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Future fleet composition with fit-for-demand shared autonomous electric vehicles

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Summary

Shared autonomous electric vehicles (SAEVs) are expected to have a disruptive impact on mobility the sector. As mobility becomes more accessible and attractive due to low-cost and high service level vehicles, induced demand is likely to arise. Additionally, SAEV fleets will consists of fit-for-demand energy efficient vehicles with many 1-person vehicles. In this research we quantify the required vehicle fleet for the Netherlands with the help of an agent-based simulation showing that full adoption of SAEVs might increase the number simultaneous vehicles on the road by 200% - 300% due to relocation and induced demand. However, the number of vehicles per 10 000 inhabitants in the Netherlands reduces from 4.488 privately owned vehicles per to 687-1.084 SAEVs.

Keywords:
Shared autonomous electric vehicles
Future fleet composition
Fit-for-demand vehicles
Induced mobility demand
Agent-based modelling

1 Introduction

Autonomous and electric driving technologies are expected to have a revolutionary impact on the mobility sector [1]–[6]. The elimination of the driver and reduced fuel costs will open a market for shared autonomous electric vehicle (SAEV) fleets. Such fleets provide mobility as a service with high utility, flexibility and at low costs [7]–[9]. How exactly this will transform the mobility sector is not completely clear. In figure 1 we present a causal diagram that shows the most important changes often found in literature. Also the public transport sector is expected to change significantly as a low-cost door-to-door service are usually more attractive than current public transport that requires transfers, waiting times, and first- and last mile solutions [10]–[13].

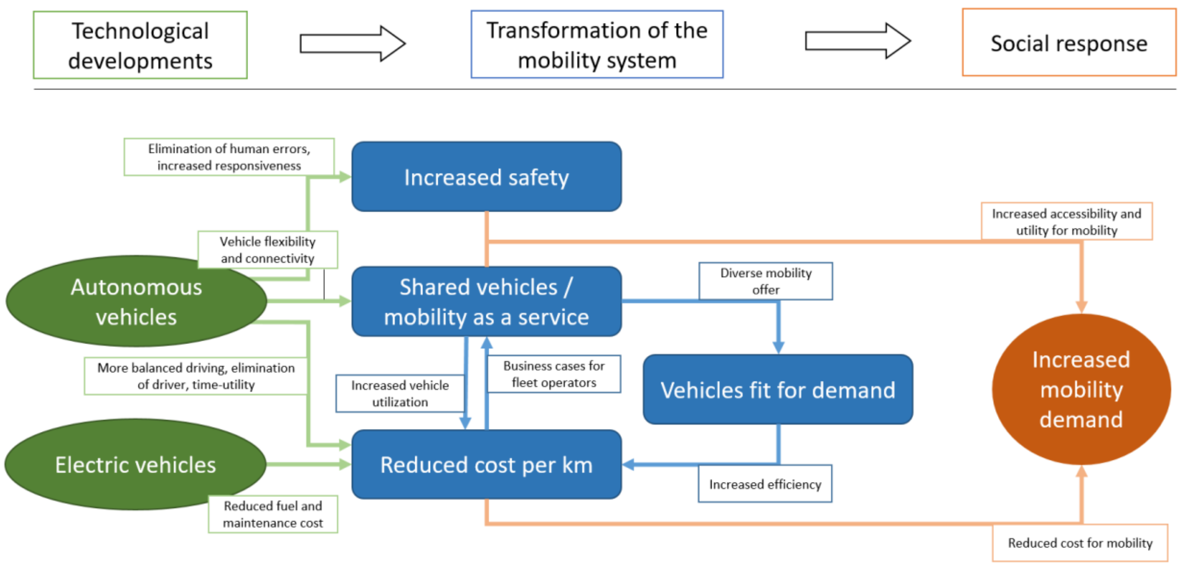

Figure 1: Key elements of the mobility transformation causes by electric and autonomous driving technologies

SAEV fleets shift car ownership from private to collective. This leads to the question of what the required fleet size is to provide in the future mobility demands of society. A variety of studies have modelled mobility systems with SAEVs to answer this question. Results, summarized in figure 2, show that one SAEV can replace 7 to 20 private vehicles. Important factors that influence these outcomes are the relocation strategy, the mobility demand and ride-sharing vs car-sharing [2], [14]–[19]. However, these prior studies largely left out two crucial aspects of the future mobility system: 1) the induced mobility demand and 2) fit-for-demand vehicles.

