher models in the hierarchy to the lower models in the hierarchy, separately; (3) Estimating model results and comparing it to the THS data; (4) repeating (1)-(3) until the difference between the simulation results and the THS results is small (less than 0.1%).

To preform step (3) we need the following two categories of variables: (i) actual observed aggregate statistics from THS (ii) computed aggregate statistics (from the model). The THS aggregate statistics are the following: number of people

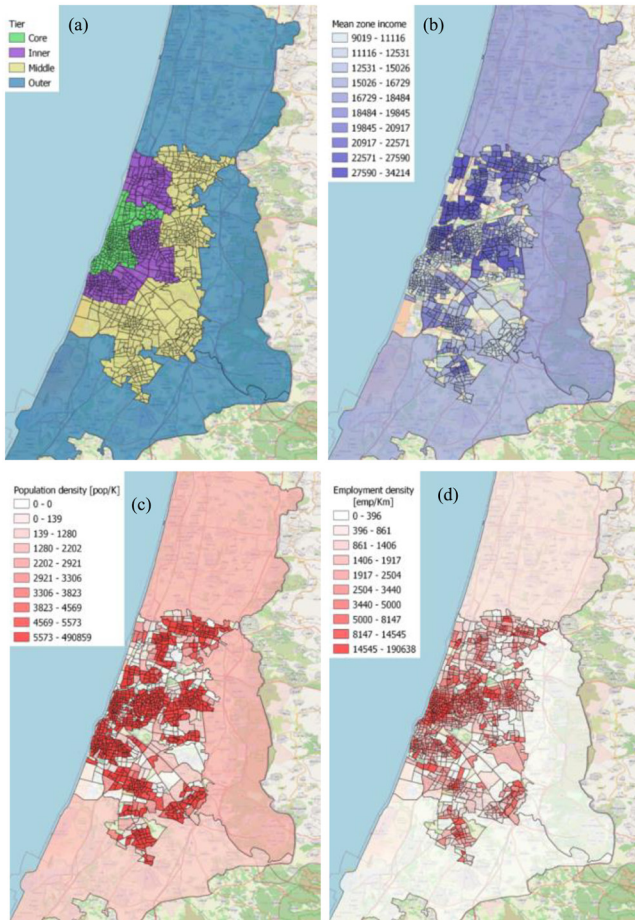


FIGURE 2. Zonal and synthetic population data: (a) Traffic Analysis Zones (TAZ) and rings; (b) Mean household gross monthly income in NIS by TAZ; (c) Population density by TAZ; and (d) Employment density by TAZ.

traveling, number of people performing each activity, number of tours corresponding to each activity, number of tours/trips corresponding to each mode, and origin and destination flows at a zonal level.

Fig. 3 shows the model components and process flow of the pre-day model. The overall system can be viewed as a hierarchical (or nested) series of choice models. The solid arrows indicate that models from lower levels are conditioned on decisions made with models from higher levels. There are three different hierarchies in the pre-day system: *day pattern level*, *tour level* and *intermediate stop level*. Each level consists of several models. The pre-day system consists of 22 behavioral models overall, which are described in detail in the *Supplementary Information* and in [30].

The calibration process of the behavioral models in pre-day was done manually, from the day pattern level to the tour level to the intermediate stop level. As the choice-models in lower levels pertain to activity-travel decisions conditional on the upper-level decisions, we explicitly considered the “dependencies” across the choice-models and consequently the activity-travel decisions while calibrating the model-system. This is done through inclusive values, which are

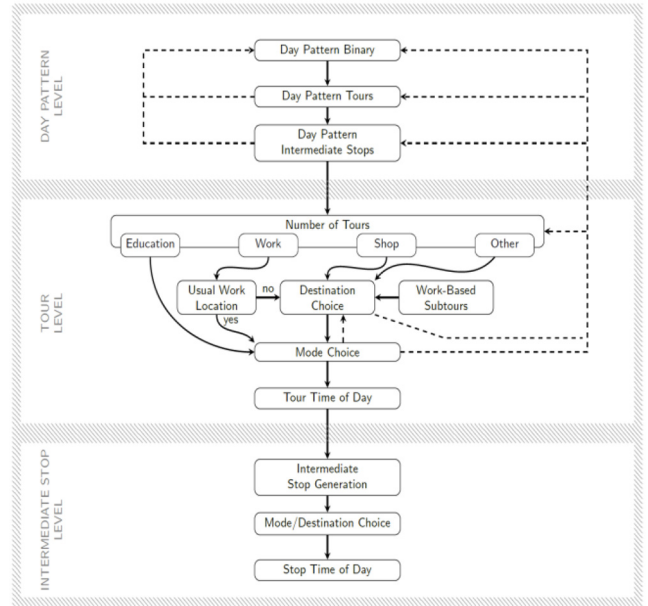


FIGURE 3. SimMobility activity-based model structure. Solid lines indicate conditional dependency in the direction of the arrows. Dashed lines indicate accessibility integration in the direction of the arrows. The hatched outlines demarcate the three levels of the model (Source: [13]).

also known as logsums (see section Accessibility measures). For example, changing the coefficients in the mode choice-model effects the number of tours an individual will make in a DAS model-system. Thus, it is a long iterative process in which dozens of constants (alternative constants only) were modified throughout nearly 100 iterations.

