SIMULATING CROSS-SUBSIDISATION STRATEGIES TO OPTIMISE SHARED AUTOMATED VEHICLES AND PUBLIC TRANSIT: USING A PROTOTYPE NETWORK OF A SUBURBAN TOKYO RAIL CORRIDOR

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This paper formulates a proof of concept for agent-based simulations to model strategies for Shared Automated Vehicles (SAVs) to optimise public transit use, using a simplified synthetic representation of suburban Tokyo. Since SAVs are forecasted to both cooperate and compete with public transit, density surcharges are applied on SAV trips in denser areas and subsidies for First Mile/Last Mile SAV trips to rail transit in suburban areas, incentivizing a total shift towards both transit and SAVs. The paper utilizes MATSim, an agent-based simulation software with an integrated mode choice model - estimated on urban-suburban Tokyo trip behaviours - to forecast dynamic transportation behaviour. The intent is to study the impact of alternative pricing strategies including cross-subsidisation on mode choice and the potential for a symbiotic coexistence between SAVs, extending the policy analysis on a comprehensive Tokyo rail corridor in future research.

Key Words : *Shared Automated Vehicles, Transit, Suburban Tokyo, Agent-Based Simulation, First Mile/Last Mile*

1. Introduction

Massive investments, running into billions, have been poured into the development of Shared Autonomous Vehicles (SAVs), buoyed by the promise of revolutionizing transportation[1)]. Many anticipate that these advances will democratize access to mobility, especially in car-reliant suburbs, by offering an affordable and efficient mode of transportation. This surge in SAV development brings with it numerous benefits. It not only heralds a new era of transportation but also promises significant returns on investment, increased flexibility in mobility choices for consumers, and potentially even a solution to the issue of urban sprawl in areas like the Tokyo suburbs.

However, the road ahead for SAVs is not without its bumps. The excitement is tempered by significant concerns and uncertainties about the long-term implications of widespread SAV adoption. Will SAVs complement or cannibalize existing public transit systems? By competing with transit SAVs could induce more trip demand through a possibly les efficient mode. The phenomenon of deadheading — where SAVs travel without passengers — might exacerbate vehicle kilometers traveled (VKT), further intensify road congestion and increase conflicts between SAVs and other road users. As we stand at the cusp of this transportation evolution, it is essential to weigh the pros and cons, ensuring that the push towards SAVs doesn't inadvertently create more problems than it seeks to solve.

(1) Background

Research into SAVs is wide-ranging and deal from microscopic simulations of individual vehicles and possible conflicts with other road users, to large scale simulations of transport demand. Using agent-

based simulations that model individual paths and dynamic interactions has yielded mixed results across a variety of indicators. Many studies forecast increased total VKT(Vehicle Kilometres Traveled for all vehicles) as well as an increase in accessibility for example[2], creating an uncertain judgment on the technology.

A large uncertainty of the purported impact of SAV is due to the urban environment and its existing car-dependency. However, SAVs can interact with transit in a complementary fashion to solve the first mile last mile problem of most mass transit. Although many travelers consider transit a viable option, the trip of the "first mile" to a mass transit station is sometimes seen as too far or cumbersome. SAVs have been simulated to fill the role of matching travelers to transit locations for commuter or long-distance trips[3]. Research into this has resulted in mostly micro-simulations that simulate the trips within a single station catchment area[3,4].

Little research has been done in regard to SAVs in its dual-purpose role as competitor and complement to transit. Researchers that have simulated this dual role of SAV use have seen a drop in transit use in dense, transit-oriented cites such as Singapore, with autonomous rideshares taking mode share from mass transit as well as private car trips[5]. Simulation in auto-dependent cites with a much less dense network have predicted positive effects, with one study of the Greater Chicago Area projected increased accessibility to rail to increase transit trips by 25%[6] This finding was mirrored by agent-based simulations of a prototype synthetic network based on auto-dependent cites, which observed increases when low-cost First Mile-Last Mile trips were considered.[7]