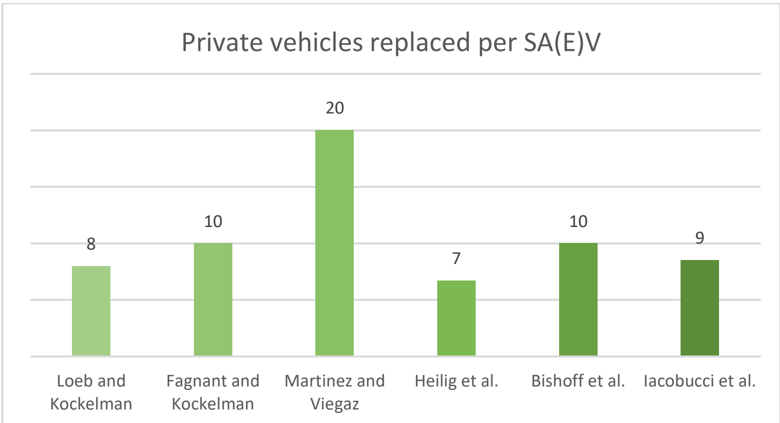

Figure 2: Vehicle fleet analysis of SAEV services of prior research

The induced mobility demand as a result of SAEVs is driven by:

- New user groups due to reduced cost and availability of mobility for children, disabled people and persons without driving license [7], [20]
- Modal shifts from public transport towards SAEVs [1], [10], [21]
- Increased comfort and utility which increases trip frequency and distance [1]
- Relocation of vehicles [15], [17], [19]

However, as shared vehicles need only be fit-for-demand for a single trip and we mostly travel alone, smaller vehicles are expected to replace current all-purpose family-cars. Such one- or two-person SAEVs are expected to be highly energy efficient. However, the previous studies that assessed the required vehicle fleet focused on SAEV ride-sharing with current day vehicles, such as minivans and 5-person sedans. In this study we fill this research gap by analyzing the required future SEAV fleet composition taking induced demand as well as vehicles fit-for-demand into account. With the help of agent-based modelling we simulate scenarios in which no private vehicles are owned and trips are made with public transport, walking/biking or shared SAEVs. The model focusses on average working days and is a case study of the Netherlands.

The next section discusses related research. In section three we discuss the methodology of this research. This is followed by the results and conclusion.

2 Related work

This section provides an overview of other work related. In Table 1 we list previous agent-based models that studied SAEV fleets dynamics. The results of these studies are discussed below in more detail. The last two columns of Table 1 show to what extent the models took vehicles fit-for-demand and induced demand into account.

