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Implications of de-carbonization policies using an innovative urban transport simulator

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A R T I C L E I N F O

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A B S T R A C T

Urban transportation is responsible for most GHG and half of NOX emissions, causing health morbidity. New innovative tools are required to accurately calculate emissions and, at the same time, analyze the far-reaching impacts of urban transportation emissions in large-scale areas. To address this gap, we combined SimMobility's agent-based demand simulator with Aimsun-Next's dynamic traffic assignment model and developed a new mesoscopic emission model. In this study, we demonstrate the use of our improved simulation framework by investigating the effects of carbon-related transportation policies in the Tel-Aviv metropolitan area. We examined the change in demand, fuel consumption, various emissions levels, as well as analyzing environmental equity impacts. Our results show that limiting car ownership at the household level is more effective in restraining emissions than the examined geographical congestion charging policy. While reducing car ownership, carbon dioxide emissions and child exposure to PM2.5 are reduced by 11% and 19%, respectively.

1. Introduction

Currently, half of the Earth's population lives in urban areas. According to predictions, this number will rise to 70 percent in 2050 (United Nations, 2018), increasing the demand for transportation and private cars in particular (Sperling and Gordon, 2009). Transport is responsible for most greenhouse gas emissions (Intergovernmental Panel on Climate Change, 2014) and half of nitrogen oxide (NOx) emissions (European Environment Agency, 2018), causing health morbidities such as asthma. Children and older adults are at an increased risk for NO2-related health effects (USA EPA, 2016), specifically in urban areas where emissions occur close to ground level and affect high-density populated areas. In urban areas, particulate matter of less than 2.5 μm (PM2.5) causes the most severe health problems (Sicard et al., 2021) and early mortality due to the deposition of inhaled PM2.5 in the respiratory tract. Exposure to this pollutant causes asthma exacerbation. The effects include significant worsening of respiratory tract-related symptoms in the long term and short term (USA EPA, 2019). According to an estimate made in New York City, PM2.5 pollution from mobility sources (vehicles) is responsible for 320 deaths a year and 870 hospitalizations and emergency department visits (Kheirbek et al., 2016). Non-Methane Volatile Organic Compounds (NMVOC) contribute to the formation of ground-level ozone (O3), which affects the human respiratory system. There is evidence that long-term exposure to these pollutants accelerates the decline in lung function with age (European Environment Agency, 2015). In recent years, many initiatives have been created to transform cities into sustainable cities (Joss, 2012) for their residents, with CO2 emissions and air quality playing a significant role in determining the level of

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sustainability of a town (European Environment Agency, 2018). Emission impacts on cities introduce great complexity and thus require new innovative tools that can adequately trace vehicles by their propulsion type to accurately calculate emissions and, at the same time, analyze the far-reaching impacts of urban transportation emissions in large-scale metropolitan areas (Hofer et al., 2018). Such tools can help predict demand for transportation and examine different environmental scenarios.

1.1. De-carbonization policies

Due to climate change, many cities are trying to reduce their carbon emissions in all sectors and in particular in the transportation sector. Many countries encourage the electrification of the vehicle fleet due to the higher efficiency of the electric engine which is able to produce the same number of kilometers with less energy (da Silva et al., 2022) and the absence of emissions. Others are promoting regulations and various emissions reduction policies. In Beijing, for example, car ownership purchase limitation at the household level is being applied. This policy is expected to lower the carbon dioxide pollution by 61% (Yang et al., 2021). In London, a congestion charge is being applied for vehicles entering the city center, combined with an additional tax imposed on polluting vehicles in specific areas (London ULEZ program). It was found that due to this measures the NO2 pollution decreased by 70% in the first 5–8 weeks of policy introduction (Ma et al., 2021). Several cities have approved and are planning for new or improved congestion pricing schemes, including New York City, Vancouver (Canada), Singapore and Jakarta (Lehe, 2019). However, there remain several challenges to the successful design, acceptance and deployment of these strategies (as indicated by the failures of previously proposed plans in Greater Manchester and New York City) (Gu et al., 2018; Schaller, 2010). Policies that can lead to carbon reduction can be investigated by monitoring station records after the policy has been applied, but it is very difficult to predict how a policy that has never been tried in a certain area will affect the reduction of emissions. In such cases, there is a need for improved simulation tools.

1.2. Environmental policy assessment

Over the years, several simulators have been developed for the purpose of environmental policy assessment. The different simulation models differ in scale. Some microscopic models represent individual vehicles and therefore can analyze immediate acceleration and velocity information for various products, such as pollutant emissions. However, their use is limited to small areas (Osorio and Nanduri, 2015). It is accepted that a combination of dynamic traffic assignment and a microscopic emission model gives the most accurate pollutant emissions calculation (Rodriguez-Rey et al., 2021). A macroscopic emissions model, on the other hand, uses average traffic flow outputs to calculate the emissions generated in the simulation (Bruzzone and Nocera, 2021). Most macroscopic emission models have lower accuracy but are more feasible in terms of runtime and computational efficiency, especially in large-scale cities. Examples of macroscopic emission models include the European COPERT 4, ARTEMIS and California EMFAC models (Samaras et al., 2016). The mesoscopic models combine features from microscopic and macroscopic traffic flow models to create a balance between accuracy and reasonable computation time. This model tries to generalize the driving dynamics of vehicle groups on macroscopic data, such as average speed, to calculate emissions. One such popular model is HBEFA, the Handbook Emission Factors for Road Transport (Keller et al., 2017; Mehrabani et al., 2021). When the supply simulator lacks an emission model that meets the research requirements, it is customary to integrate it externally. For example, Tu et al. (2019) developed a cluster-based approach that analyzes microscopic emissions to characterize driving patterns and calculate later emissions in a mesoscopic simulator without relying on existing AIMSUN emission models. In another case, the output of the PTV VISUM macro simulation tool was used as an input for the COPERT emissions model (Samaras et al., 2016). In addition, the AIMSUN microscopic simulator was used to evaluate a new emission model based on the Australian fleet while comparing it to the COPERT model (Smit et al., 2013). Therefore, examining advanced emission forecasting capabilities requires extending the framework of the simulation platform.

Several built-in emission models can meet the challenge of reasonable running time. Aimsun-Next, for example, contains the London Emission Model (LEM), which uses the average speed to predict CO2 and NOx emissions when the relationship between the emissions to fuel type and European vehicle emission standards is determined by nonlinear regression (Aimsun, 2018). This tool cannot calculate other pollutant emissions, such as NMVOC and PM2.5, which are critical for assessing air quality in the urban environment. Its calibration is based on traffic conditions in the city of London and cannot be used for other urban environments. Its advantages are its integration in the friendly interface of the Aimsun-Next simulator and the fact that the emission model is running simultaneously while running the cars on the road system. The LEM model was used to demonstrate the prediction of Co2 and NOx while testing congestion policy scenarios in a large-scale network (Triantafyllos et al., 2019) and emission prediction due to the adoption of electric vehicles (Mello et al., 2020).

More advanced agent-based and activity-based models such as SimMobility (Adnan et al., 2016; Nahmias-Biran et al., 2019) also include built-in emission models. The emission model of SimMobility evaluates emission factors using a linear regression (Smit et al., 2007) between a sample of emissions from reality and variables that can affect pollution, such as the number of stops, speed, and acceleration. This emission model can be considered mesoscopic because the regression that creates the emission factors is performed for each type of vehicle, traffic situation, and pollutant, although the data accuracy required for the regression can be obtained using only a microscopic simulation. The SimMobility energy model is based on a microscopic model that requires acceleration and velocity between intervals (Rakha et al., 2011) to calculate the consumed energy for different vehicle types. Unlike SimMobility, the MATSim simulator does not include a built-in emission model (Linton et al., 2015) but has previously been used as an input for an external emission model (Hatzopoulou et al., 2011). The most advanced work, which included a more complex environmental analysis as part of a developed activity-based simulator such as the one reported in this work, is that of Wu et al. (2022), who used the MATSim simulator while applying the HBEFA methodology. However, this work has some limits: (1) characteristics describing the vehicle fleet, such as European emission standards and fuel types, were not considered; (2) the behavioral models that are used as part of the MATSim simulator are simplistic compared to SimMobility and cannot capture complex behavior such as mutual impacts of various decisions modeled at different levels in the hierarchy (Axhausen et al., 2016); and (3) for efficiency reasons, only a sampled traffic volume is taken, from which conclusions are drawn for a large-scale study area. In this work, we close the gap in knowledge by (1) using the most advanced agent-based and activity based demand simulator; (2) using a detailed emission factors as specified by the HBEFA model that allows the calculation of various pollutants; and (3) using the full traffic volume along with fleet characteristics for a complete and accurate calculation of energy consumption and emissions in a large metropolitan areas.