Limited research has been conducted in the Japanese context, with an agent-based simulation model focusing on the central areas of Tokyo forecast a considerable reduction of transit use[8] while an equivalent optimisation model of central Nagoya observed less of an impact on rail as a main mode[9]. Mori et al. [9] observed a larger drop across all access modes more than 15 minutes walk from the station than near it. While Ishibashi et al.[8] did not incorporate a mode choice model into the simulation, Mori et al. [9] was limited by inconclusive results from a stated preference survey. The varied forecast of SAV impact seems to follow a trend, with denser, more transit-oriented areas suffering from decreased transit use while less dense auto-dependent cities increasing transit use due to its increased FMLM service. This leads to a gap in forecasts on the unique transit-oriented sprawl in suburban Japan, being both dependent on mass transit and increasingly sprawling into auto-dependent suburbs. There is a need to explore the unique systemic effects of SAV fleets on this varied built environment, as the degree of suburbanization/urbanization will be key to understanding the impacts on specific areas throughout greater Tokyo. These ideas are condensed into research questions for the entire project:

- How does difference in built environment across Greater Tokyo effect SAV impact on transit use?
- How can we optimise policy or Automated Vehicle strategies to optimise transit use across Greater Tokyo?

In this work-in-progress paper, a snapshot of the process to answer these research questions is presented, with a prototype network answering a sub-question to the above-mentioned larger research questions:

- How can we model the dynamic interaction of SAV use in a unique (Suburban Tokyo) environment?

(2) Objective

The objective is to understand, simulate the impact, analyse SAV fleet implementation across a variety of urban typologies. An analysis of urban to suburban networks is needed to see the varied impact of SAVs. Creation of a synthetic "toy" network will help bridge the feasibility gap and to generate exploratory ideas quicker. Successfully modeling the dynamic interactions on an individual basis using an agent-based simulation will prove the suitability of this tool for future SAV research.

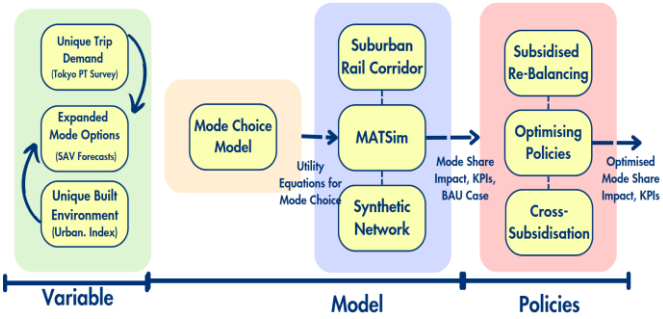


Fig. 1 Research Framework

2. Methodology

In our research, we explored an urban typology of different areas within a select suburban rail corridor, and introduced a research framework that projects a transport demand through a mode choice model, and simulates and analyses it through a multi-agent simulation software called MATSim. We explain the general architecture of MATSim and then delve into the network and supply creation for the traffic simu-

lation. As seen in Figure 1, data on the unique trip demand and network conditions of Japan will be simulated through this model, eventually testing different policy and technical strategies to optimise SAVs and public transit. This paper will use a synthetic prototype model to detail the process and methodology in successful SAV agent-based simulation that will lead into further research and simulation of a larger suburban corridor. Performance of the model is chiefly evaluated through a mode shift analysis; with Key Performance Indicators (KPI) such as wait times and total system VKT to be observed as well.