Day Pattern Level: In the pre-day activity-based travel demand model, the day pattern level (see Fig. 3) includes 8 models overall, with each of them changed to reflect the desired results. We divide the models into two types of discrete choice models: day pattern model, and exact number of tours model for different primary activity purposes. The day pattern model predicts occurrence of tours for various purposes and availability of intermediate stops for various purposes. The purposes are defined by four activity types: Work, Education, Shopping, and Others. Tour purposes that are predicted to occur will be passed to a second model to determine the exact number of tours for that purpose. The predicted availability of intermediate stops has no immediate effect at the day pattern level. However, the results will be provided to the intermediate stop generation model to constrain the availability of each activity purpose. Day pattern level generates a list of tours as well as intermediate stop availabilities for each individual in the synthetic population.

Tour Level: In the pre-day system, tours are home-based, except for tours predicted by the work-based sub-tour model, which are work-based. In the pre-day activity-based travel demand model, the tour level includes multiple discrete choice models: usual/unusual work location, travel mode choice or travel mode/destination choice, work-based sub-tour generation, and tour time of day. These models provide

detailed information for each predicted tour. These details include destination, travel mode, and time of day (arrival time and departure time). This level includes 11 models and provides activity and travel information for tours.

Intermediate Stop Level: The intermediate stop level considers the existence of intermediate stops during a tour. Trips for secondary activities are represented as intermediate stops within a tour, and the available types of secondary activities have been predicted in the day pattern model. The intermediate stop level (see Fig. 3) includes three types of discrete choice models: intermediate stop generation, mode/destination, and time of day. These models first generate intermediate stops for each tour and then predict the timing and destination of stops for secondary activities, as well as the travel mode.

After applying the intermediate stop level models to the synthetic population, the pre-day output is the daily activity schedule which is generated for each individual in the population. The generated activity schedules provide the timing (arrival time and departure time) of each activity at a resolution of 30 minutes, the destination at zonal level and the travel mode for each trip/tour from a list of considered modes. The day activity schedule is then translated into a series of mode based, time-dependent O-D matrixes. The car matrixes are then imported to Aimsun Next, using a dedicated Python script, as an input for the supply model. Trips that are done by other modes are either teleported (Walk, Bike, Bus, Private Bus) or injected to the network during the simulation using API (AMoD, MoD, etc.).

Accessibility Measures: Disaggregated utility-based accessibility measures [32] that originated from random utility theory are included within the pre-day activity-based modeling framework. These measures represent the expected maximum utility of a set of alternatives from a choice set of a discrete choice model and are consistent with random utility theory. In a hierarchical modeling system, accessibility measures are essential to capture the sensitivity of activity and travel decisions modeled in lower levels of the modeling hierarchy, and therefore are especially important when we try to estimate future modes such as AMoD. In formal nested modeling hierarchies, such as the one for the pre-day model, the upward integrity comes from the composite measure of expected utility across the lower-level alternatives, or the so-called “logsum”, which is used to link different choices. The accessibility measures, or logsums, introduced in the pre-day model for Tel-Aviv are shown in Fig. 3 with dashed arrows.

Fig. 4 (a-d) provide demand calibration results with respect to the overall simulated number of tours and stops, as well as mode shares and time of day pattern for Work tour as compared to the observations in THS, in the Tel Aviv metropolitan area.

B. SUPPLY GENERATION AND CALIBRATION

A hybrid meso-micro simulation is applied using Aimsun Next [31]. A meso-micro model covers most of the Tel-Aviv

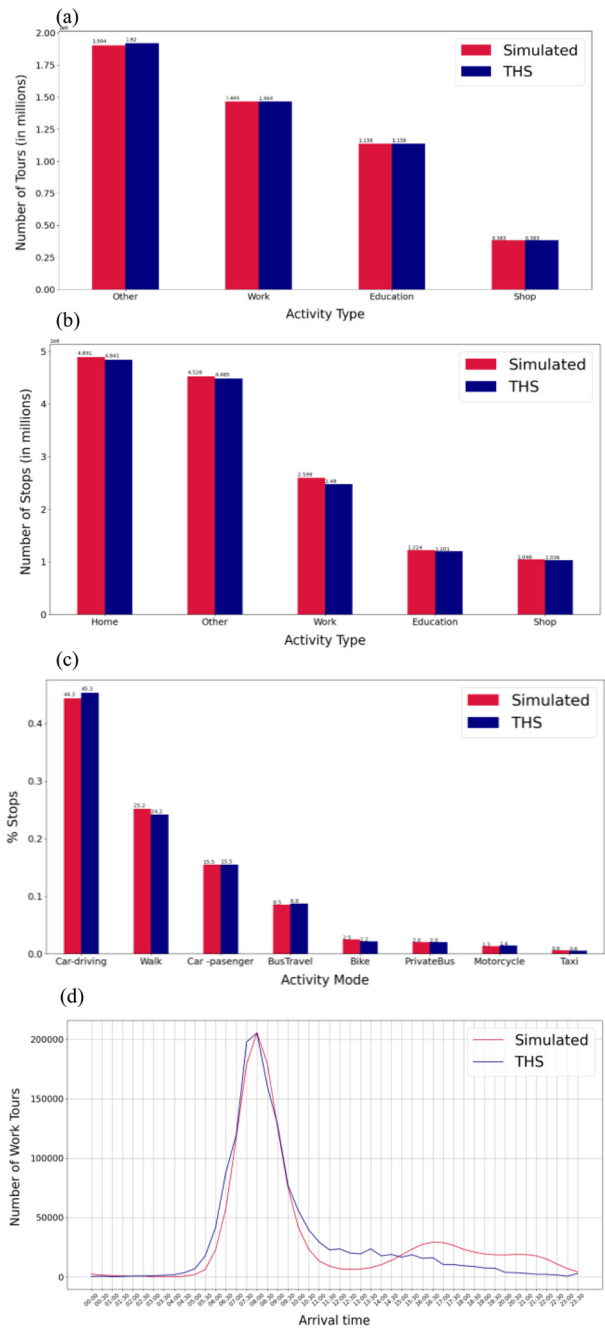


FIGURE 4. Demand calibration results: Simulated and observed for the Tel Aviv metropolitan area: (a) Tours by activity type; (b) Stops by activity type; (c) Mode share by activity type; and (d) Time of day pattern for work purpose.

metropolitan area was developed (see Fig. 5). The Tel-Aviv metropolitan hybrid model was coded and calibrated at the most detailed level of network by [33] for Ayalon Highways. This work included detailed geometrical representation of roads, intersections and traffic devices; detailed description of the intersections (traffic lights, give-ways, stops), transit priority, actuated control, public transport plans, and associated parameters. Later, it was expanded and validated by the authors.

