Article

Assessment of Spatiotemporal Peak Shift of Intra-Urban Transportation Taking a Case in Bangkok, Thailand

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Abstract: Reducing congestion has been one of the critical targets of transportation policies, particularly in cities in developing countries suffering severe and chronic traffic congestions. Several traditional measures have been in place but seem not very successful. This paper applies the agent-based transportation model MATSim for a transportation analysis in Bangkok to assess the impact of spatiotemporal transportation demand management measures. We collect required data for the simulation from various data sources and apply maximum likelihood estimation with the limited data available. We investigate two demand management scenarios, peak time shift, and decentralization. As a result, we found that these spatiotemporal peak shift measures are effective for road transport to alleviate congestion and reduce travel time. However, the effect of those measures on public transport is not uniform but depends on the users' circumstances. On average, the simulated results indicate that those measures increase the average travel time and distance. These results suggest that demand management policies require considerations of more detailed conditions to improve usability. The study also confirms that microsimulation can be a tool for transport demand management assessment in developing countries.

Keywords: urban transport; microsimulation; MATSim; developing countries; traffic congestion; public transport; travel time; peak shift; decentralization

1. Introduction

The global passenger transportation demand was 51 trillion passenger-km in 2014, which is expected to more than double and reach 110 trillion passenger-km in 2060 [1]. Most of the increase is expected to emerge in developing countries where the population and economy are growing significantly. Many cities, both in industrialized and developing countries, have faced severe traffic congestion problems due to increased transportation demand. Reducing congestion has been one of the key targets of transportation policies for various purposes, including alleviating economic loss, reducing pollutants and energy consumption, and reducing travel time. In particular, cities in developing countries suffer severe and chronic traffic congestions caused by the surging travel demand and insufficient transportation infrastructure [2]. Many studies have demonstrated that the road infrastructure cannot be a single solution to relieve congestion [3–6]. Other studies suggest that a combination of various transportation demand management measures, including public transport provision [7], pricing [8], information service [9], coordination with land use [10,11], and active transport promotion [12,13], are needed to tackle congestion. These measures usually require public policies. Recently, the use of smart technologies in the transport sector has also been investigated intensively, such as bike-sharing [12,13], application of big data [14–16], implementation of mobility as a service platform and information

services [17–21], and new urban transit system [22]. Bangkok, Thailand, is the target city in this study. It is known as one of the most severely traffic-congested megacities in the world [23]. Various countermeasures to alleviate the congestion have been implemented, including expansion of road capacity, improvement in public transport [24], but its congestion remains at a very high level. These measures were mainly related to infrastructure development and improvement, while the demand management measures were not successfully implemented. There are various studies that analyze important aspects of this situation, including automobile dependencies [25], a spatial demand–supply gap of public transportation [24], assessment of accessibility to the metro system [26], investigation of impact factors on transportation mode choice [27], obstacles towards sustainable transportation [23], and impact of telecommuting on traffic [28].

Most of these studies employed statistical approaches or static transportation models rooted in the four-step transportation model design [29]. After 2000, agent-based modeling approaches [30] have been applied in transportation research to answer various research questions considering the individuality of travelers and temporal transportation behavior. This highly disaggregated approach provides some insight into transportation research, spatial development, quality of life, and social equity, becoming more prominent in urban policies [31]. Nevertheless, this approach usually requires massively disaggregated activity data [32]. Therefore, applying agent-based models to developing countries is a challenge in terms of data limitation.

The purpose of this study is to apply the agent-based transportation model MATSim [33] for transportation analyses in Bangkok to assess the impact of spatiotemporal transportation demand management measures, including working place dispersion and departure time shift. We conducted this research as a part of a Japan–Thailand bilateral international research project, and transportation and planning authorities in Thailand provided various transportation and spatial data. We also utilized unconventional data, including data compiled by private companies. We took advantage of existing statistics and data for the analysis and did not collect new data in the field. However, available data were not sufficient to generate the input for MATSim. To complement the data, we proposed a method to estimate a model to generate complementary data. With these generated data, we analyzed the impact of transportation policy measures on travel demand. Hereafter, Section 2 shows the features of data used in this study, and the needs for complementary data are discussed. Section 3 describes a method to generate the complementary data for a microsimulation. Section 4 shows the spatiotemporal demand shift policy scenario. Section 5 describes the analytical results. Section 6 is the discussion and conclusion.

2. Data

In general, official statistics for transportation in developing countries are insufficient for microsimulation transportation models. In transportation analysis, trip distribution data are essential information to capture the spatial travel pattern; however, it usually requires many samples in the survey. In addition, road network data are indispensable for traffic assignment. Recently, open data, such as OpenStreetMap, are available for transportation analysis in many cities. For the public transportation analysis, common format data, such as General Transit Feed Specification (GTFS), are used in many cities, and it is being utilized as input data for transportation research.