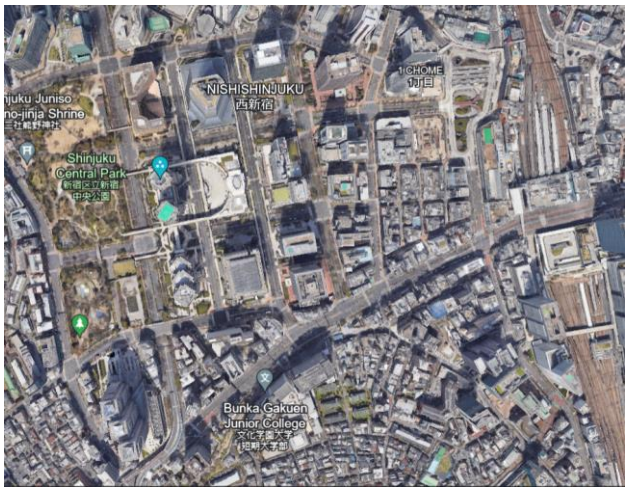


Fig. 2 Nishi-Shinjuku – CBD

(1) Urban Typology

Examining and simulating the greater Tokyo area in its entirety is a difficult and time-consuming task. Using subsections of the various types of built environment can hopefully represent the entire area. We analyse an entire corridor along the Odakyu Odawara suburban rail line as it travels along and connects the very urban Shinjuku district to very expansive sprawl and suburban cores built around stations such as Machida, or Ebina in between. As most of the Kanto area has developed along these transit corridors, the findings through simulating this corridor can be applied elsewhere. Images of archetype neighbourhoods for the four general Urban Typologies are displayed in Figure 2 – 5.

A more fine-tuned classification is needed to understand the neighbourhood level SAV interactions, and to hopefully apply fine-tuned, geo-coded policies to encourage access/egress trips to transit. We collected vital data on the built environment across the Odakyu corridor through MLIT open data and 2020 Tokyo PT survey.



Fig. 3 Setagaya Ward – Urban

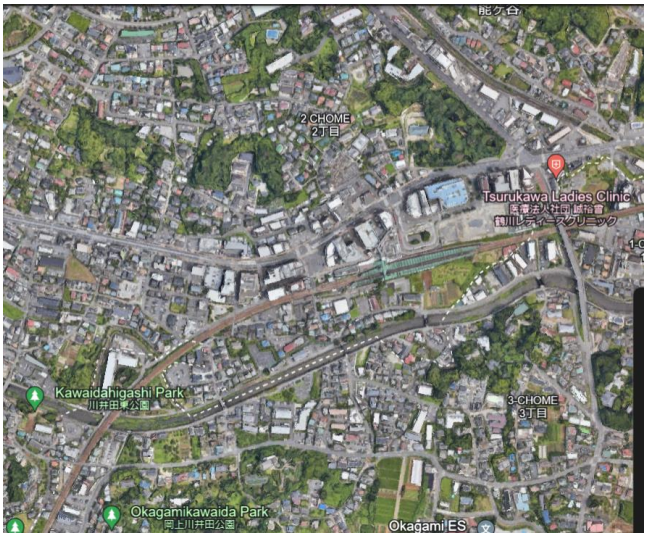


Fig. 4 Tsurukawa, Machida City – Suburb



Fig. 5 Kushihashi, Isehara City – Rural

The key variable of Intersection Density was calculated through importing the street network from OpenStreetMap's and performing a GIS analysis to extract intersection data. Other values such as population density, commercial business density, and

distance from station were correlated with each other as seen in Figure 6. The Commercial density is a measure of the number of business addresses registered within a square kilometre area.

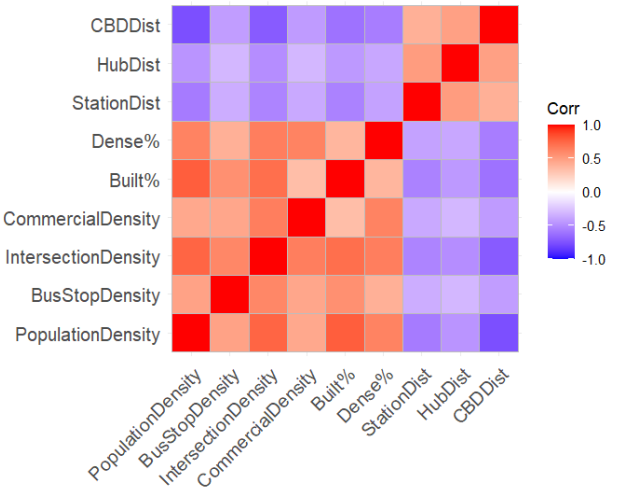


Fig. 6 Correlation Matrix for Urban Environment Variables.