Table 1: Overview of previous ABMs of SAEV fleets

Authors	Scope	Vehicle fit-for-demand?	Induced demand?
Martinez & Viegas [16]	Modelled ride-sharing services in the city of Lisbon with current-day mobility patterns. Full replacement of private vehicles was considered in two scenarios: 1) door-to-door ridesharing taxi's, and 2) door-to-door ridesharing taxi's + high frequent shared minibuses. Modal choice, which also included metro, rails and walking, was based on a decision tree.	Partly, demand was fitted to vehicles (4p sedans + minivans) trough ride-sharing	No
Fagnant and Kockelman [15]	Explored service level and vehicle miles travelled of different relocation strategies with mid-sized SAVs. The model involved random trip generation on a synthetic grid. SAV service was limited to a 15 mile distance. Lack of realistic narrative.	No	Partly, relocation strategies
Zhang et al. [22]	Studied the amount of parking space saved with SAV system compared to current. Used hypothetical gridded city where 2% of people use SAVs instead of private vehicles.	No	No
Kamel et al. [10]	Developed an ABM methodology to analyze modal choices when SAVs become an additional option. The method requires input about user preferences of modal choices. Cost and travel time are the main components determining heterogeneous decisions. Mobility behavior of Paris was implemented.	No	No
Scheltes et al. [11]	Looked at the SAEV feasibility as an alternative last mile solution for a 1.8 km corridor from a train station to university.	Partly, vehicle fit for trip type. However, just one trip type was modelled	No
Milliard-Ball [23]	Studied how private AVs can impact congestion and parking dynamics with three strategies to avoid parking costs. It was found that there is incentive for AVs to induce congestion if private AVs intent to avoid parking costs by free-floating.	No	Partly, additional parking mileage
Shen et al. [12]	Examined how SAVs can replace scheduled-fixed route buses as a last-mile solution from metro stations in the city of Singapore.	No	No
Iacobucci et al. [19]	Studied fleet size and charging dynamics of an SAEV fleet in order to assess power grid integration. Car and taxi trip dynamics of Tokyo were implemented.	No	No
Heillig et al. [17]	Modelled a future scenario with 100% AVs and without private cars to determine the number of AVs required to cover the mobility needs of the city of Stuttgart.	No, four person ridesharing SAEVs	Partly, longer trips

Martinez and Viegas used an agent-based approach to study the fleet size, travel times and CO2 emissions in a situation where ride-sharing SAEVs replaced all car and bus trips in the city of Lisbon, Portugal. They found that CO2 emissions can be reduced with up to 40% (without changing the current vehicle technology), and congestion can achieve a 30% reduction due to greater traffic fluidity. Additionally, they found that the vehicle utilization increased from 30 km per day to 250 km per day, which could imply a replacement rate of up to 8.33 vehicles per SAEV [16].

Fagnant and Kockelman developed an agent-based model to study the fleet requirements and environmental impact of a SAEV fleet when trips are generated in a grid-based neighborhood. The study only looked at ride-sharing. The results indicated a replacement rate of 11 vehicles per SAEV and increased travel distances of 10% due to reallocation and pick up [15].

Heilig et al. modelled a future scenario with 100% AVs and without private cars to determine the number of AVs required to cover the mobility needs of the city of Stuttgart. The model also simulates modal choices. Current private car trips are in this study performed by all other available modes (including SAVs), this means that, for example, also number of walking and bus trips increased. The study involved only ride-sharing SAEVs and assumed that the conditions of using SAEVs is similar to that of current day passengers in private cars. In time steps of 15 minutes trips with the same destination and departure zone are bundled in SAEVs. The results show that the number of vehicle trips may reduce by 46%, the vehicle kilometers by 20%, and that a fleet size can be reduced to 15% of the current fleet. The number of vehicle trips reduced because of 1) a high degree of modal shifts from vehicles towards other modes, and 2) modal shifts towards SAEVs as well as induced trips were not taken into account. This study lacks a realistic narrative as the advantages of SAEVs are not regarded in the modal choices and it assumes that every person is willing to constantly share rides with three other passengers [17].

Several studies developed agent based models to assess the impacts of SAEVs on urban space and parking demand. Zhang et al. developed a ride sharing agent-based model and concluded that parking demand can be reduced to about 90% with sufficient SAVs in the system. The authors state that at the expense of vehicle-miles-travelled even greater reductions can be achieved [22]. Miliard-Ball identified and modelled three strategies of how privately owned AEVs can avoid parking costs in city centers. He argues that AEVs have the incentive to cause congestion and advocates congestion tariffs in order to counteract this effect. However, he states that shared fleets will reduce the induced congestion and he doesn't take increased driving fluidity and or more packed parking of AEVs into account [23].