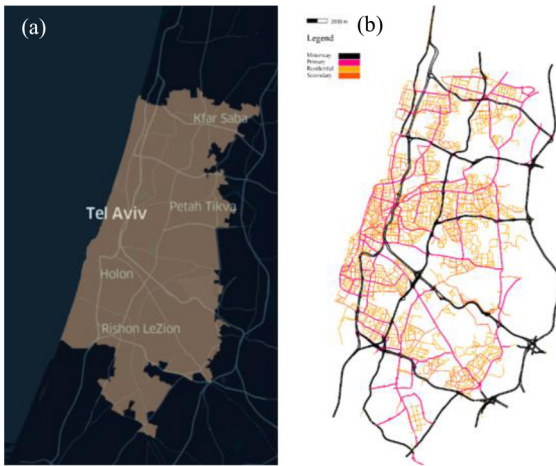


FIGURE 5. The road networks of the Tel-Aviv metropolitan area: (a) map by network boundaries; (b) road map by hierarchy.

Overall, the Tel-Aviv metropolitan area has a total area of 1,516 km² and its transportation system includes 3,356 km of roads, which includes 10 expressways. The road network consists of 6,220 nodes (intersections), 30,585 segments (road sections with homogeneous geometry) and 14,799 links (groups of one or more segments with similar properties).

The public transportation system is based primarily on busing, with 728 bus lines spanning the metropolitan area with a total of 4,607 bus stops. The rail system consists of 15 lines with a total of 124 stations while the light rail/subway system is under construction.

The Tel-Aviv metropolitan area is divided into 1,169 Traffic Analysis Zones (TAZs). The same network representation and the same flow, speed, and delay information is used in both meso-micro simulation modes shared in a common database.

In the new simulation framework, the network and its attributes are used as inputs to the hybrid model as well as the O-D matrixes from SimMobility that were processed to fit Aimsun's format. The hybrid model uses Dynamic Traffic Assignment: when a vehicle is generated at its origin, it is assigned to one of the available paths, connecting this origin to the vehicle's destination. These paths are computed as the simulation starts and re-computed at the route choice cycle time interval. The vehicle will travel along this path to its destination unless it is allowed to dynamically change it en-route when a better route exists from its current position to its destination or when the vehicle is guided by a controller as in the case of AMoD services. Route choice decisions are consistent between both modes of simulation. Fig. 6 illustrates the general modeling framework of the hybrid meso-macro model in Aimsun.

Using the hybrid model is beneficial for networks where changes or strategies require precise knowledge of vehicle behavior, but, at the same time, may have a wider influence in terms of the network. Running the entire network at microscopic level would increase the computation time, so

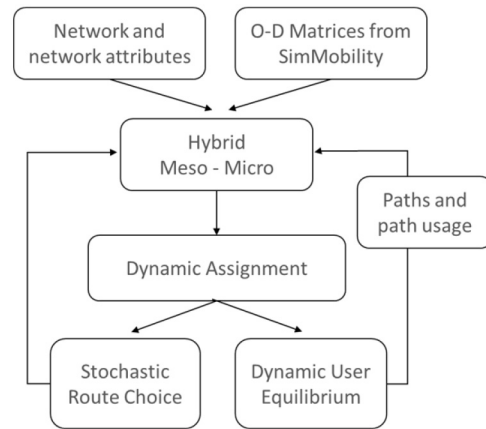


FIGURE 6. Aimsun Next general modeling structure.

the use of the mesoscopic model outside of the areas where micro is strictly needed allows the user to increase the size of the model without impacting adversely on the runtime.

To validate and calibrate the traffic simulation model, the simulator should be able to emulate the traffic detection process and produce a series of simulated observations. A statistical comparison of response times in selected road sections, traffic counts, travel times compared to times from Google data and travel speeds compared to speeds from Google data were performed and compared, for morning peak, in order to determine whether the desired accuracy in reproducing the system behavior was achieved. The full calibration and validation results can be found in [33]. In addition, travel times were compared with destination origin pairs, for which travel time data from Google data were available.

Fig. 7 shows the comparison of travel times obtained from Aimsun supply model, considering the new estimated demand from SimMobility, compared to travel times from Google data. The gaps in travel time between the supply model and Google are smaller than 10 min on average and are due to limitations as follows: Definitions of origin-destination pairs are not the same. Google's origin-destination pairs are from a specific and exact address, while the entry and exit points for the simulation are obtained from SimMobility at the traffic area level. In addition, roadmap comparisons were made for which mileage data from Google was available. This validation is designed to make sure that the model correctly reflects traffic congestion in the system.