A Principal Component Analysis (PCA) was performed to reduce the dimensionality of these factors into a single Urbanisation Index. This Urbanisation Index explains up to 92.5% of the variance between the many intercorrelated factors of urban density and land use such as percent of development that is dense. The most important factors are Intersection Density and Population Density as seen in figure 7. Using this Urbanisation Index, the entire Odakyu Corridor was classified along four Urban Typologies – CBD, Urban, Suburban, Rural.

These typologies are a result of analysing the natural patterns of the data and applying classes using Jenks natural breaks algorithm to every square kilometre in the corridor of analysis. As seen in figure, the population density rises the more urban the typology gets, except when it reaches the CBD akin to Shinjuku station, where population density drops in favour for a sharp rise in commercial density. Mapping out these areas along the Odakyu corridor results in a gradual Urban- Suburban Axis that reveals the uneven yet natural development of the corridor, with pockets of urban development around suburban cores. Using a measured and more granular classification of urban development rather than jurisdictional boundaries allows for a more effective and realistic measure of SAV impact on these areas. This allows for a transferable analysis, where areas that have similar Urbanisation Index values would most likely respond the same to similar transportation innovations.

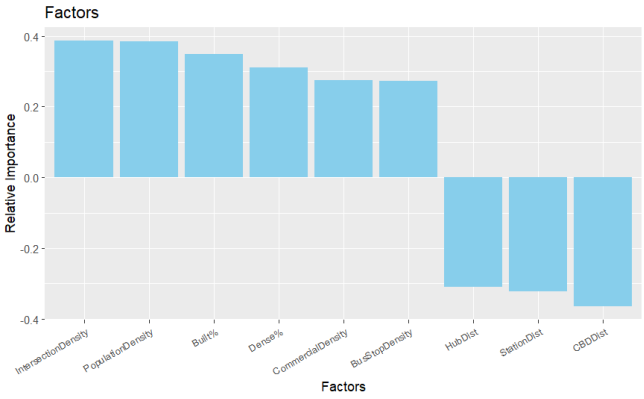


Fig. 7 Importance factors for Urbanization Index PCA.

While the goal for further research is to model and simulate the entire suburban rail corridor, an iterative approach was taken where the complex SAV-transit interactions were modeled on a synthetic toy network that approximated the Urbanisation Index of existing areas.

The synthetic network is approximates a suburban core with a single 1000x1000m block of Urban type next to blocks of network that were designed to be Suburban. Synthetically creating a network that matched the intersection density and a demand that reflected the population and commercial density, the toy network could replicate the demand-supply optimizations of existing areas of similar Urbanisation index.

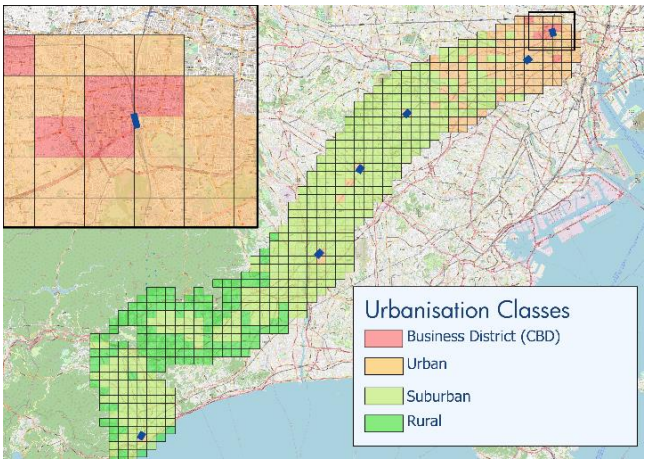


Fig. 8 Odakyu Rail Corridor classified with Urbanization Index

(2) Simulation framework - MATSim

Forecasting the complex demand-supply systems dependent on various interrelated behavioural choices requires detailed, individual level simulation. Using the open-source agent-based simulation software MATSim is an effective way to model disaggregated demand and judge the performance of transport modes by their impact of personal trips and travel impacts. MATSim is a one-day simulation that utilises evolutionary algorithm to iterative-

ly optimise a traffic simulation based on every agents given plans. Plans are scored on mode choice utility parameters and the extent to which they are successfully executed, considering disutility caused by traffic delays. Changing variable such as route or mode choice, various plans for the same tour or person are scored, ultimately choosing the optimal travel behaviour after successive comparisons with previous planned trips.