Other studies looked at SAEVs demand as a last/first mile solution trough integration with a public transport (PT) system. Scheltes et al. concluded that, in their case study (a last mile solution of a 1.8 km connection from train station to a university campus), an automated last-mile transport system may have difficulties to compete with bicycles. However, they pointed out the benefits that can be obtained by using existing road infrastructure with SAEVs as opposed to constructing new rails or roads [11]. In the agent-based model of Shen et al. passengers on the least economical bus routes from a metro station in Singapore were transported their last mile with SAEVs instead of with buses. They found increased service quality, financial benefits and less congestion as a result of SAEV implementation [12].

Iacobucci et al. studied fleet size and charging dynamics of an SAEV fleet in order to assess power grid integration. Car and taxi trip dynamics of Tokyo were implemented. They found that the more trips per hour the shorter the waiting times. From a fleet size of 1.4 times the number of trips per hour waiting times seem to converge to 15 to 25 minutes depending on the number of trips per hour. This implied about 5-7 vehicles per 100 trips per day and replacement of 7-10 private vehicles per SAEV. Increased driving fluidity of SAEVs was not taken into account as the Tokyo driving speed during peak hour of 20 km/hr was applied. Charge scheduling and V2G employment was found to reduce the cost/km with 33% in the case of high adoption of renewable energy. With the current energy system costs may reduce about 10%, most of which results from charge scheduling instead of V2G. V2G and charge scheduling was set up such that it did not influence the service level of the SAEV fleet [19], [24].

Kamel et al. developed an agent-based model to simulate modal choices of a synthetic population of travelers based on heterogeneous user preferences. Whenever a trip is generated, a trip score, representing the disutility of that specific modality, is calculated for all the available modalities. The model was calibrated with travel data from Paris, after which hypothetical user preferences for SAVs were implemented. They concluded that 3.8 to 5.3 percent of the trips will be made with SAVs of their hypothetical preferences are correct [10]. The authors suggest further research into user preferences of SAVs in order to draw adequate conclusions for modal choices with SAV systems. These results are not directly transferrable to other regions, since modal choices are region specific.

Papadoulis et al. modelled AV driving behavior on motorways and assessed the safety impacts connected AVs. They found that with 25% penetration of connected AVs up to 47% of road accidents can be avoided. At 100% adoption this increases to about 95%. Although less accidents, travel time increased with higher AV adoption according to their model. This is the result of long vehicle platoons with a slow leader have decreased speeds. They do note that this result is susceptible to the desired speed distribution in their model [9].

In summary, previous modelling studies on SAEV fleets have primarily been based on current demand figures. Most of them focused on ride-sharing services, possibly because this is seen as the core method to increase capacity utilization and the reduce energy consumption of urban mobility. Ignoring 1) a realistic narrative pointing to induced demand and 2) the potential of purpose built, fit-for-demand, one-person vehicles as an energy efficient and cheap SAEV service with a high service level. To our knowledge there have not been any attempts to quantify fleet size and composition of a future mobility system with those two aspects. So in this research we developed an agent-based model that can simulate a future mobility system with induced demand and purpose built SAEVs.

3 Methodology

This section explains how the SAEV fleet requirements are assessed with the help of agent-based modelling. It consists of three parts: 1) developing an agent-based model that simulates realistic travel behavior, 2) implementing SAEVs as a modality option, and 3) defining scenarios for the changes in mobility demand with an SAEV system and applying the case of the Netherlands.

3.1 An agent based model for travel behaviour

There are many approaches to modelling travel behavior. Depending on the research focus, elements such as traffic fluidity, geo-spatial routing, modal choices, and financial preferences can all be considered. Because this research is set around the fleet requirements of an SAEV system, we require a realistic narrative of the temporal mobility demand of a (large) synthetic population of people. In other words, the dynamics of the model should focus on: when do people go on what sort of trip with what type of mode? With this in place, the mobility behavior input defines the case study and induced demand can be defined by changing parameter settings.

When people go on a vehicle trip they will require a private vehicle of SAEV. This construct of interaction in a socio-technical system where different people have different behavior is very suitable to be modelled with an agent-based approach. Agent-based modelling allows for simulating heterogeneous agents that make unique decisions and that is easily calibrated with real world data. Agent-based modelling is also a powerful tool for exploring new scenarios when a core model is in place. Like in the case of this research, adding SAEV dynamics to the travel behavior.