C. AMOD SCENARIO DESIGN AND IMPLEMENTATION

To analyze the impacts of AMoD across the Tel-Aviv metropolitan area, using our improved and calibrated simulation tool, we implemented six scenarios. We conducted 24-hour simulations for each scenario using the study area. Through these, we expect to explore plausible AMoD futures in which demand strategies are employed to manage AMoD across the study area. In the scenario framework, the AMoD fleet is assumed to be a battery-electric fleet, a Taxi like

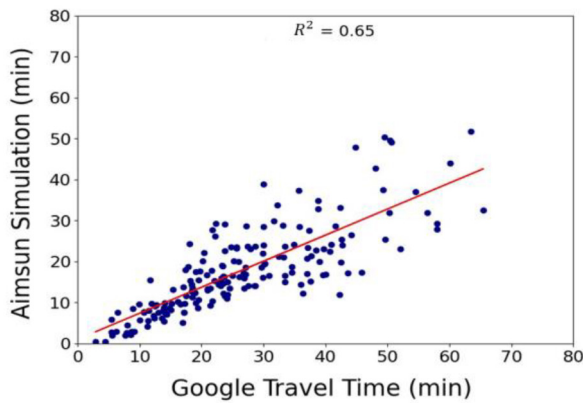


FIGURE 7. Comparison of travel times by origin-destination pairs.

vehicle up to 4 seats, other private vehicles are powered according to their distribution in the population, at the household level, as collected by THS. This represents an optimistic environmentally friendly future where such a regulation is imposed. Vehicle operational costs per km are derived from maintenance costs, vehicle management costs, and fuel costs and are 0.16 \$ per km for Internal Combustion Engine (ICE). Where gasoline cost per liter is assumed to be 2.34 \$ and ICE fuel economy is assumed to be 0.068 liter per km [34], [35]. Please note that AMoD’s service fare is calculated relative to a taxi fare (see ‘AMoD as a substitute for Mod’ scenario) and is not a result of Battery-Electric Vehicles (BEV) fuel cost calculation.

Base Case: The Base Case represents current conditions for the Tel-Aviv metropolitan area in terms of mode availability and choice as well as network performance. Available modes are Private Car (single and pooled), Mobility on-Demand (taxi), Mass Transit (bus and rail), Active Mobility (bicycle and walk) and Other (motorcycle and private bus). Mobility on-Demand fares are modeled according to city regulations:

- Base fare = 4.46 \$ when the taxi is booked
- Fare per distance = 0.47 \$ /0.57 \$ (0.47 \$ between 6 am-11 pm, else 0.57 \$)
- Fare per time = 0.47 \$ /0.57 \$ (0.47 \$ between 6 am-11 pm, else 0.57 \$)
- Mobility on-Demand cost = Base fare + Fare per distance * d + Fare per time * t * 60

Were d is the distance in km and t is the time in hours.

AMoD as a Substitute for Mod: This scenario describes a future where AMoD services are introduced in replacement of MoD at a discount from regular taxi fares, but without further policy interventions or strategies. We considered 6 cost reduction scenarios: 30%, 40%, 50%, 60%, 70% and 80% discount from taxi fares. As such, the AMoD fare is not derived from BEV fuel costs. Earlier studies investigating the cost implications of AMoD provide context for this cost range (Pavone, 2015; Bosch *et al.*, 2018; Hörl *et al.*, 2021). The AMoD service will offer both single and shared ride (pooling) options to enable further reduction

TABLE 1. Mode fare parameter values.

MoD Mode	Fare Component	Base Case	Cost Reduction					
			30%	40%	50%	60%	70%	80%
Bus and Private Bus	Fixed (by ring)	0.17	-	-	-	-	-	-
Car	Operational cost (per km)	0.16	-	-	-	-	-	-
	Parking cost *(USD)	0 to 7	-	-	-	-	-	-
Motorcycle	0.5 of Car cost	0.25	-	-	-	-	-	-
Car Sharing	0.5 or 0.33 of Car cost	0.16/0.11	-	-	-	-	-	-
Taxi	Base fare (USD)	4.46	-	-	-	-	-	-
	Distance charge (per km)	0.47/0.57	-	-	-	-	-	-
	Travel time charge (USD/min)	0.47/0.57	-	-	-	-	-	-
AMoD	Base fare (USD)	-	3.12	2.68	2.23	1.78	1.34	0.89
	Distance charge (per km)	-	0.33	0.28	0.24	0.19	0.14	0.09
	Travel time charge (USD/min)	-	0.33	0.28	0.24	0.19	0.14	0.09
AMoD Pool	Base fare (USD)	-	2.19	1.87	1.56	1.25	0.94	0.62
	Distance charge (per km)	-	0.23	0.20	0.16	0.13	0.10	0.07
	Travel time charge (USD/min)**	-	0.23	0.20	0.16	0.13	0.10	0.07

* Parking cost was determined by proximity to CBD: In the CBD we set the parking cost to 7 USD per hour; outside the CBD, in large employment areas and large transportation facilities the cost is set to 3.33 USD per hour; in crowded residential areas and large public institutions we set the cost to 2.22 USD per hour; in areas characterized by mixed uses the cost is set to 1.47 USD per hour; and in residential areas the parking cost is set to 0.

** Travel time in AMoD Pool includes the waiting time for passengers (5 min for each passenger) and the extra time for pickup and drop-offs (3 min for each pickup/drop-off).

in fares and in energy consumption. Shared AMoD service is a service where travelers share an AMoD vehicle (e.g., ride-sharing) with at least one traveler and assumed to be 30% cheaper than single AMoD rides.

The demand models assume that consumer preference—modeled via coefficients—for AMoD is the same as for MoD. Please note that the assignment of passengers to vehicle was not conducted on the supply side via a controller, thus the consumer preference—modeled via coefficients—for AMoD pool is the same as for MoD pool given travel time, fare and waiting time estimates. The supply models treat AMoD vehicle as a regular vehicle (car), while robotic movement was not implemented. The fare values for all services are shown in Table 1.