In this study, we developed a comprehensive mesoscopic energy consumption and emission model as part of a new evaluation framework, which is a hybridization of SimMobility's agent-based demand simulator with the Aimsun-Next dynamic traffic assignment model, to fill in gaps and enrich the understanding of the type of pollutant emissions we can measure. Our energy consumption and emission model was calibrated and validated according to Israel's local vehicle fleet, and emission factors to engine volume were adjusted. Three policies are chosen and examined with an explicit focus on air quality improvement: (1) using a base case that represents current conditions for the Tel-Aviv metropolitan area in terms of demand, supply and fleet composition without congestion charging; (2) applying a geographical congestion charging policy following Israel's government plan; and (3) reducing car ownership in the city center that is created by taxing private vehicle purchases. We examined the change in demand concentrating on private car usage vs sustainable transport modes, change in fuel consumption, CO2 and GHG emissions, NOX, PM2.5, and NMVOC emissions per road section by time of day. Environmental equity impacts were also analyzed by examining the relationship between emissions and the socioeconomic and age characteristics of those exposed.

This paper is organized as follows: Section 2 introduces the methodology used in this study, where a new simulation environment model with an emphasis on energy consumption and emissions is introduced. Furthermore, scenarios designed to examine pricing policies using the simulation framework are discussed. Section 3 discusses the study area and the different pricing scenarios that are examined. Section 4 includes the results of our analysis in terms of demand and emission impacts as well as individual-level implications. Finally, section 5 presents the main conclusions and findings of this study.

2. Methods and data

In this work, we develop the capability to examine the environmental impacts, energy consumption and emissions of various pollutants in large-scale areas. For this purpose, we developed a new simulation framework that is a hybridization of SimMobility's agent-based and activity-based demand simulator with Aimsun's multiscale dynamic traffic assignment model. Furthermore, we developed a mesoscopic emission model based on the HBEFA framework that takes into consideration road traffic conditions as well as vehicle and propulsion type. The key elements of this research framework are thus (a) the simulation environment, which includes a representative synthetic population, demand and supply modeling; (b) a mesoscopic emission and energy consumption model; and (c) the scenario design and evaluation.

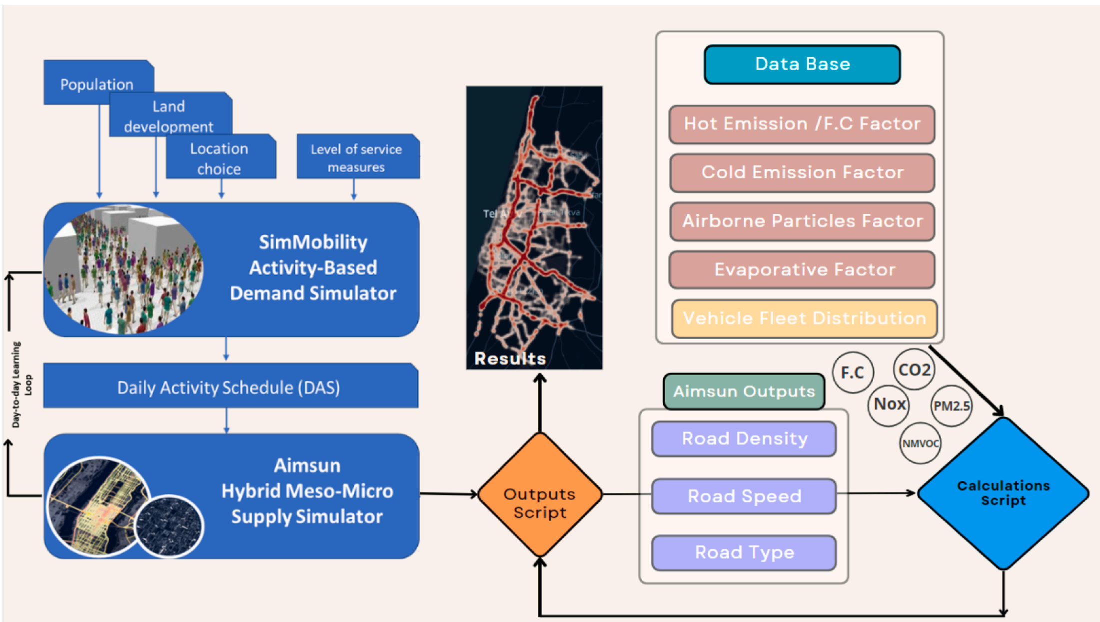

Fig. 1. Simulation system structure.

2.1. Simulation environment

In a former study, we built a hybrid activity-based and mesoscopic simulation tool for simulating future services and policies. Such a system consists of SimMobilty, which takes synthetic population, land development, and level of service measures, producing a Day Activity Schedule (DAS) via an activity-based model (ABM). In the ABM, the number and types of tours, the mode, the departure time, and the origin and destination nodes are hierarchically specified. This DAS is then 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 fuses micromeso simulation, allowing the scope of large-scale models while applying a detailed simulation in a well-defined area. Network performance, in the form of travel times and costs, is fed back to the demand simulator to update the agent's knowledge and enable a day-to-day learning process.

The supply outputs are processed as part of the emission model, which takes the density and speed of each road section at a 15 min time resolution. For each vehicle and propulsion type, the emissions are calculated according to emission factors that link pollution to activity based on the HBEFA methodology. The final outputs represent road section-based emission volume by pollutant type throughout the entire network. Fig. 1 shows the system structure of the combined simulation framework used in this study.

We describe each element of the simulation system framework in the subsequent subsections.

2.1.1. Population and land-use synthesis

First, we built a representative synthetic population for the study area based on population characteristics that were analyzed using a travel habits survey conducted in 2016–2017 for the Tel-Aviv metropolitan area, relying on Israel CBD, the Ayalon Highways model, and other data sources. A population of 2.6 million people was synthesized. At the individual level, we controlled for age, employment status, education, gender, and the living and working area locations of the residents. At the household level, we controlled for income and vehicle ownership. For a thorough explanation of the synthetic population construction process, see (Nahmias-Biran et al., 2022).

2.1.2. Demand modeling

A main tool utilized to generate the demand in this research is the SimMobility travel demand simulation tool. SimMobility is an open source, multiscale simulator to design and test mobility portfolios (Adnan et al., 2016). In this study, we utilized SimMobility's demand simulator (preday), which generates travel demand in the form of daily activity schedules (DAS) 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 are presented in (Nahmias-Biran et al., 2022). The demand for Tel-Aviv was initially estimated for Boston; we then calibrated it to match the average mode shares, activity shares, and trip generation rate of Tel-Aviv. This was accomplished by manually adjusting alternative-specific constants and scale parameters. In the Tel-Aviv metropolitan area, passengers make over 8.16 million trips on a daily basis with an average stop rate of 3.1 per individual. In addition, 3.7 million trips are made using private cars.

2.1.3. Supply modeling

A hybrid *meso*-micro supply simulation that simulates vehicle movements and operations is applied using Aimsun Next. The Tel-Aviv metropolitan hybrid model was coded and calibrated at the most detailed level of network by Ben-Shabat (2021) 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, and public transport plans, with associated parameters modeled as well (Nahmias-Biran et al., 2022). Later, it was expanded and validated by the authors to include various fuel types, costs, and energy consumption and emissions models. Overall, the Tel-Aviv metropolitan area has a total area of 1,516 km2 and 946 traffic zones. 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.