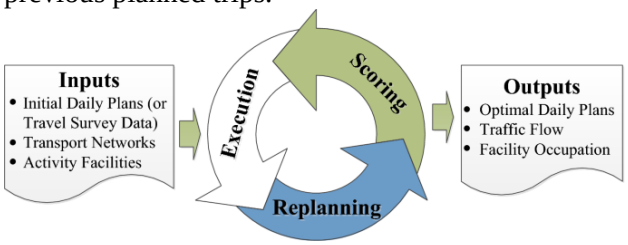


Fig. 8 MATSim Theoretical Framework

As Dynamic Ride Sharing can result in a large range of possible routes based on the everchanging exact location of the SAV every minute, MATSim can model the significant number of possibilities through many iterations to predict this complex interaction and trip mode. Improvements in wait time and travel time are directly tied to routing algorithms and positioning to accurately optimise pick ups and drop offs during shared rides.

Plans in MATSim are parts of a single person's daily activity, with the model able to generate alternate subtours and access egress modes to reflect the detailed routes people take to get to the main rail network. In creating the representative simulation various steps were taken to generate synthetic supply and demand. The urban environment variables for Urban Typologies were approximated by assuming a Gaussian distribution, and stochastically selecting from this range when generating an area of that type. The median values of decisive factors in Urbanisation such as Intersection Density are displayed in in Table 1, along with the values one standard deviation above and below the median to show the inherent variability in the classifications.

a) Network Generation – Synthetic Network

The creation of the synthetic network was an operation to extract the transferable characteristics of the built environment and reflect them in a simplified toy network to allow for the initial simulation of the complex SAV interactions. As seen on Figure 7, the decisive variables of transport supply are the intersection density and station distance, with both reflecting the ability to drive or take rail transit. Maintaining the values for both, an adaptable grid pattern and single rail line similar to existing corridors was constructed. The intersection density can be adjusted to be more or less dense to reflect the existing heterogeneity across the simulated area.

Table 1 Median Values and Reasonable Range of Built Environment Variables of Urban Typologies

Urban Context	*Urbanisation Index (PCA)*	*Intersection Density (Links/sq. km)*	*Population Density (/sq.km)*	*Commercial Density (/sq.km)*	*Station Distance (m)*
CBD	4.91- 8.80	~1200 (710 - 1400)	~17 000 (7000 – 20 400)	~2700 (1370 - 4250)	~190 (130 - 350)
Urban	1.57- 4.91	~540 (400 - 700)	~18 300 (12 500 - 22 700)	~560 (330 - 1190)	~350 (190 - 600)
Suburb	-2.35-1.57	~300 (170 - 430)	~6400 (2700 - 11 800)	~130 (60 - 290)	~1000 (480 - 1800)
Sprawl	-5.16- - 2.35	~90 (40 - 140)	~1000 (300 - 2000)	~45 (10 - 80)	~1800 (1000 - 2800)

The transit schedule utilised was mirrored from the Odakyu Line and other suburban rail operators, with up to 3 – 5 minute headways at the morning rush hour peak, ending in a dummy link to represent trips to and from the end of line CBD. Shown in Figure, a visualisation of the simulation at work shows the gradual intersection density decrease through the 5km subsection, starting from the Suburban Core.

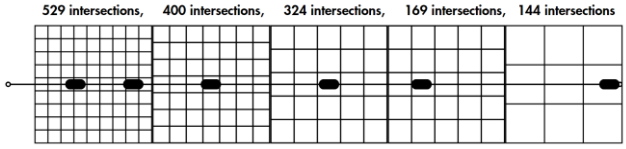


Fig. 9 Simplified Diagram of Suburban Core Synthetic Network

While the Synthetic Network is generated in an adaptable grid pattern, the complete network for the Odakyu Line will be imported from OpenStreetMaps data, to capture every intersection in the organic street layout.

b) Supply Generation – Synthetic Demand

The decisive factors determining transport demand in select areas were the population and commercial density, reflecting the destinations of commuting and return home trips. The household and commercial density were estimated for urban and suburban areas and stochastically generated around transit station or network grids. The household and commercial density was drawn from publicly available