The target area in this study was Bangkok and its five surrounding provinces, namely, Nonthaburi, Samutprakarn, Pathum Thani, Samut Sakhon, and Nakhon Pathom. Figure 1 shows the target area. The total population was 15 million in 2017, and the total area is 7735 km^2. Table 1 summarizes the data used in this study.
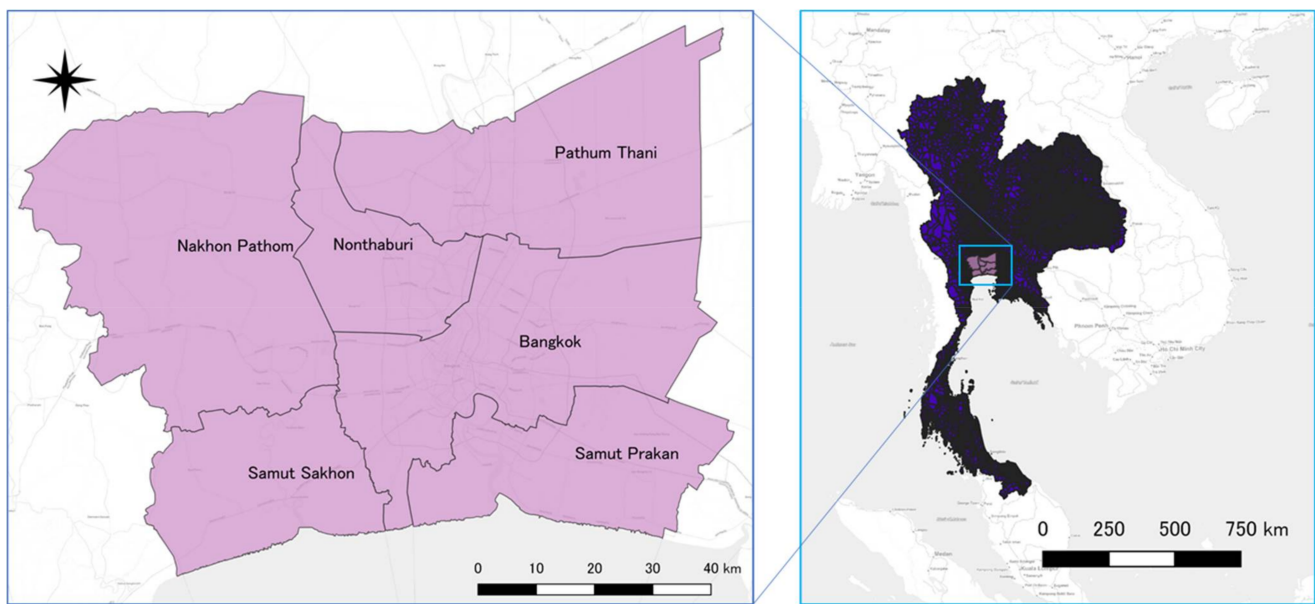
Figure 1. Thailand, Bangkok, and five provinces.

Table 1. Data used in this study.

Name	Provider	Description
Household Travel Survey (HTS)	The Office of Transport and Traffic Policy and planning (OTP)	Travel survey data of 18,833 households accounting for 38,054 people conducted in 2017
Traffic analysis zone (TAZ)		846 zones
Public transport		GTFS data for rail lines, bus routes, and ferry (2019)
Population and household	National Statistical Office	Number of population and household (2010)
Employment		Number of employment (2014)
Population	MapFan DB Data Model	Population estimates of subdistrict by age and gender (2017)
Road network		Road link attributes (2018)

First, the essential data to capture the transportation behavior was the Household Travel Survey (HTS) provided by the Office of Transport and Traffic Policy and Planning (OTP). These data record daily personal travel behaviors, including the origin and destination zones, departure and arrival time, transportation mode with attributes of respondents, including age, gender, and household information. These data contain essential information for the agent-based simulation model. However, the number of samples was 38 thousand, which is only 0.2% of the population in the target area. These data were not sufficient to capture the metropolitan-wide travel pattern. Past study indicates that the trip generation and trip attraction volumes correlate with the population at the origin and economic activities at the destination, respectively [34]. In this study, we estimated the zonal trip attraction volume based on the number of employees at the destination zone and estimated the destination choice model combined with HTS data. Here we utilized the trip data for all purposes, not limited to commuting trips. We assumed that the number of activities other than work was also spatially correlated with the number of employees. Therefore, the trip concentration for all purposes except go-home was also estimated based on the number of employees.

Here the population by age classes and gender in Table 1 are given only for subdistrict level. For the Traffic analysis zone (TAZ), which are smaller zones than the subdistricts, the population was provided for total number only. This study estimated the population by attribute for TAZ as proportional to the belonging subdistrict population by attributes.