2.2. Mesoscopic energy consumption and emissions model

To calculate emissions of different types and evaluate the amount of air pollution in the metropolitan area of Tel Aviv, and in the absence of a mesoscopic emission model built for Israel's transportation conditions, the methodology that is described in detail in this subsection was formulated. Scripts that calculate the amount of emissions for each road section in units of grams and grams per km were built based on the simulation outputs, such as road density, volume, and average speed. The correlation between the information coming out of the simulation and emission from each vehicle is made by the emission factor. The emission factor is a representative value that relates pollution to activity. In the field of transportation, the emission factor is how many grams of emissions come from km of driving (hot emission) or engine start (cold emissions). The HBEFA database connects the emission factor to the road jam and type as well as car characteristics such as European emission standards and engine size. The pollutants to be evaluated as part of this study are carbon dioxide (CO_2), nitrogen oxide (NO_X), fine particulate matter ($PM_{2.5}$), and volatile organic compounds (NMVOC). The use of HBEFA's emission factors database requires information regarding road utilization in terms of density (vehicle per kilometer), the number of vehicles in a given road section, and parameters related to the vehicles themselves, such as engine size, fuel type, and conformity level with the European standard for air pollution (Euro 1–6).

Therefore, it was necessary to obtain the share of each combination of parameters of the vehicle fleet in the study area. The vehicle fleet data, by year of manufacture, engine volume, and vehicle classification, are essential to connect the emission factors with the road conditions in the simulation. Our mesoscopic emission model assumes that the distribution of vehicle characteristics on a particular road section is the same as the characteristics of vehicles at the state level; i.e., if in a particular section of road 100 cars drove for 15 min, their distribution by fuel type, engine volume, and European standard is similar to the distribution at the state level. Therefore, out of the 100 cars, there will be 23 petrol cars with an engine volume of 1400–2000 cc in the EURO 6 standard, 18 cars with an engine capacity smaller than 1400 cc in the EURO 6 standard, etc.

The HBEFA model assigns traffic flow properties to each road section according to which the emissions of the various vehicles are calculated, and, therefore, the model distinguishes between three traffic properties: free flow, heavy flow, and stop & go. Car densities smaller than 12 vehicles per kilometer are considered "free flow". A density of between 12 and 30 vehicles per kilometer is considered "heavy flow" and over 30 vehicles per kilometer until jam density is considered "stop & go".

The emissions model framework combines two python scripts. One exists on the Aimsun Next GUI scripting platform and manages the emission model. The Aimsun script is responsible for collecting the simulated data and sending it to an external python script. The external script estimates traffic flow conditions and calculates emissions using the HBEFA databases. The result returns to Aimsun for visualization and analysis. For a thorough explanation of the coding and database structure, visit GitHub (see 'Data Availability' section).

In this study, we considered the following types of emission factors: (1) hot emission factors that are generated when the engine is at its normal operation temperature and (2) cold emission factors that are created during transient thermal engine operation. In Israel, the mean vehicle km traveled in cold conditions is estimated to be 2 km (Ministry of Environmental Protection Israel, 2016). All four pollutants (CO2, NOX, PM2.5, and NMVOC) are considered to be cold and hot emissions. Equation (1) describes the calculation process of hot and cold emissions:

$$E_{p,t,s} = \sum\nolimits_{i=0}^{numberofvehtypes} \left(K\% \cdot C_{s,t} \cdot \left(f_{hotp,s,i,t} + f_{coldp,s,i,t} \right) \cdot L_s \right) \tag{1}$$

where:

Ep, t, s° - is hot & cold emission from pollutant p during time t in road section s (g).

Ct, s° - is the number of cars during time t on section s.

$K_i\%$ is the percentage of cars belonging to vehicle type i according to the national distribution.

L_s- is the length of section s (km).

$f_{hotp,s,i,t}$- is the hot emission factor of vehicle type i for pollutant p according to the density conditions on road s at time t (g/km).

$f_{coldp,s,i,t}$- is the cold emission factor of vehicle type i for pollutant p according to the density conditions on road s at time t (g/km after aggregation from g/engine start).

Emissions PM2.5 and NMVOC must be added to assess the PM 2.5 airborne particle emission. These particles are produced as a result of the interaction between a vehicle's tires and the road surface during ride or braking. Evaporative emissions (NMVOC) are emissions from the fuel system (fuel tanks, fuel injection systems and fuel lines). Evaporation of fuel in the tank during driving and parking is due to normal diurnal temperature variation. Equations 2–3 describe the evaporative emission and airborne particle emission calculation process, respectively:

$$\Delta E_{pm2.5,t,s} = \sum\nolimits_{i=0}^{numberofvehtype} \left(K_i\% \cdot C_{s,t} \cdot \left(f_{tires,i} + f_{brakes,i} + f_{roads,t} \right) \cdot L_s \right) \tag{2}$$

$$\Delta Enmvoc, t, s = \sum\nolimits_{i=0}^{numberofveh} Ki\% \cdot Cs,\ t \cdot f_{runingi} \cdot L_s \tag{3}$$

Fuel consumption is modeled similarly to the method used for hot emission factors. Equation (4) describes this process:

$$F.C = \sum\nolimits_{i=0}^{numberofveh} Ki\% \cdot Cs, t \cdot \cdot f_{Feulconsumption} \cdot L_s \tag{4}$$

where:

$\Delta E_{pm2.5,t,s}$- is airborne particle emission during time t in road section s (g).

$\Delta E_{nmvoc,t,s}$ is the evaporative emission during time t in road section s (g).

$K_i\%$- is the percentage of cars belonging to vehicle type i according to the national distribution.

$C_{s,t}$- is the number of cars during time t on section s.

L_s- is the length of section s (km).

f° – is the emission factor.

3. Case study

To analyze the environmental impacts of decarbonization policies using the developed simulation tool across the Tel-Aviv metropolitan area, we consider three scenarios. Through these, we explore plausible sustainable futures in which active strategies are employed to manage energy consumption and emissions across cities. In this scenario exploration, we simulated the trip demand of the three inner rings of the metropolis in great detail (see Fig. 2) during the morning peak period (6 AM to 11 AM).

3.1. Base case

The Base Case represents current conditions for the Tel-Aviv metropolitan area in terms of demand, supply and fleet composition. 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), 21,548 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.

In the Tel-Aviv metropolitan area, available modes are Private Car (single and pooled), Mobility On-Demand (taxis), Mass Transit (buses and rails), Active Mobility (bicycles and walks) and Other (motorcycles and private buses). In morning peak, 849k car trips were generated by the demand simulator and were assigned in the supply simulator, when intrazonal trips could not be assigned. Background traffic was created to simulate trips that are entering or leaving the study area borders. In the Base Case, more than 200k trips were created and assigned based on a cellular survey collected nationwide in Israel in 2018–2019 (Nahmias-Biran et al., forthcoming).

The study area is highly congested due to public transportation system inefficiencies. Due to the challenges of increased car usage, air pollution and energy consumption as well as the limited availability of land for roads, demand-oriented solutions, particularly pricing schemes, have been increasingly considered as viable strategies for improved outcomes in cities (Gu et al., 2018). Therefore, in this study, we designed and tested various pricing solutions.

3.2. Congestion pricing scenario

A congestion pricing scenario is implemented to describe a situation where a geographical pricing policy is applied following Israel's government plan. To simulate such a pricing policy in the SimMobility simulator, a cost matrix was built for three time periods: morning peak, off-peak, and evening peak following the government's plans to tax with respect to congestion direction. The travel cost by different modes is specified in Table 1, while the charge is applied to private cars only, depending on the congestion direction by time of day. Fig. 2 shows the charge rings and the price charges crossing those rings.

3.3. Car ownership reduction scenario

A car ownership reduction scenario is implemented to describe a situation where car ownership is reduced by 25% in the center of the metropolis, which is created by taxing private vehicle purchases or other instruments. Reducing car ownership has been proposed as a viable and even desirable policy for improving sustainability outcomes in cities (May, 2013; Sperling and Salon, 2002). We thus test such an approach under this scenario by simulating the impacts of restricted car ownership, which is actualized by a 25% reduction in household car ownership. Thus, the household car ownership rate in car reduction is brought down to 63% from a value of 77% in the Base Case.