III. RESULTS AND DISCUSSION

In this section, we present the results of the AMoD cost scenario simulations in the Tel-Aviv metropolitan area. We analyze the impacts on demand in terms of mode choice, demand elasticities, travel distance, travel activity type, and by population groups in the following subsections while accompanying figures and tables summarize the results. All percentage changes are referenced relative to Base Case, unless otherwise explicitly stated.

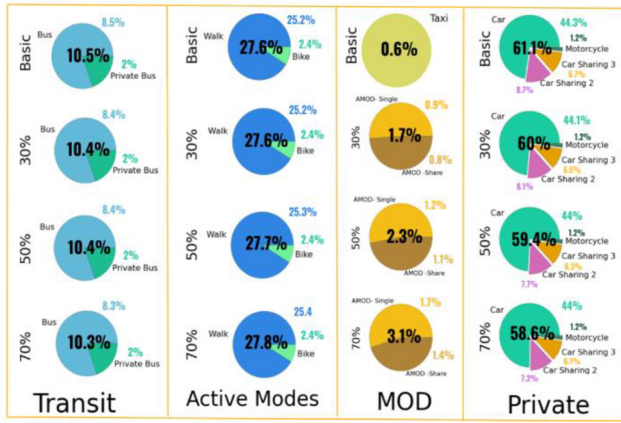


FIGURE 8. Mode shares across scenarios.

A. MODE CHOICE

The introduction of AMoD does not appreciably increase the number of trips (0.24%) demanded relative to Base Case. Under all AMoD cost reduction scenarios similar effects are observed. These results indicate that there is no existing latent demand in the Tel-Aviv metropolitan area, which is a dense and car dependent city. We show the mode shares across all scenarios in Fig. 8.

It can be seen that as service fare reduces, the share of AMoD services increases compared to Base Case where traditional taxi services are present. While at the Base Case scenario MoD share was about 0.6% of total trips, with 30% reduction in fare the total share of AMoD services was about 1.8%, and it increases to 3.8% with 80% reduction in fare. It can also be seen that the share of AMoD as a single passenger increases faster with fare reduction. The additional demand for MoD services clearly originated in Car sharing 2, which drops from 8.7% at the Base Case to 6.9% with 80% reduction in fare, and Car sharing 3, which drops from 6.8% at the Base Case to 6.9% with 80% reduction in fare. The rest of the additional demand originated from Car with more than 40k trips (0.5% trip reduction), Bus with more than 30k trips (0.3% trip reduction), and Bike with more than 10k trips (0.1% trip reduction). Thus, impact on public transportation and active modes is negligible. This is due to a significant gap in average travel cost between on-demand services and other modes, as can be seen in Fig. 9. Please note that the day-to-day loop, which feedback travel time and costs to the demand simulator to update agent’s knowledge was not used in these experiments. Although, this may introduce disruption in the results, we believe that mode shifts will not change significantly with respect to the result obtained, due to the highly congested network of Tel Aviv metropolitan area and the lack of attractiveness of the public transportation.

B. AMOD DEMAND ELASTICITIES

AMoD service average travel costs are quite high as compared to all other modes, even with the largest fare reduction

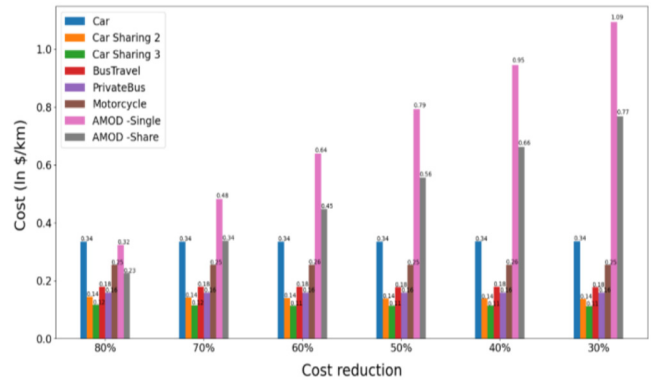


FIGURE 9. Mode average cost in USD per km by scenarios.

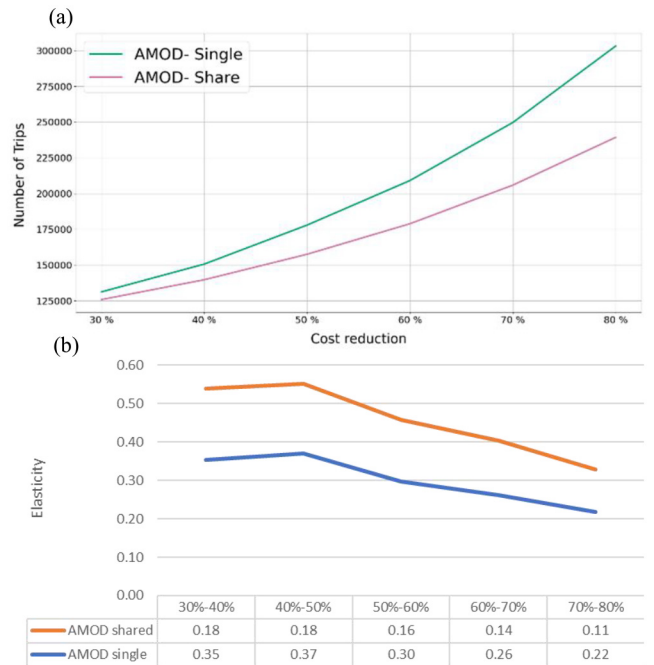


FIGURE 10. AMoD demand and fare elasticities of trip demand. (a) Number of trips in AMoD by cost reduction; (b) AMoD fare elasticities by scenarios.

examined (80% fare reduction as compared to traditional taxi and additional 30% reduction for the AMoD pool). Only with 80% reduction in fare did the AMoD services become slightly more attractive than Car, and AMoD-pool travel costs became lower than Motorcycle costs but still higher than Bus costs. Fig. 9 indicates the average trip cost in terms of \$ per km travel for all transportation modes including the AMoD average trip cost as a single and shared service in all 6 scenarios.