MILT data. The supply demand was validated by comparison to daily plans around the Machida station and its surrounding suburban areas, reflecting the number of commuting trips out of the area, number of access/egress trips to and from the rail line, and the number of local trips conducted within the neighbourhoods. Comparing to an archetype area that is a peak of urban development in a largely suburban area, this network can act as a representation of other such suburban cores around the Tokyo Area.

c) Shared Automated Vehicles

The SAVs are simulated as Demand Responsive vehicles that respond to Extensive Insertion Search requests during rides or standby, accurately redirecting to pick ups and drop offs during shared rides. The vehicles can have at maximum 4 passengers and follow the same road rules as private manually driven cars. They operate on a door-to-door basis, picking up and dropping of passengers directly to origins and destinations. The capabilities of stop based or service area-based operations will be tested in further research. The vehicles are positioned across the operational area to equalise them spatially. The rebalancing operation after picking up a ride is to return to an empty zone, hopefully to pick up another ride from that area. Different strategies such as positioning and rebalancing by population and trip density or dynamic positioning based on servicing time-limited rush hours will be tested in further research. The SAV fare is determined to be 30 yen/km based on previous research[10)]

d) Behaviour Choice Model

To forecast the behavioural choices of future automated vehicles is a difficult endeavour, as almost no public data about SAV use is available. Conducting a stated preference survey is an error-prone method since the public image and choice behaviour of new technology like automated vehicles is dependent on perceived risk and perceived technical ability of the vehicles at the current moment.

To bridge this gap of uncertainty, parallels are drawn between carpooling and Automated Vehicle use, and behavioural choices and mode choice parameters are adopted from this existing mode of transport.[11)] The assumption rests on the shared experience of being in a car yet not driving and being able to read, sleep, or other activities that may reduce the disutility associated with driving. The types of passengers are separated on whether the person has the ability to drive or is unable to (no car plus no license) to distinguish the persons willingness to choose to be a car passenger versus their own private car. Persons who have the ability to drive and use a private car are defined as passengers by choice or Choice Passengers and those who can't are Captive Passengers, those who have to carpool or take transit.

Table 2 Mode Choice Model Parameters

Variable Name	***Coefficient***	***t-statistic***
Walk Constant	0	0
Bike Constant	-1.472	-47.0
Car Constant	-1.962	-55.75
Choice Passenger Constant	-3.271	-52.19
Captive Passenger Constant	-3.862	-57.34
Walk to Rail Constant	-0.690	-15.27
Bike to Rail Constant	-5.410	-77.73
Car to Rail Constant	-8.64	-45.77
Choice Pass. to Rail Constant	-7.544	-57.60
Captive Pass. to Rail Constant	-6.969	-43.31
Travel Time of walking (/h)	-7.478	-83.74
Travel Time of biking (/h)	-5.823	-48.83
Travel Time of driving car (/h)	-5.387	-46.61
Travel Time of Choice Pass. (/h)	-6.043	-27.89
Travel Time of Captive Pass. (/h)	-6.951	-31.37
Travel Time of Rail (/h)	-0.146	-0.48
Travel cost/yen	-0.0013	-6.13
ρ2	0.517	
Adjusted ρ2	0.516	

The translation of mode choice parameters to SAV use are from the Choice Passenger utility estimates,

since the assumption is that passengers will feel more comfortable due to their active choice to be a passenger. The rail mode is further segmented by access/egress mode, to determine the crucial first mile and last mile trip behaviour and examine whether SAV First mile operation can induce some non-transit trips to take SAVs and rail instead. The model is then segmented by purpose, to work around the relative lack of sensitivity of work trips by rail, as the presence of an employer-purchased passes(teikiken). A Nested Logit Choice model was unable to increase the predictability enough to warrant the increased effort in MATSim incorporation, so each choice is modeled in a single-level Multinomial Choice Model. The parameters were weighted in the synthetic network to calibrate an accurate mode share. Currently Bus and Private AVs are not included in this simulation and will be incorporated in the future corridor-wide simulation.