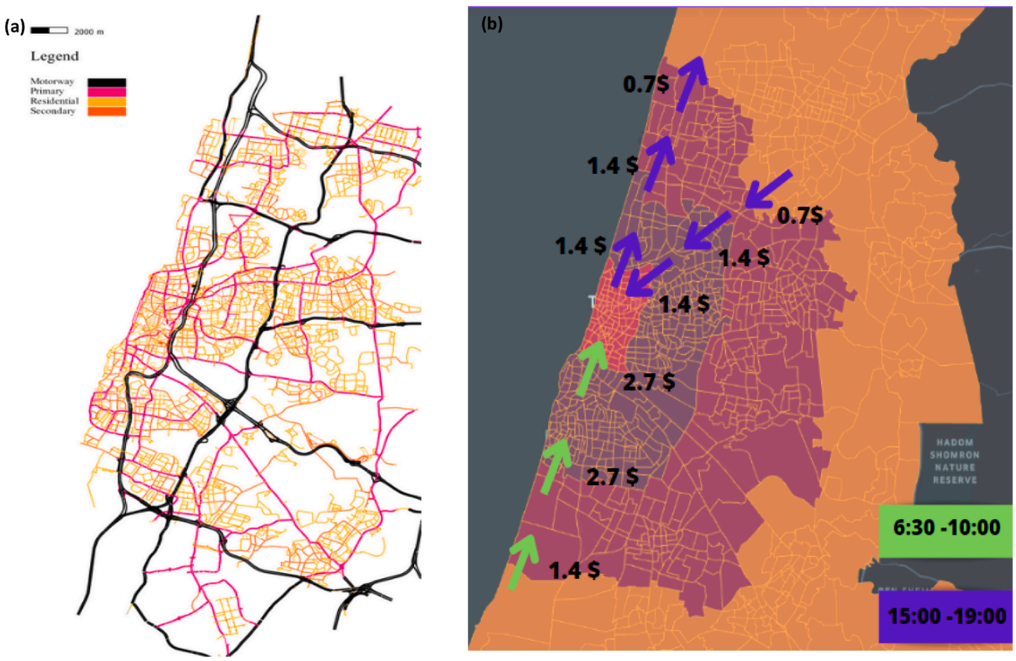

Fig. 2. The road networks of the Tel-Aviv metropolitan area: (a) road map by hierarchy and (b) congestion pricing plan.

Table 1
Travel cost by different modes.

Mode	Fare Component	Base Case	Congestion Pricing Scenario
Car	Operational Cost (per km)	USD 0.16	USD 0.16
	Parking Cost	USD 7.00	USD 7.00
	Congestion Charge	USD 0.00	USD 6.80
Taxi	Base Fare	USD 4.46	USD 4.46
	Distance charge (per km)	USD 0.47	USD 0.47
	Travel Time charge (per min)	USD 0.47	USD 0.47
Bus and Private Bus	Fixed	USD 6.65	USD 6.65
Motocycle	50% of car price	USD 3.58	USD 6.98
Car Sharing 2	50% of car price	USD 3.58	USD 6.98
Car Sharing 3	33% of car price	USD 2.38	USD 4.65

4. Results

The simulation results are divided into three subsections: results that are produced by the demand simulator; results that are produced by the supply and emission model; and results that combine the two. The demand side results include the agent's choice of travel modes and activity in the examined scenarios. The supply side results include air pollution and energy consumption by road type and time of day. Finally, environmental equity analysis results that combine individual characteristics and supply outputs are presented.

4.1. Travel demand impacts

Fig. 3 presents the relative portion of the total number of trips in each mode conducted by the individuals in our synthetic population when the modes are classified into four mode classes: transit, active modes, mobility on demand (MOD), and private modes. In the Base Case, the agents make more than 63.8% of the trips by car, while active modes consist of 24.3%, and transit and taxi consist of only 11.2 and 0.31%, respectively. The mode choice diagram (Fig. 3) indicates a reduction of 1% in car travel in favor of bus, walk, and bike as a result of the congestion pricing scenario. A much more significant reduction of 10% in car travel in favor of these alternative modes is observed as part of a car ownership scenario but also an increase in the car sharing share of 3.7%. As a result of the scenario implementation, 51k trips per day are canceled in the congestion charge scenario and 195k trips per day as part of the car reduction scenario.

Next, the demand distribution throughout the day is shown in Fig. 4 by private car, bus, taxi, and bicycle modes. The peak demand is approximately 7:30 am and 4:30 pm by motorized modes, while for using bicycles, the highest demand is in the off-peak period at

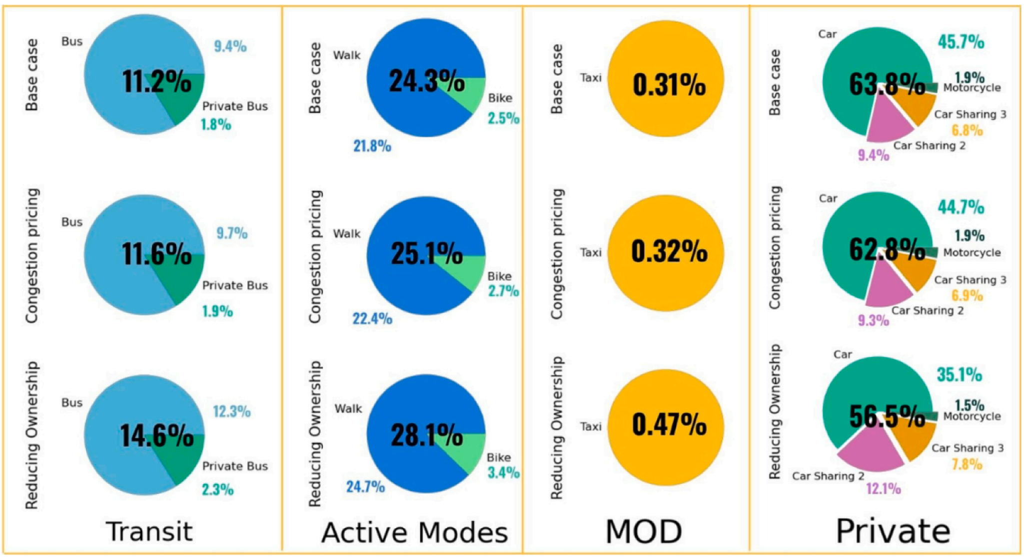

Fig. 3. Simulated mode choice by scenarios.

approximately 2:00 pm. The scenarios do not lead to demand shifts in time, even in the congestion pricing scenario where the agents are expected to shift their return trips before the charge is applied. Although the impact of congestion charging scenario is very small, individuals prefer to cancel their trips or make more inner-ring activities, rather than change the time of activity. We think this result is related to model structure that takes logsums (which is used to link different choices) from different levels of decision but not from the time-of-day model, as a result, individuals less tend to re-schedule their activities.

In Fig. 5, we investigated the demand by type of activities within travel modes. We identify Two trends can be seen in the activity distribution of alternative modes for private cars. First, individuals who chose “Other” activity are sensitive to the congestion pricing scenario, although individuals who selected “Work” activity are sensitive to the car reduction scenario.

Furthermore, as part of the congestion pricing scenario, the number of trips by alternative modes for the “Other” activity increased more compared to the car ownership reduction scenario, so individuals who are traveling using the “Other” activity do not receive a significant benefit from choosing private vehicles. Moreover, they tend to make more trips inside the rings by alternative modes which are tax-free as to avoid the tax forced by car trips while crossing the rings. By looking at the “Work” activity, we see that the car reduction scenario significantly increases the number of trips by alternative modes, as travel to the “Work” activity is usually non flexible, thus individuals are forced to take alternative modes.

4.2. Emissions and fuel consumption impacts

As discussed earlier, the energy consumption and emissions are computed for each vehicle after the supply simulation run, using the speeds and density in successive timeframes. The various emissions can be calculated on any road section in the network at a 15 min time interval. When we investigate the distribution of the emissions in the different road types during the morning peak, we see that the motorways accumulate the highest pollution, as shown in Fig. 6.