Since different socio-demographic groups have different mobility patterns, we start the model by developing a population of people agents with adjustable socio-demographics and trip patterns. Three main trip types who have clearly distinct patterns are distinguished in the model: commuting trips, school trips, and leisure trips. In essence, leisure trips include all trips that are not commuting and school trips, such as shopping, sports, and visiting trips. The categorization of people agents is shown in Table 2. To create the synthetic people population, an age distribution is required. This distribution can be set as the prospected age distribution in several decades. Each category of people needs to be accompanied with their respective mobility behavior. The statistics and distributions required for this are shown in Table 3.

Table 2 Categorization of people agents

Category	Age group	Mobility characteristics
Very young children	0 – 6 y/o	No mobility demands
Young children	6 – 12 y/o	Primary school, infrequent leisure trips
Teenage children	12 – 18 y/o	Secondary school, leisure trips
Adults	18 – 69 y/o	Commuting and leisure trips
Elderly	69 + y/o	Leisure trips

Table 3 Key input data that defines mobility behavior

Input	Remarks
Family statistics	Such as family composition, number of commuters, income and car ownership
Modality statistics	Probabilities of what type of trips are made by what modality
Trip distance distributions	Per modality and per trip type
Departure time distributions	Per trip type
Trip frequency statistics	Heterogeneous probabilities of frequencies per trip type

At the start of a simulation run, 10.000 heterogeneous people agents are created according to the provided input. Each simulated day these agents follow their unique stochastic mobility patterns. Some people may go daily to work/school with public transport to work or school, while others chose the car. Other people may stay at home all day, or make on average three leisure trips a day. Vehicle agents are used for a trip when a person decides to make a trip with a private car or SAEV. Each trip has its specific distance and purpose, however, the trip is not modelled in a geo-spatial manner. In other words, the trip is not mapped onto GIS space.

3.2 SAEVs as an modality option

In the future scenario people-agents are able to use the SAEV mode for their trip. When a people-agent decides to use a SAEV, a SAEV virtually picks up the person at his location at the desired departure time. The simulation assumes that SAEVs will always be available and establises the number of vehicles needed accordingly because we attempt to quantify the required vehicle fleet in a mature SAEV-only situation. The number and types of SAEVs on the road are monitored. The SAEV induced mobility is modelled as follows:

1) Children can make trips with SAEVs
2) Elderly and adults have increased probabilities of making leisure trips
3) The average trip is a certain percentage longer
4) Trips formerly made with public transport have a probability of being made with SAEVs
5) 10% extra mileage and usage time (as found by [15]) is added for SAEVs after a passenger is dropped off to account for relocation

Three types of SAEVs are available in the model: basic, standard and premium. The type of SAEV used depends on the user and the trip characteristics. The choice model implemented for this is quite basic, but is intended to give an impression of not only the number of required vehicles but also the diversification in within the vehicle fleet. This is crucial because the operational impacts, such as energy requirements and costs, of an SAEV greatly differ between a 5-person sedan and a purpose built 1-person SAEV. Clearly, a more diverse offer of SAEVs is expected is. The choice model for the type of SAEV is shown in Table 4.

Table 4 SAEV choice model implemented

Vehicle type	Used for trips	Vehicle characteristics
Basic vehicle	Trips < 15 km and trips made by children	1-person
Standard vehicle	Trips > 15 km	1-person
Premium vehicle	All trips have 20% change of being a premium trip	Multi-person

It is assumed that SAEVs carry sufficient battery capacity for a day and the fleet is recharged at the start of a day. This is reasonable as fuel efficiency of SAEVs and battery technologies are expected to greatly improve during the next decades [1]. Additionally, the fleet may be managed in such a way that charging and vehicle utilization is optimized outside of peak hours. Hence, we model no recharging constraints on the usage of the SAEV fleet. There may however, be a significant value in large, flexible, and predictable storage capacity that SAEV fleets represent, specifically in combination with a high penetration rate of renewable energy sources, see also [19], [24].