We then investigate the AMoD cost elasticities (Fig. 10). The fare elasticity is defined as the percentage change in the number of trips demanded (of a certain mode) given a 1% decrease in service cost. It can be seen that AMoD demand as a single service is more elastic than AMoD as a shared service, and the demand for AMoD shared is less sensitive to

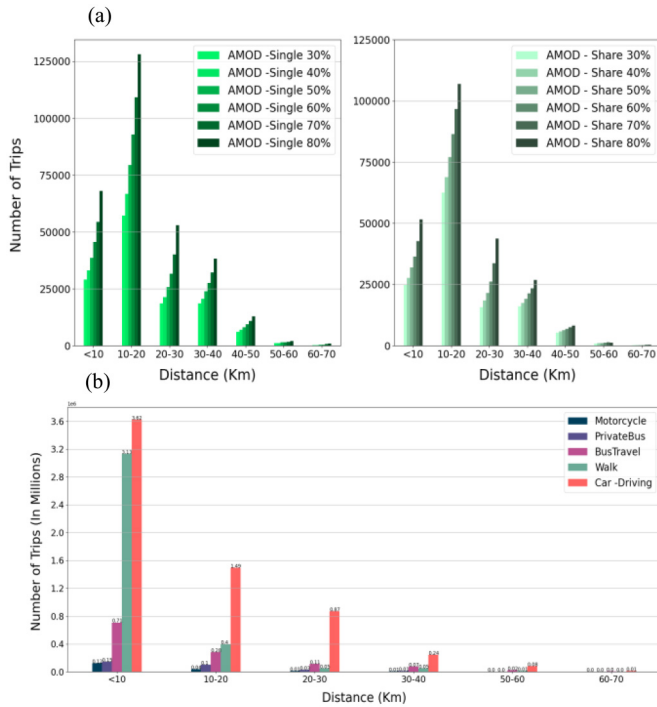


FIGURE 11. Trip distance by scenarios. (a) Demand for AMoD by distance in all scenarios; (b) Modes average demand by distance in Base Case.

fare reduction than for AMoD single. AMoD cost elasticities drop as fare reduction increases for both AMoD services.

C. TRAVEL DISTANCE

We calculate the passenger travel distance as the distance covered by all passenger vehicles during a 24-hour day. Fig. 11 shows the number of trips done by different transport modes as a function of trip distance. While in all modes the number of trips decreases as the distance increases, in both single and shared AMoD services, the maximum number of trips obtained for trips between 10 and 20 kilometers with over 125k and 100k trips, respectively. A large proportion of the trips is also short trips under 10 km, with more than 70k AMOD single trips and 50k shared AMoD trips. Note that active modes were constrained so that a walk trip will not exceed 10 km and a bike trip will not exceed 25 km, thus competing with AMoD for short rides.

Fig. 12 displays travel fare by distance for each observation. Each point represents a trip in AMoD in both shared and single service. In the 30% cost reduction scenario, it is possible to travel by AMoD shared at a price of \$14 for a range of almost up to 20 km. However, in AMoD single it is possible to travel up to 10 km only at the same cost. When fare reduction is increased, the differences between shared and single AMoD rides become smaller and a trip for \$14 can take the passenger a distance of about 50 km. Finally, under a heavy reduction in cost, the trips are made at a more or less uniform cost (as in a bus service), when the slope between the travel cost and the distance decreases if the discount is increased. In contrast, in the case of low-cost

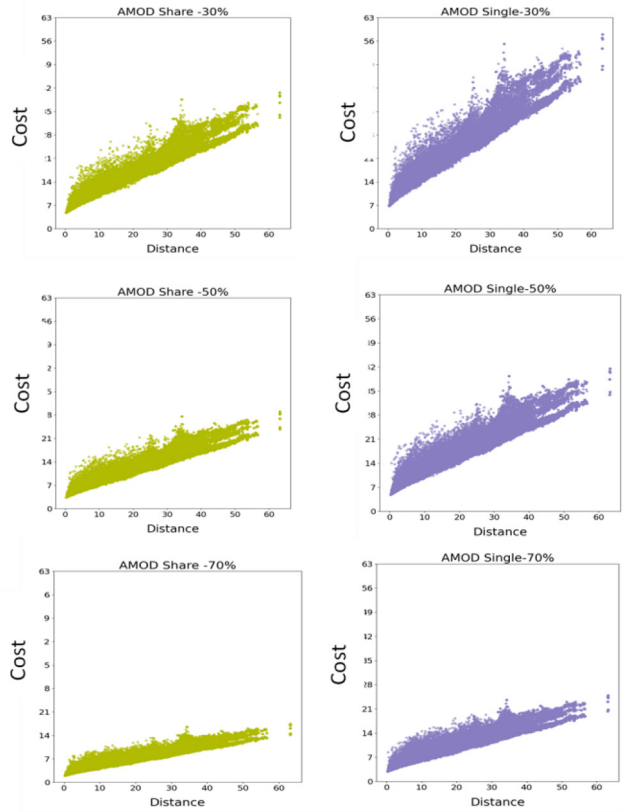


FIGURE 12. Travel cost by distance: On the right AMoD shared; On the left AMoD single.

reduction, the travelers pay different prices as a function of distance (as in a taxi). The average driving distance in AMOD is about 20 kilometers.