The results indicate that the emissions on urban roads (primary, secondary, suburban) in both the base case and congestion pricing scenario constitute 50% of the total pollution (more than 2.3 M kg of pollution), while the car ownership reduction scenario reduces that share to 41%. The highest impact on emission levels was due to the car ownership reduction scenario when 257 K kg of carbon dioxide was reduced, 173 K kg in urban roads and 84 K kg in motorways. The distribution of GHG emissions (carbon dioxide and nitrogen oxide) by time of day is shown in Fig. 7.

It is evident that peak emissions are attained near 8:30 am in all scenarios. Pollution in the base case and congestion pricing scenario is significantly higher between 8 and 9 am compared to the car ownership reduction scenario. After the peak, drivers who arrived from outside the metropolis and reroute to inner rings of the metropolis are more dominant than the inner metropolis travelers, and, thus, we see that base case and congestion pricing curves have similar trends after 9 am.

The simulated fuel consumption results, as shown in Fig. 8, indicate similar trends to PM2.5, NOx, and NMVOC emissions. The results show that the carbon dioxide emission to fuel consumption ratio in the Tel-Aviv metropolitan area in the base case is 3.6 and rises to 3.8 in the two scenarios. The car ownership reduction scenario managed to reduce the amount of kg fuel burned in the metropolis by 11%.

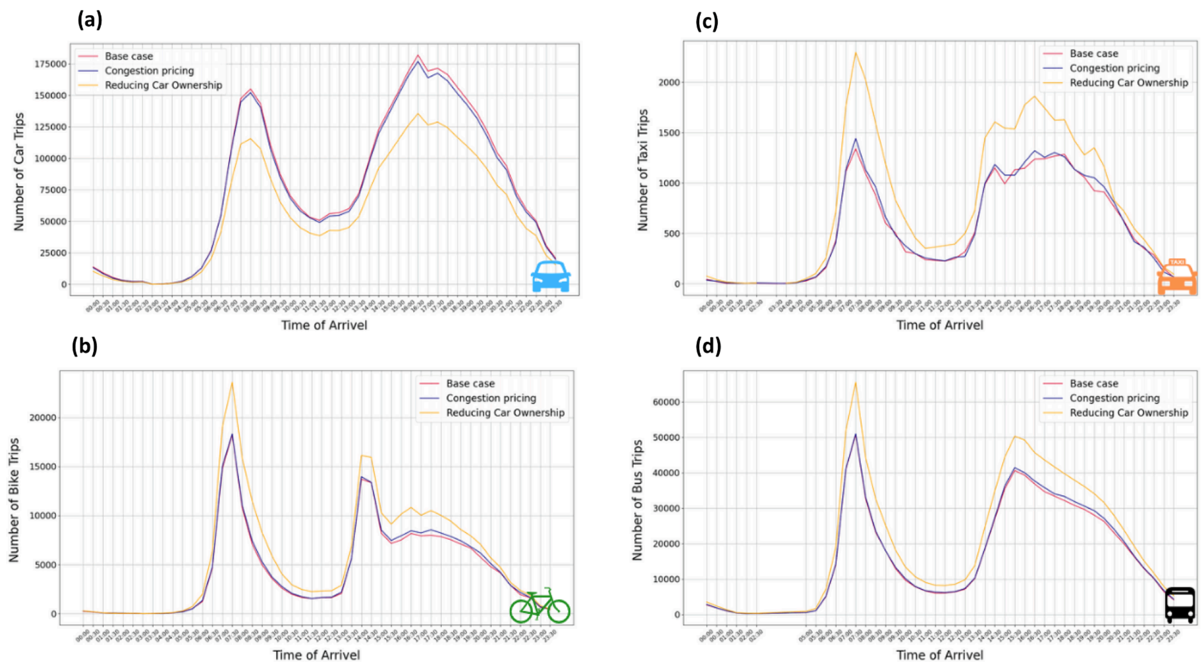

Fig. 4. Simulated demand by time of day and mode choice: (a) Car; (b) Bus; (c) Taxi; and (d) Bike.

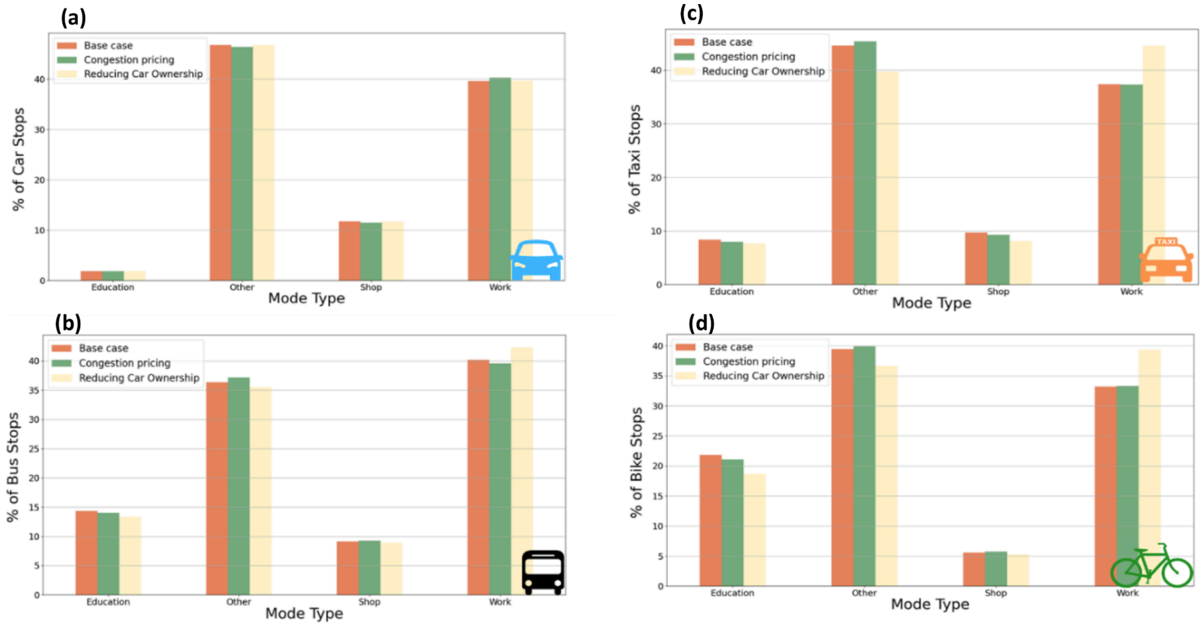

Fig. 5. Simulated demand by activity and mode: (a) car; (b) bus; (c) taxi; and (d) bike.