3.3 Case study and scenarios

The experiments performed in this research are based on mobility behavior of Dutch residents. To do so, the statistics and distributions shown in Table 3 used in this study are derived from a nation-wide Dutch survey performed by KIM. This survey contains the mobility behavior of a complete day of 40.000 respondents. Of each trip made by the respondents detailed trip characteristics, such as modality, purpose, and vehicle and passenger information is provided. The data is corrected for weekends and holidays, since this research focusses on the average workday.

In total four scenarios are simulated: one reference scenario with current mobility behavior and three SAEV scenarios. A variety of parameters in the model define these scenarios. For example, the percentage of adults that use SAEVs instead of private cars and the probabilities of people to make more than one vehicle trip a day. The first SAEV scenario is the transition phase. In this scenario we take the exact same mobility demand as in the reference scenario, except 50% of the people make their car trips with SAEVs. The other two SAEV scenarios assume 100% adoption and have induced mobility demand. The amount of induced demand differs between those two scenarios. The values used for the most important parameters (many of which define the induced demand) are shown in

Table 5.

Table 5 SAEV scenarios and parameter setup

Scenario	Transition	Everything shared	Mobility explosion
Percentage of SAEV usage	50% of adults	100% of adults	100% of adults
Modal shift probability*	0%	30%	50%
Reallocation time	0%	10% of trip time	10% of trip time
Reallocation distance	0%	10% of trip distance	10% o trip distance
Avg. increase trip distance	0%	10%	30%
Elderly first trip probability	36%	40%	55%
Elderly additional trip probabilities	8%	12%	20%
Adult day trip probability	30%	35%	45%
Adult additional trip probability	15%	20%	30%

Perc. teenage children using SAEVs	0%	20%	60%
Teenage children avg. SAEV trip distance	0	6.8 km	12 km
Perc. young children using SAEVs	0%	10%	25%
Young children avg. SAEV trip distance	0	5	8

4 Results

In this section we display the simulation results of each scenario. First we look at the amount vehicles simultaneously on the road versus the amount vehicles simultaneously in use. Then we examine the required SAEV fleet composition as a result of the SAEV type choice model.

4.1 Vehicle and road utilization

First we need to define the distinction between vehicles 'in use' and vehicles 'on the road'. In this research a vehicle 'in use' is defined as a vehicle that cannot yet be assigned to a new user. A vehicle is 'on the road' when it is currently moving on a road. This means, for example, that a privately owned vehicle of a commuter might be in use from 8:00 to 18:45, while it is on the road for only the first and last 30 minutes of that period. Within the scope of this research there is no distinction between SAEVs being on the road and being in use. This is because we assumed no charging constraints (see section 3.2) and we are not considering things such as maintenance. However, it is important to realize that a SAEV is in use for a certain period of time after a passenger has been dropped off. This time corresponds the movement of the vehicle for relocation, charging and/or parking purposes. With the described framework the number of vehicles 'on the road' is a measure of road utilization, while the number of vehicles 'in use' is measure of the amount of vehicles required to provide the mobility demands of the system. Figure 3 shows the simulated daily profile of these metrics in all four scenario.