D. TRAVEL PATTERNS

The AMoD trips were also analyzed according to travel purpose and time of day. Figure 13 shows the distribution of main trip activity by AMOD for the 50% price reduction scenario. It is shown that most of AMoD single and pool trips were for the “Other” activity, with a large portion for “Work” and only few for Education and Shopping activities. Fig. 13b shows the distribution of demand by time of day using AMOD. In all scenarios, the demand for evening travel is greater than the demand for morning travel. These findings are consistent with Fig. 13b where it is shown that travel for educational purposes, most of which is carried out in the morning, is not common among AMOD users. For most of the day, the simulator predicts that the demand for shared AMoD trips is lower than the demand for single AMoD trips, except for 2:30 pm when the demand under all scenarios is about the same. Furthermore, there are large gaps in morning peak demand between AMoD shared and single service, which are 5 times larger for single rides as compared to shared rides in the 80% fare reduction scenario. The morning peak demand in all scenarios is at 8:00 am, while the evening peak demand in all scenarios is at 5:00 pm and the lowest demand appears at 12:00 pm.

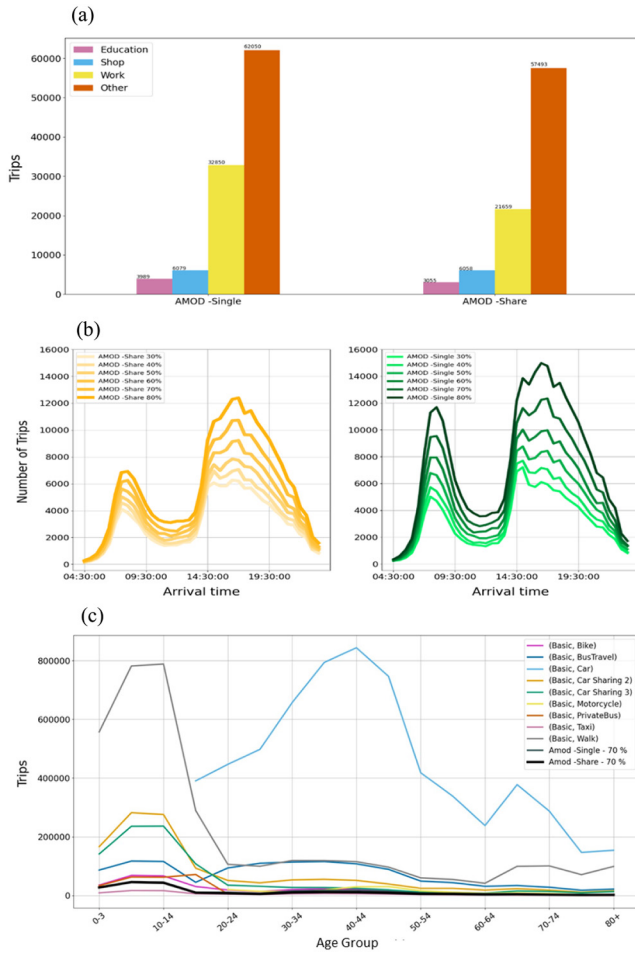


FIGURE 13. AMoD demand by: (a) Travel main activity; (b) Time of day; and (c) Age groups by mode relative to the Base Case.

E. DISTRIBUTION BY POPULATION GROUPS

Figure 13c show the number of trips in AMoD in each age group under the 70% reduction in fare scenario, comparing trip distribution by age, in all modes, to the baseline scenario. The second group affected by the reduction in travel fare is the working age group (age 30–55). For this group, trip demand doubled from a 30% to 80% fare reduction scenario. The most affected group is younger passengers under the age of 14. These results are consistent with Fig. 8 which shows that Car Share 2 and 3 stops are done by the same age group. Unlike the working age groups, which clearly favor single AMoD trips, younger passengers are more likely to share their ride with an almost equal number of single trips as compared to shared AMoD trips. The seniors (age 75+) showed the lowest demand for AMoD when even the largest fare reduction failed to significantly increase the number of stops made by this group. Overall, the younger age groups are responsible for most AMoD service usage due to fare reduction.

Fig. 14 shows population distribution by employment status and main activity, while Figure 14a shows employment status by main activity of AMoD as a single and shared service respectively. In the Base Case scenario, for all modes

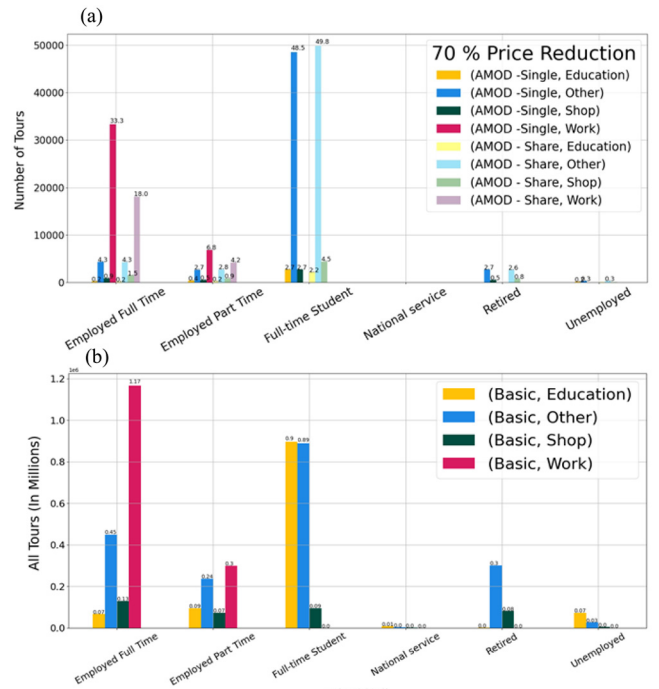


FIGURE 14. Population distribution by employment status and main activity: (a) Employment status by main activity of AMoD as a single service and as a shared service; and (b) Employment status by main activity of all modes.