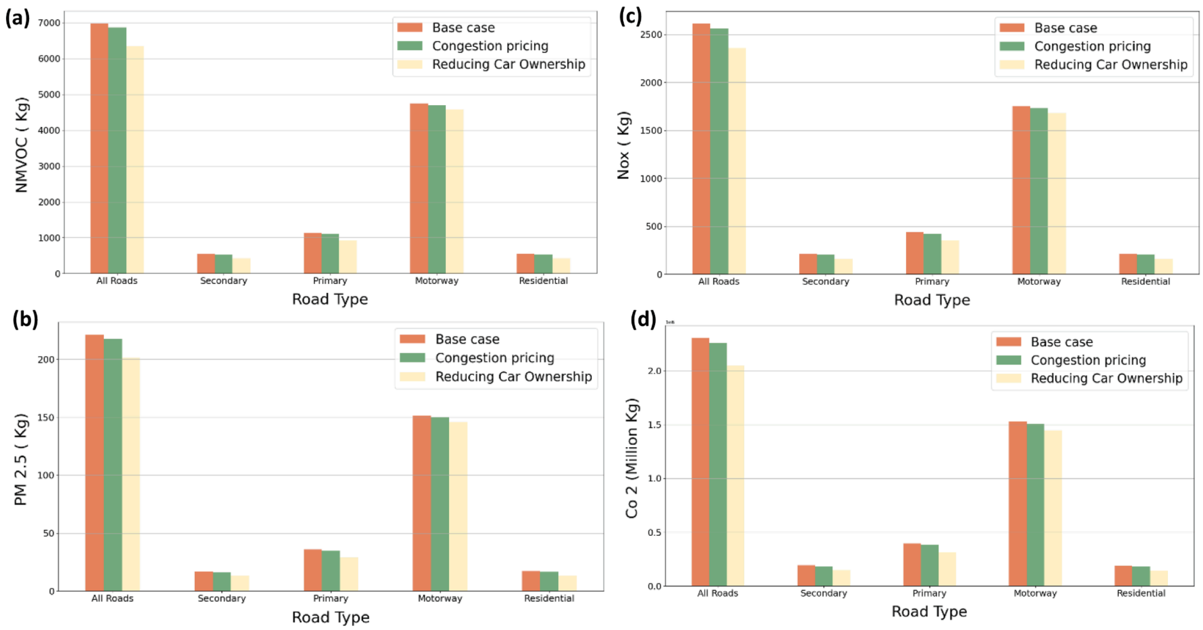

Fig. 6. Simulated emissions by road type during morning peak: (a) NMVOC emissions; (b) PM2.5 emissions; (c) NOX emissions; and (d) CO2 emissions.

4.3. Environmental equity impacts

In this section, we wanted to determine the relationship between pollution levels and individual characteristics. Therefore, we divided the metropolis into statistical areas ranked from 1 to 10 according to their socioeconomic clusters following the Israeli CBS data (CBS, 2019). A rating of 10 represents the highest economic well-being, while a rating of 1 represents the lowest economic well-being. The results of GHG pollution by socioeconomic clusters can be seen in Fig. 9. The result shows that although most CBD is populated by the "rich" (see Fig. 9(b)) – that is, 37% of the area of the metropolis ranked 9 on the socioeconomic cluster – the poorest areas receive the most GHG emissions. Furthermore, Co2 emissions are 30% higher in the five lower social economic clusters than in the five highest social economic clusters, and clusters 2–4 are extremely polluted relative to the rest. Cluster 2 is most affected by the

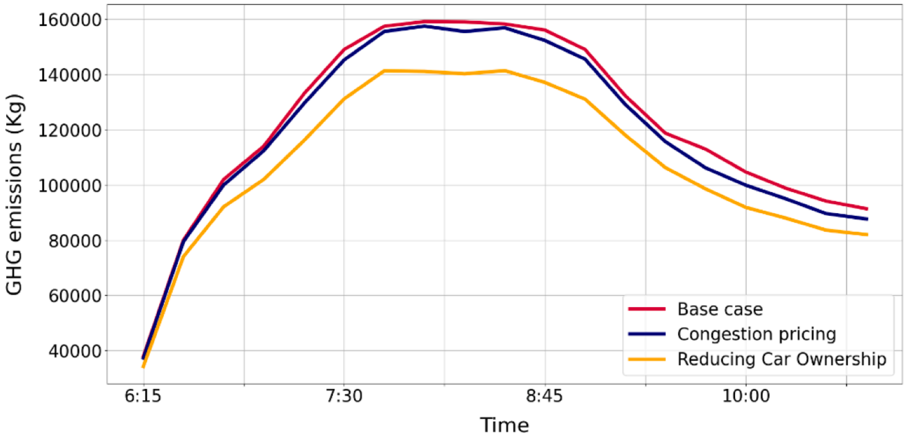

Fig. 7. Simulated GHG emissions by time (morning peak).

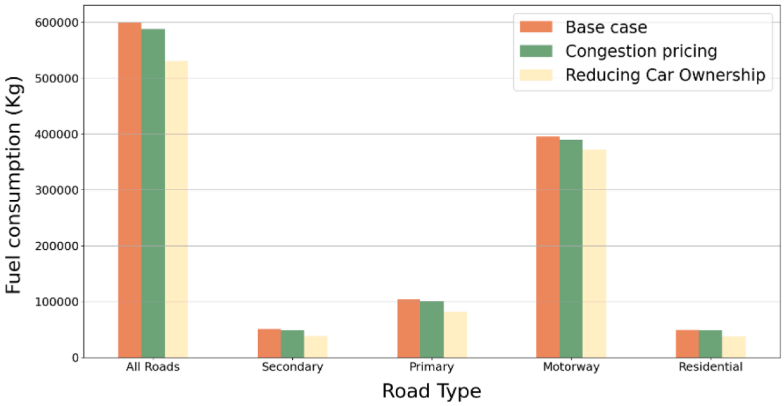

Fig. 8. Simulated fuel consumption.

tested policies – 5% less exposure to carbon dioxide in the congestion charging scenario and 25% less exposure in the car ownership reduction scenario.

As the residential addresses of all households in our synthetic population are known as well as the number of children in each household, we aggregated this information to examine the number of children in each statistical area and the amount of pollution to which children are exposed. This analysis can be seen in Fig. 10. In the base case and congestion pricing scenario, most of the children are exposed to 0.2 kg to square km of PM 2.5. This amount of pollution has a significant negative impact on children's health. In the car ownership scenario, most of the children are exposed to 0.1 kg of square km PM2.5. The results show that a 1% reduction in car travel in the pricing policy scenario reduces the number of children's exposure to high PM 2.5 emissions (higher than 0.3 kg/km^2) by 3%. Furthermore, a 25% reduction in the car ownership scenario reduces the number of children's exposure to PM 2.5 emissions by 19%.

To visualize pollution results, we built a heatmap of the center of the metropolis showing the statistical areas where the Tel-Aviv residents live. In creating the heatmap, we ignored roads that are not in residential areas; the results can be seen in Fig. 11. Fig. 12 shows that in the Tel-Aviv metropolitan area, the lower social economic clusters suffer from higher concentrations of emissions relative to other residential areas. The car ownership reduction scenario can reduce the emission concentration in most areas. Employment areas in Tel Aviv create separation between main roads and "rich" neighborhoods. However, there is no such separation between poor neighborhoods and main roads, and, thus, significant pollution comes directly from motorways to poor socioeconomic areas.

4.4. Model sensitivity

In this subsection, the sensitivity of the model to changes in congestion charges and car ownership reduction was tested. In the congestion pricing case, the charge was increased by 10% and 20% between each origin and destination compared to the charge that was set following the government plan. In the vehicle ownership reduction case, 20% and 30% reductions in ownership in the synthetic population were tested alongside the 25% scenario. Table 2 shows the reduction in demand for car trips as well as air pollution reduction, in percentages, due to each case compared to the base case scenario. In the same way, Fig. 13 shows the reduction in car trips by activity type.