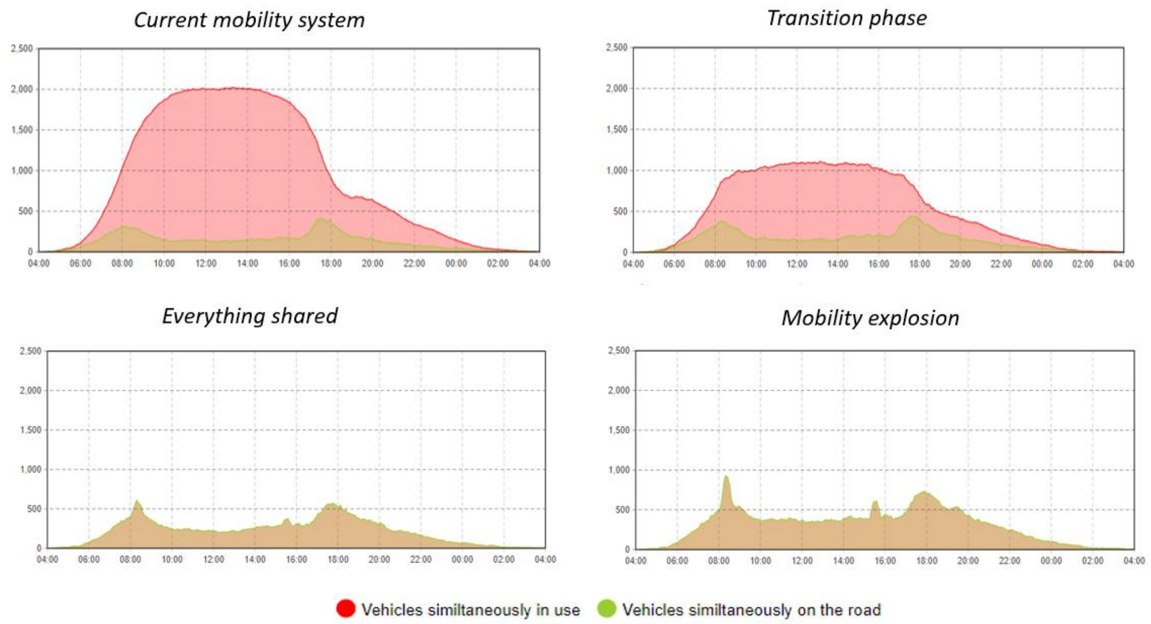

Figure 3 Daily profile of vehicles simultaneously on road and vehicles simultaneously in use per scenario

Figure three demonstrates that the current mobility demand results in a maximum number of vehicles in use of 2.020 per 10.000 residents. Car ownership is expected to be higher than this since vehicles are not shared, some people own more than one vehicle, and many people do not use their vehicle daily. Indeed, in the Netherlands car ownership is 4.488 per 10.000 residents. The maximum number of vehicles simultaneously on the road with the current mobility system is about 460 vehicles per 10.000 residents. Note that the simulation is based on the mobility behavior of the Dutch but does not take traffic fluidity (such as slower movement in rush hours) into account. This is suitable approach for a system with greatly improved traffic fluidity and highway capacity due to SAEV driving dynamics. It is less suitable to depict an exact picture of the traffic dynamics of the current mobility system, which is not the purpose of this paper.

In the transition scenario the number of vehicles on the road is higher than in the current situation, even though the mobility demand is exactly the same. This is a result of the additional relocation mileage of the SAEVs after trips. The number of vehicles 'in use' almost halves to 1.100 per 10.000 residents for the most part of the day. At 100% SAEV adoption the number of vehicles on the road increases to 600 and 950 per 10.000 residents, respectively, in the 'everything shared' and the 'mobility explosion' scenarios.

4.2 SAEV fleet composition

Figure 4 shows the daily demand profile for each SAEV type each of the scenarios. The highest point each graph reaches is taken as the required amount of vehicles for that specific type. The total number of vehicles required in the full adoption scenarios are 687 and 1.084 per 10.000 residents. A large part of this demand (70% - 90%) consist of basic and standard SAEVs. Both of which are expected to be highly energy efficient purpose built vehicles. Significant peaks can be seen in the demand for basic SAEVs. This is mainly caused by children making school trips.