of travel, it can be seen that full time students will travel mostly for “Other” purposes. This population will shift to AMoD and, in all scenarios, a majority of AMoD trips are carried out by full time students. Full-time workers also take a significant share of the trips for “Work” purposes by AMoD, which is similar to the Base Case. Interestingly, the number of trips for “Education” purposes increased dramatically using AMoD single by 110% in the transition from 50% to 70% fare reduction, respectively. Full-time students prefer to travel by AMoD shared (29,000 trips in the 30% fare reduction scenario), and this preference was also maintained in the 70% fare reduction scenario with 49,000 trips. That is, the gap between shared and single trips has narrowed among this population, with the fall in price. In contrast, full-time workers prefer to travel by single AMoD under all scenarios as the number of trips increased by 120% in the transition from the 30% to 70% fare reduction scenario, while using AMoD shared service the number of trips increased by only 50%.

IV. CONCLUSION

A new simulation framework is introduced combining SimMobility’s demand simulator with the hybrid meso-micro supply model of Aimsun. We developed and calibrated a model of a city representing the Tel-Aviv metropolitan area. The demand and supply generation and calibration approach are described, and calibration results are presented for both demand and supply simulators. We then present and demonstrate 6 AMoD cost scenarios for the AMoD service which will offer both single and shared ride (pooling) options to enable further reduction in fares and in energy consumption.

We use the following cost reduction scenarios: 30%, 40%, 50%, 60%, 70% and 80% discount from traditional taxi fares.

While Israel is a hub of advanced mobility technologies, very little is known about individual behavior and network performance, at the city scale, as a result of the introduction of AMoD technologies, in general, and in large metropolitan areas that are car dependent such as Tel-Aviv, in particular. This work, which focuses on analyzing the demand for AMoD scenarios, is, therefore, a significant improvement in this area. Scenario results were analyzed in terms of mode choice, demand elasticities to cost, change in travel distance and travel patterns, and AMoD uses were examined by looking at age groups and employment status.

Our results indicate that the introduction of AMoD does not appreciably increase the number of trips (0.24%) demanded relative to Base Case. These results indicate that there is no existing latent demand in Tel-Aviv metropolitan area. While at the Base Case scenario MoD share was about 0.6% of total trips, with 80% reduction in fare the total share of AMoD services reaches 3.8%. The demand for AMoD services is originated in Car sharing 2 and 3, while only 0.5% are originated in Car, and only 0.3% and 0.1% are originated in Bus and Bike respectively. Thus, the impact as a result of the introduction of AMoD on public transportation and active modes is neglectable.

AMoD services average travel costs are high as compare to all other modes, even with the largest fare reduction examined. Only with 80% reduction in fare the AMoD services became slightly more attractive than Car, and AMoD-pool travel cost became lower than the Motorcycle cost but still higher than Bus cost. AMoD demand, as a single service, is more elastic than AMoD, as a shared service, and the demand for AMoD shared is less sensitive to fare reduction than for AMoD single. AMoD cost elasticities drops as fare reduction increases for both AMoD services.

While in all modes the number of trips decreases as the distance increases, in both single and shared AMoD services, the maximum number of trips obtained for trips between 10 and 20 kilometers. Most of AMoD single and pool trips were for “Other” activity, large portion of the trips were for “Work” purpose and only few were for Education and Shopping activities. In terms of time-of-day demand pattern, large gaps are observed in morning peak demand between AMoD shared and single service, which are 5 times larger for single rides as compared to shared rides in the 80% fare reduction scenario. While analyzing AMoD use by different population groups, we found that the most affected group by the introduction of AMoD is young passengers under the age of 14. These results are consistent with findings from Car-depended cities in the US [36], which shows that children were able to travel more using AMoD service. The seniors (age 75+) showed the lowest demand for AMoD when even the largest fare reduction failed to significantly increase the number of stops made by this group. Overall, it seems that the younger age groups and full-time students are responsible for most of AMoD services usage due to fare reduction.

In the present study, we fed the new AMoD cost reduction data to the agent and activity-based transport simulator. Therefore, prices do not reflect actual simulated fleet usage which would introduce disruption in the results. Furthermore, an AMoD controller was not used in this study; this component is under development and will be described in detail in future research. It should also be noted that UBER, an on-demand service, does not exist in Israel. We, therefore, do not know the willingness of individuals to share the vehicle. Thus, we assumed that the choice between AMoD shared and non-shared services is due to the difference in travel cost, however this assumption is not necessarily correct and requires further research. Finally, the effects of induced traffic were not fully considered as the day-to-day loop, which feedback travel time and costs to the demand simulator to update agent’s knowledge was not used in our experiments. Thus, we plan to use the day-to-day loop and show such an effect in future research.

V. DECLARATIONS

A. COMPETING INTERESTS

On behalf of all authors, the corresponding author states that there is no conflict of interest.

B. ACKNOWLEDGMENT

The authors would also like to acknowledge the partial institutional support of Ariel University. The authors are grateful to Ayalon Highway that supported this research by sharing and providing data.

C. AUTHOR’S CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: B. Nahmias-Biran, and Y. Levi; data collection and method development: B. Nahmias-Biran, and Y. Levi; analysis and interpretation of results: B. Nahmias-Biran, G. Dadashev and Y. Levi; manuscript preparation: B. Nahmias-Biran, and G. Dadashev.

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