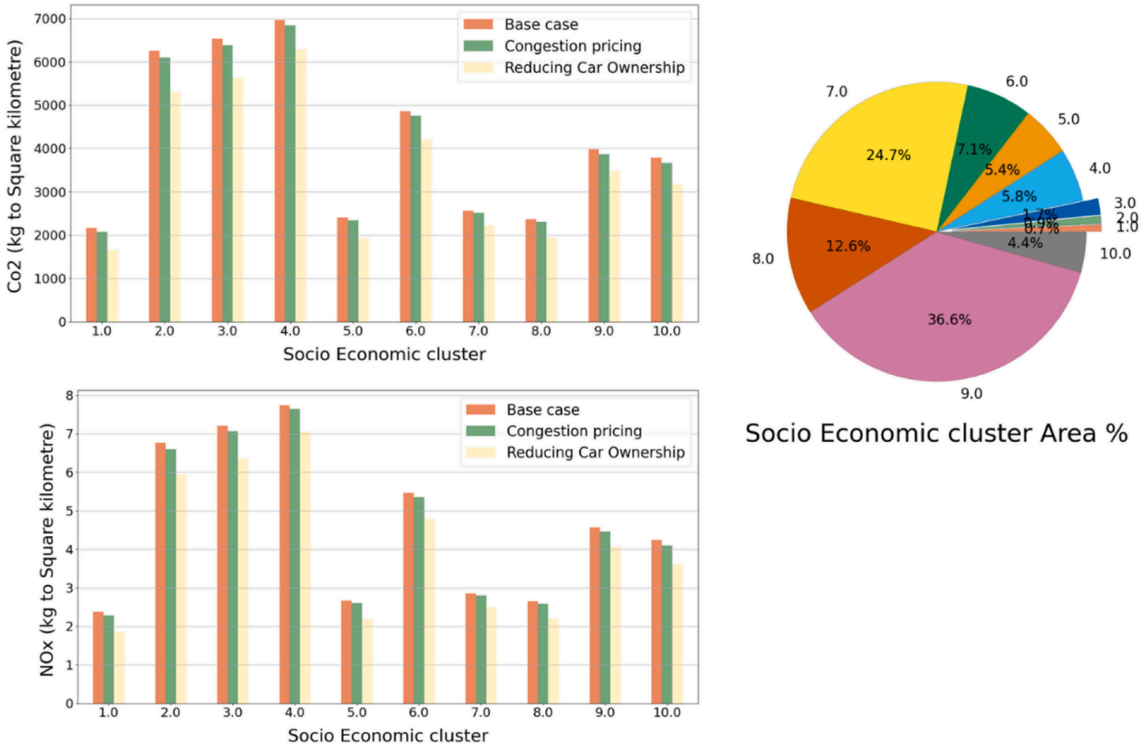

Fig. 9. Emissions impact by socioeconomic cluster: (a) CO2 emissions; (b) socioeconomic coverage by area; and (c) NOx emissions.

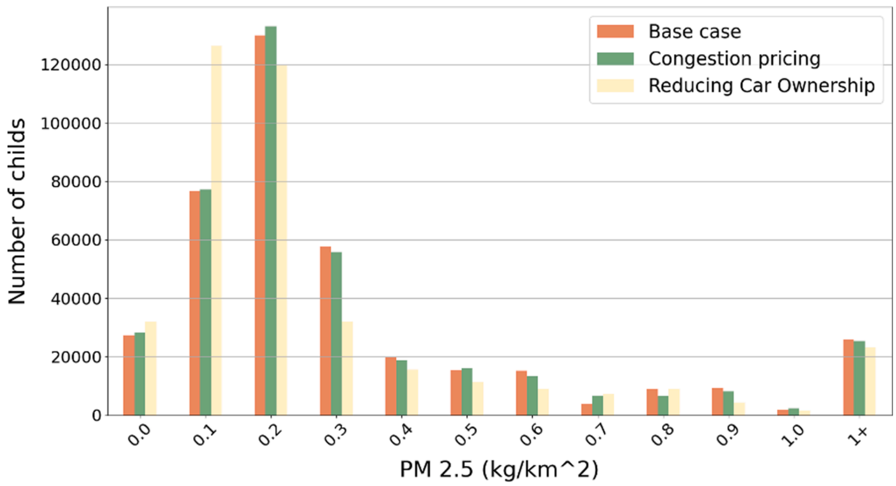

Fig. 10. Children's exposure to PM2.5 pollution.

The implementation of congestion charging causes a reduction of 2.62% in the demand for private cars compared to the base case demand. A further increase in charge by 10% reduces demand by another 0.11%, and a 20% increase in charge will reduce demand by 0.3%. The activity that was least affected by the tax increase was work activity. A charge higher than 20% relative to the government's original tax causes a decrease of 1.15% in demand for work activities and a 5.86% decrease in demand for shopping activity, 4.14% for Other, and 2.1% for Education. In terms of the sensitivity of the emissions model, it can be seen that a 20% reduction in vehicle ownership in the synthetic population will result in an 8.69–7.03% reduction in carbon dioxide, nitrous oxide, volatile organic compounds and practical matter. Every 5 percent reduction in ownership of private vehicles is equivalent to a 2.32 to 2.5 percent reduction in carbon dioxide compared to the base scenario and a 0.11–0.3 percent reduction for every 10% increase in congestion charge.

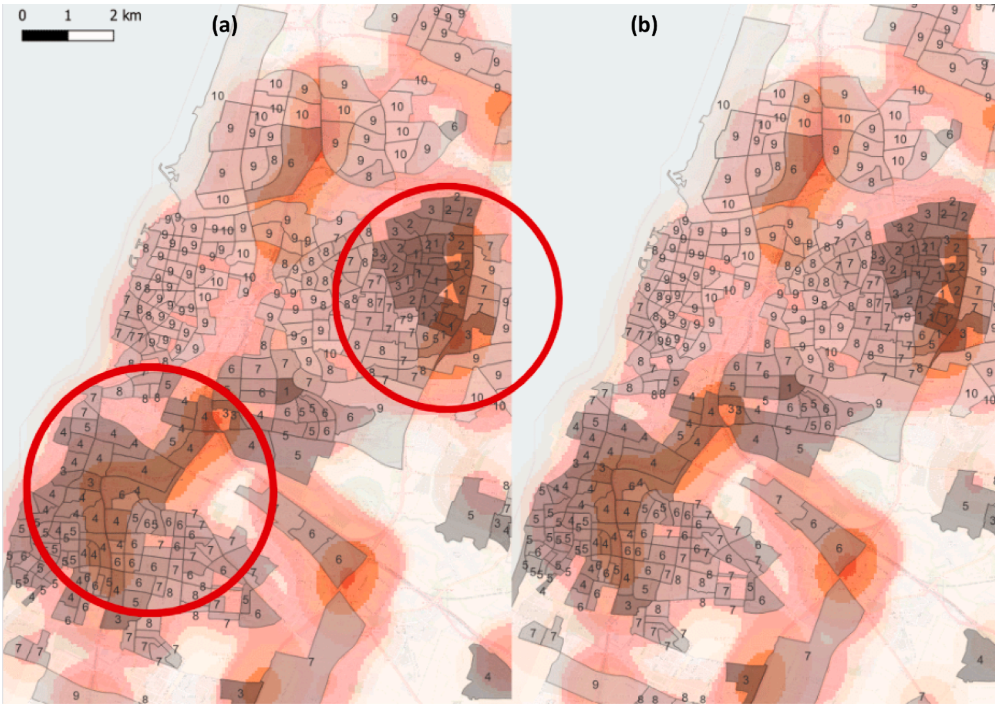

Fig. 11. Residential area exposure to GHG emissions: (a) Car Reduction scenario and (b) Base Case.

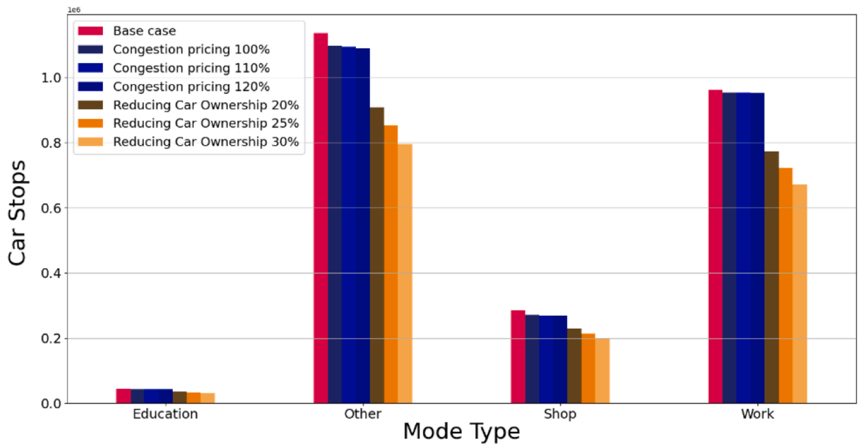

Fig. 12. Sensitivity analysis: of the change in car stops due to congestion pricing and car ownership change.

4.5. Validation

Validating the model outputs in the Tel-Aviv metropolitan area is quite challenging because there are very few pollution monitoring stations that measure emissions from transportation, and they do not produce pollution in gram units. Therefore, validation of results was carried out on two primary levels; first, we carefully calibrated the supply model and validated the number of vehicles crossing the metropolitan rings in our supply model versus the number of vehicles crossing the rings as calculated from the travel habits survey, as seen in Fig. 13. In addition, we compared our model results to the closest (terms of capabilities) emissions model results, and pollution outputs were compared throughout the simulation time. The LEM model of AIMSUN NEXT was chosen, and the input to the model was the distribution of the Israeli vehicle fleet according to fuel type and European emission standards. The results show a compatibility between the models, as described in Fig. 14.