While person trip data was determined through 2020 Tokyo PT survey with exact locations rather than zones, the travel times and distances for car, walk and bicycle modes were calculated with Google Distance Matrix API, while transit travel time and cost were calculated using Jorudan(ジョルダン) a transit route navigation website. The access/egress times and distances to and from transit using each mode was again estimated through Google Distance Matrix API. The avg Japanese gasoline prices was taken at 150 y/L and the average fuel consumption was taken at 20 km/L. The calibration results are shown in Table 2.

Table 3 Scenario Parameters

Scenario No.	Door to door SAV	First Mile to Last Mile SAV	Fleet Size to population ratio
Scenario 1	-	-	-
Scenario 2	X	-	100
Scenario 3	X	X	50
Scenario 4	X	X	100
Scenario 5	X	X	200
Scenario 6	X	X	375

To test the sensitivity of the synthetic network, several scenarios were run and compared to each other, ranging from the status quo (Scenario 1), a scenario where only door to door SAV capabilities is modeled, (Scenario 2), and several scenarios with varying fleet sizes of SAVs that perform First Mile Last Mile trips to public transport. Unfortunately, the cross-subsidisation strategy of twin surcharges in Urban areas and subsidy in suburban areas is incomplete and will be present in the complete model.

3. Preliminary Results & Discussion

The preliminary results for each scenario are aggregated and the mode share is examined first as a main mode of travel, and then as travel of access/egress modes to rail. A considerable adoption of Shared AVs is observed, with the demand responsive SAV use making up 13% of the mode share, with SAV use mostly replacing carpooling and decreasing the use of all modes in favour of direct door to door SAV service.

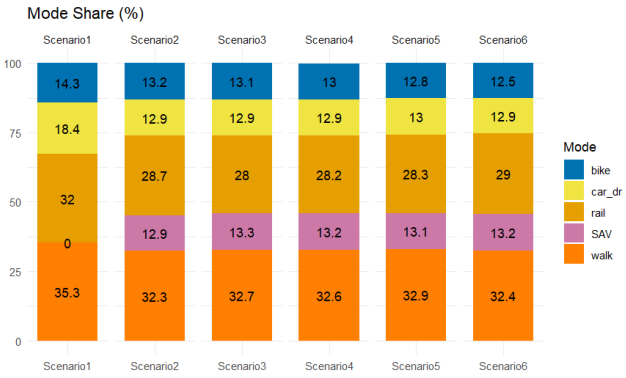


Fig. 10 Mode Share Shift across scenarios

A slight increase in SAV and transit use is observed when the First Mile – Last Mile capabilities are introduced. This is most likely due to the actual effect being relatively small due to the shift to joint SAV-transit trips. choice evaluating access/egress mode choices as well. The intensity of the mode shift shows that door to door SAV introduction will have a noticeable impact in suburban areas.

Table 4 Mode Share of Access/egress trips to Synthetic Rail Line

Scenario No.	Walk to Rail Share (%)	Bike to Rail Share (%)	SAV to Rail Share (%)
Sc. 1	72.08	27.92	-
Sc. 2	65.20	34.80	-
Sc. 3	56.42	18.44	25.14
Sc. 4	50.54	19.07	26.77
Sc. 5	52.16	17.20	30.36
Sc. 6	52.07	16.86	31.07

Analysing the access/egress mode share, the introduction of SAVs can be seen as taking relatively small share, yet steadily increasing with fleet size as more and more access/egress trips use SAV. The different reactions of SAV door to door and SAV Access/egress trips suggest that increase in fleet size can be limited to a local area rather than have an impact on long term trip behaviour. It also highlights a worrying concern that automated vehicles will take trip demand away from active modes.