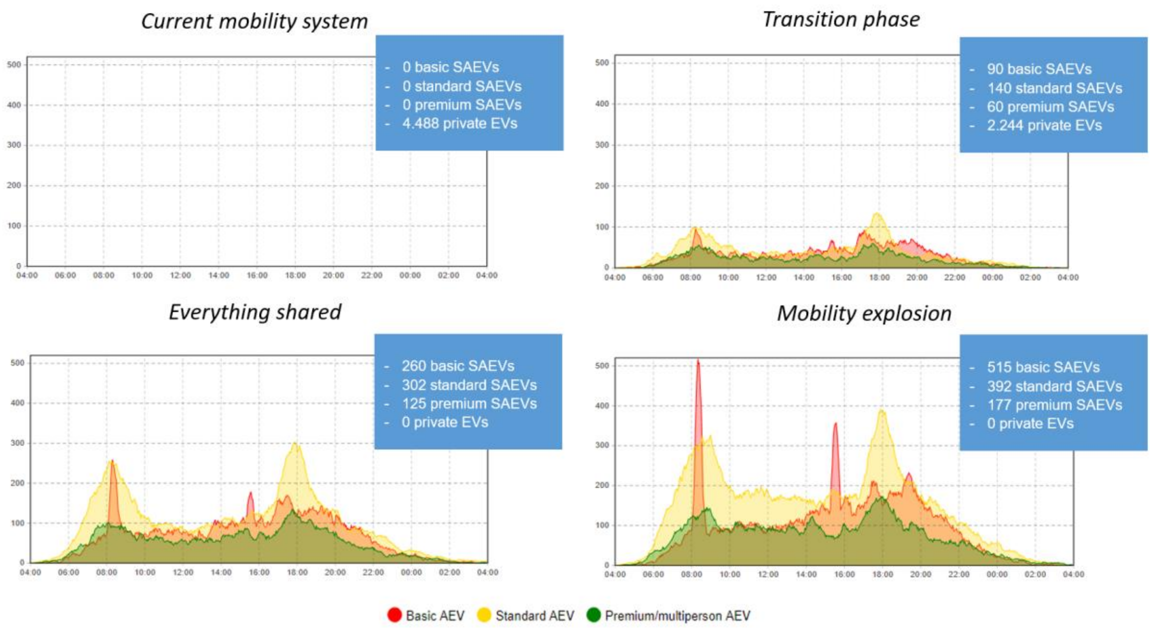

Figure 4 Required SAEV fleet composition based on daily profile of types of SAEV demanded

5 Conclusion and discussion

In this research an agent-based simulation model has been developed that simulates heterogeneous mobility behavior of a large population of people-agents. Detailed mobility statistics of any case study can easily be implemented with this bottom-up approach. The model allows researchers to set up a realistic narrative of the induced mobility demand in order to study the required fleet composition of a future SAEV system. In this paper the mobility behavior of the Netherlands was implemented and three different SAEV scenarios were studied.

The simulation results show that the number of vehicles required per 10.000 residents reduce from 4.488 to only 687 vehicles in the 'everything shared' scenario. This includes 260 basic class, 302 standard class and 125 premium class vehicles. In the scenario 'mobility explosion' 1.084 SAEVs will be required, of which 515 basic, 392 standard and 177 premium SAEVs. The large share of basic class vehicles required result partly from induced demand by children using SAEVs to go to school in the morning. In the afternoon this peak is flattened out due to a more dispersed out-of-school time. The results from the induced demand can be seen in the highest number of vehicles simultaneously on the road. This number increases from 460 to 600 or 950 vehicles per 10.000 residents, depending on the scenario. However, more vehicles on the road does not directly imply more demand for road infrastructure and increased energy demand of urban mobility. After all, traffic fluidity, road capacity, and energy efficiency are expected to improve with SAEVs.

We recognize that fleet operators may implement a variety of methods to optimize the fleet composition. For example, financial incentives can influence the demand of specific SAEV types, or vehicle upgrades can be offered when demand for certain SAEV types exceeds capacity while other types unoccupied. However, there are also several factors, such as overcapacity for non-average workdays and maintenance, that may results in a larger required fleet size. Additionally, because geo-spatial elements were excluded in this research, it is possible that 10% relocation time is not sufficient during peak hours to relocate SAEVs. As peak hours in some cases may be tilted towards a specific traffic direction. However, fleet operators may solve this issue with other measures than increasing the fleet size influencing the temporal distribution of the mobility demand. These dynamics of the SAEV fleet can better be modelled using geo-spatial models.

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