Area A is the inner congestion rings of the metropolis (the city of Tel Aviv-Jaffa). Areas B and C are the middle and outer rings, respectively, as described in Fig. 2. We can see that the simulation results match well with the travel habit survey results. The estimated difference is 3.4% in crossing the outer ring and a lack of 4.4% and 2.3% of vehicles crossing the inner and middle rings, respectively.

Table 2
Sensitivity to congestion pricing and car ownership change.

	Demand	Morning peak emission			
	Car Trips	Co2 (Kg)	Nox (Kg)	NMVOC (Kg)	PM 2.5 (Kg)
Base case	2,428,994	2,304,924	2,612	6,979	221
Congestion pricing 100%	-2.62%	-2.09%	-1.80%	-1.64%	-1.63%
Congestion pricing 110%	-2.83%	-2.20%	-1.94%	-1.80%	-1.79%
Congestion pricing 120%	-3.12%	-2.50%	-2.17%	-1.98%	-1.96%
Reducing car ownership 20%	-19.90%	-8.69%	-7.69%	-7.10%	-7.03%
Reducing car ownership 25%	-25.03%	-11.19%	-9.81%	-9.00%	-8.91%
Reducing car ownership 30%	-30.01%	-13.51%	-11.89%	-10.93%	-10.83%

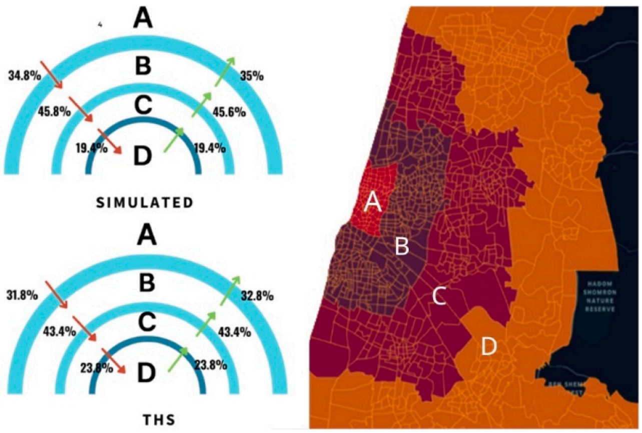

Fig. 13. Simulation results vs travel habit survey: Precent of vehicles crossing congestion rings.

Fig. 14 shows high compatibility between the London Emission Model (LEM) and the newly developed emission model presented in this work. Our model predicts an average carbon dioxide emission of 1.22 times that of the LEM model. The two models are different; LEM is based on a non-linear model of average speeds, and our model is based on emission factors. However, similar trends point to the strength of our new model, which was matched to the LEM under the Israeli vehicle fleet. Even so, other pollutants could not be validated, as the LEM cannot compute pollutants such as PM2.5 and NMVOC.

5. Conclusions

This study contributes to the development of a state-of-the-art simulation tool for the evaluation of air pollution and energy

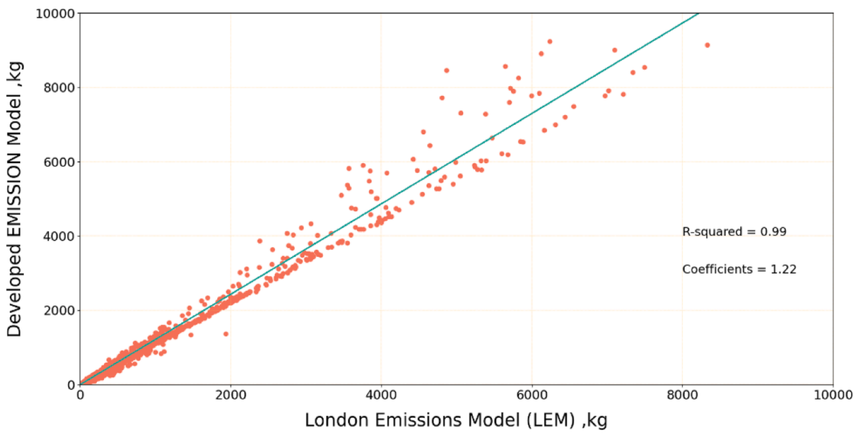

Fig. 14. London emission model vs the newly developed emission model: Co2 emissions for each road section.

consumption in large-scale urban areas while closing the gap found in previous works. Equally important is the ability to analyze the impact on individuals as a result of transport policy implementation. Our simulation framework is flexible, allowing for the examination of demand-oriented and supply-oriented solutions simultaneously. The very detailed energy consumption and emission model can be calibrated to any fleet and produce a variety of outputs, including changes in CO2 and GHG emissions, as well as NOX, PM2.5, and NMVOC emissions per road section at a 15 min time resolution. Thus, it avoids the limitations of previous studies where emission evaluations were performed on small-scale networks, neglected the impacts of congestion and the dynamics between supply and demand, and enriched the variety of pollutants we can analyze.

We demonstrated the use of our new simulation framework by examining pricing policies in the Tel-Aviv metropolitan area. We showcase potential scenario configurations designed for a better sustainable future and their impacts on demand, supply, emissions, and energy consumption as well as individual-level impacts. The results show that taxing vehicle purchases and forcing a reduction in car ownership in the city center of Tel-Aviv is an effective tool for reducing demand for cars and their accompanying emissions. Nevertheless, it should be noted that the change in travel habits of passengers coming from outside the city can increase emissions in certain areas relative to the base case. Due to the high dependency on private vehicles and the lack of attractive public transportation alternatives in the Tel Aviv metropolitan area, the demand does not change largely due to the implementation of the congestion charging scenario. Nevertheless, this policy has advantages, such as reducing children's exposure to pollutants and reducing air pollution on urban roads.

This study does not recommend any policy but rather promotes a better environmental policy examination by developing practical simulation-based tools for policy-makers and planners. Another aspect that such a tool can promote is the examination of environmental equity and the impacts on individuals in the implementation of government policies, as demonstrated in this work. It was found that poor neighborhoods are more exposed to air pollution than wealthy neighborhoods, even in municipalities where most of the area consists of neighborhoods with relatively high socioeconomic levels.

This work has some limitations. First, we do not model the very short trips, as those are made on the smallest roads that were removed from the network to allow the simulation of this very large-scale Tel-Aviv network. Such a limitation may affect the pollution results. On the other hand, excessive modeling of the city can lead to difficulties in calibrating and running the supply in the dynamic-mesoscopic environment. Furthermore, the data from which the background traffic is generated are very detailed but have several disadvantages: (1) trips under 1.5 km are missing and (2) the data cannot differentiate between modes of travel. Future work will try to tackle these challenges. In addition, in this study, we did not examine pollution by freight vehicles, as we do not model their specific behavior. Freight traffic inside the metropolitan area of Tel-Aviv is not large, yet it may still influence the pollution levels and should be considered. Finally, the simulation structure should be extended to include logsums from time of day models to capture better individuals sensitivity to re-scheduling of their activities.

Future work will study pollution by routes from origin to destination using a similar methodology. This analysis will give us the tools to understand if there are unnecessary urban detours that cause high levels of pollution in residential neighborhoods and through which government transportation policy they tend to be created. A natural continuation of this research is the evaluation of the energy consumption of electric vehicles in a mesoscopic framework. This development has many challenges, especially on the supply side, when the movement of electric vehicles depends on the level of charging, the duration of charging and loads on the electricity grid given large fleets of electric vehicles.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared a link to the data/code on GitHub. The full data set used for this study is publicly available. All the emission factor databases that were used, the scripts in the emission model structure, and more can be downloaded from our GitHub repository: https://github.com/futuremobilitylabariel/EnvironmentModel, 2022. The repository also contains truck emission factor databases that can be used in a freight emission model with similar methodology. Please read the 'read me' file for file descriptions.

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Author contributions

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

Author Statement

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