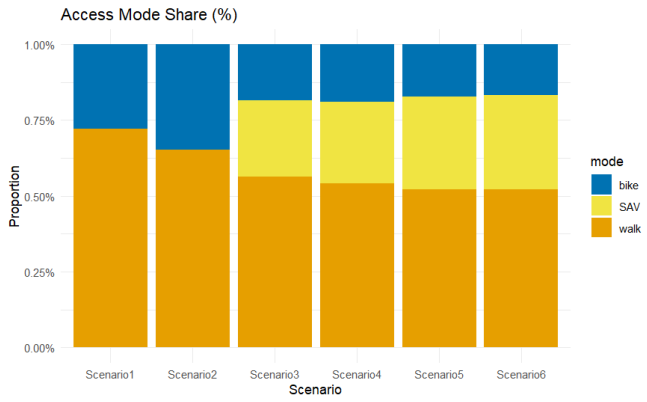


Fig. 10 Access/Egress Modal Shift across Scenarios

This is highlighted by the increase in total VKT. This increase seems to highlight the phenomenon of deadheading, with SAVs replacing bike or walking modes as well as private car use. This impact seems to level of as an area gets over-saturated with enough automated vehicles.

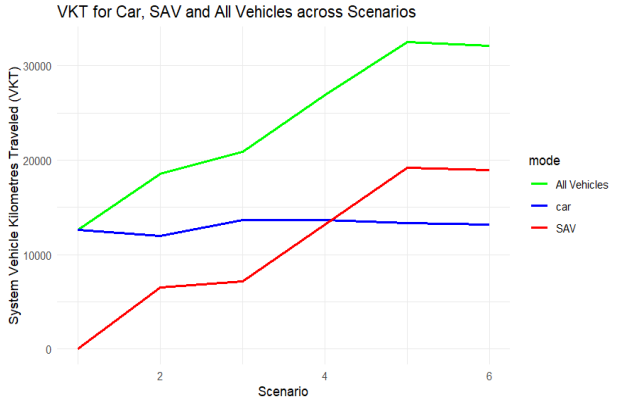


Fig. 11 VKT of all cars and SAVs across Scenarios

The relative lack of change to SAV door to door service is most likely due to the increased density around stations, reflecting a dense built environment specifically around facilitating walking trips to rail stations. The impact on transit will need to be explore much further in terms of long-distance simulations.

This result of SAVs in a relatively suburban yet transit-oriented area can be compared to SAV impacts in Tokyo proper by Ishibashi et al.[8] where a larger SAV mode share (around 20 to 30% dependent on scenario), was captured largely from rail and active modes. The relative insignificance of private car trips in the Tokyo area seems to be the biggest cause of this difference in intensity of mode share. A different area such as Nagoya, studied by Mori et al. [9] using a mode choice and optimization model, seems to have tamer expectations, with a 5% drop across the board in all modes and a resulting adoption SAV in about 5% of trips. While the Synthetic network falls in between these forecasts, it lacks a proper analysis of long-distance trips that further increases the results uncertainty.

The lack of a continuous network is an important limitation to be solved by the expanded model of the entire Odakyu Corridor upon the completion of this research. The usefulness of the model has been to examine the rate of adoption around a unidirectional Tokyo suburban station, and to identify the relative weakness of pricing in a small transit-dependent area, regardless of its sparse road network and higher automobile use.

Another key limitation is the simplified road network and OD matrix that may have reduced relative travel times and distances. An organic street pattern could result in a much different system utilisation.
due to the dynamic nature of ride sharing and varied network accessibility of areas. The expansion of the transit and road network is key to further clarifying possible scenarios across Tokyo and beyond.
An updated fleet sizing and positioning model is another limitation that would help in understanding the actual benefits of SAVs and technical solutions to improve their relationship with transit. This increase in complexity and scope will be completed in the final version of the simulation. The lessons learned of the different SAV mode shifts based on different operational strategies will be key to accurately forecasting SAV impact in suburban Tokyo.

4. Conclusion

The paper suggests that the introduction of SAVs will result in a modest adoption in suburban Tokyo, and that the ability of SAVs to fill a First Mile Last Mile niche would most likely be more than forecasted. However, it is mostly a successful proof of concept of a simulation of the increasing complexity that SAVs will bring to the transport system of Tokyo. Completion of the research by simulating a detailed model of the Odakyu corridor will help explore and confirm these effects more definitively. There is a need for more area-based policy and the difference between Urban, rural, and everything in between, needs to be treated with its uniqueness in mind.

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