We utilized MapFan DB Data Model to construct a road network model. A private company provided these data for the base data of car navigation systems. It included the road type and the number of lanes for each link. We obtained the GTFS data from OTP for the public transportation network and its schedule. The public transport modes included railway, metro, tram, bus, and ferry. Figure 2 shows the population and employment density of TAZ and the road and public transportation network of the target area.
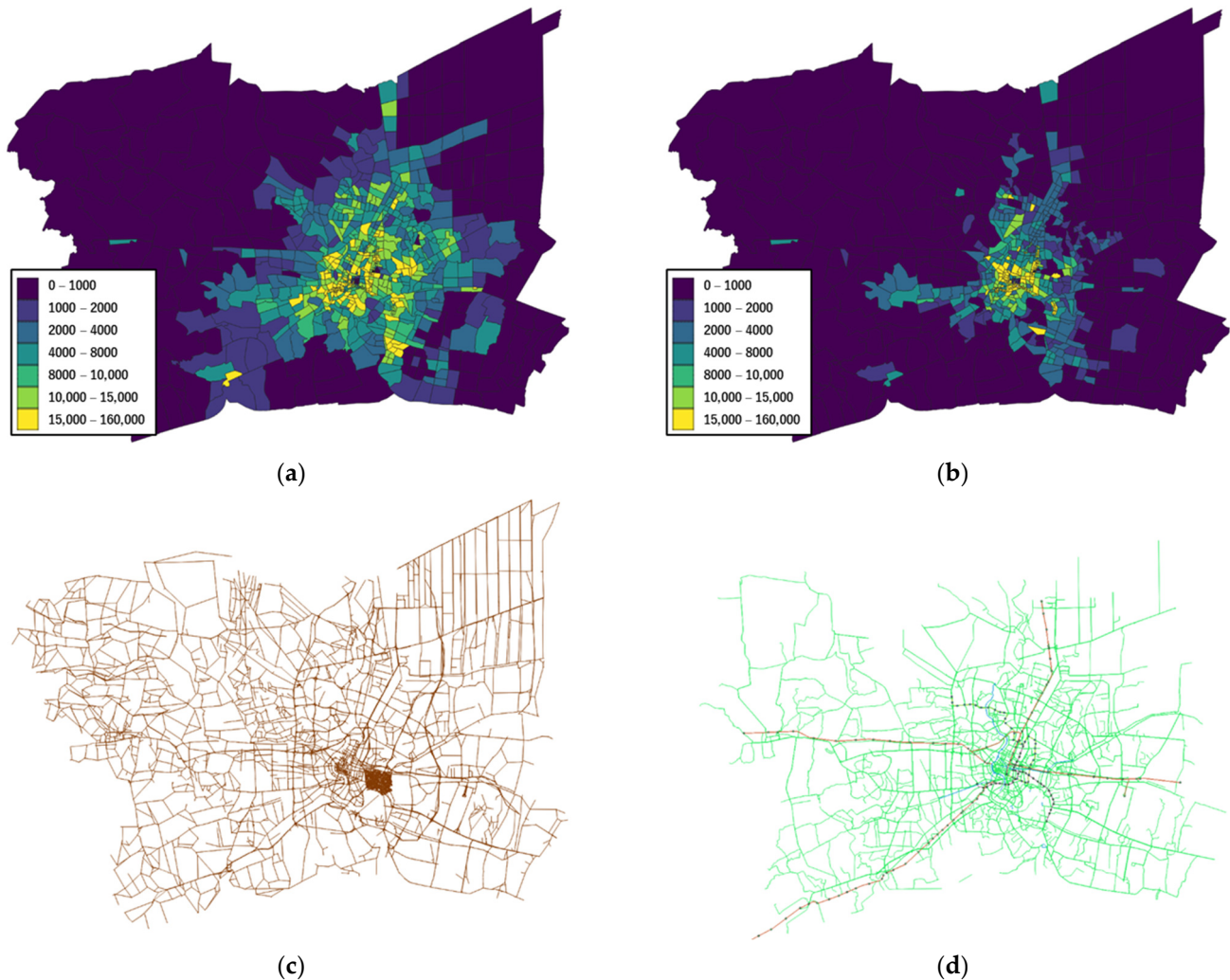

(**a**)

(**b**)

(**c**)

(**d**)

Figure 2. Target area data: (**a**) Population density of TAZ; (**b**) Employment density; (**c**) Road network; (**d**) Public transport network.

3. Method

Figure 3 shows the analytical flow of this study. First, we estimated the travel time matrix (skim matrix) using MATSim. For the estimation, tentative origin-destination (OD) travel demand was generated based on the zonal population and employment. The home-based trip generation volume was assumed to equal to the population, and the volume of trip attraction was assumed to be proportional to the employment at the destination zone. We estimated a gravity model parameter so that the average Euclidean distance equaled the average trip length of the HTS data. Using this gravity model, we estimated the initial OD pattern and modified it to make it consistent with the assumed trip generation and attraction volumes using the Fratar method. Sampling from this OD pattern and departure time distribution in HTS data, we generated the initial travel plans of agents for MATSim. As a result, we calculated the skim matrices for car and public transport based on the simulated travel time, which represented the daily average of travel time between zones.

The skim matrix for non-motorized mode was obtained by dividing Euclidean distance between zones by the assumed walking speed of 5 km/h.
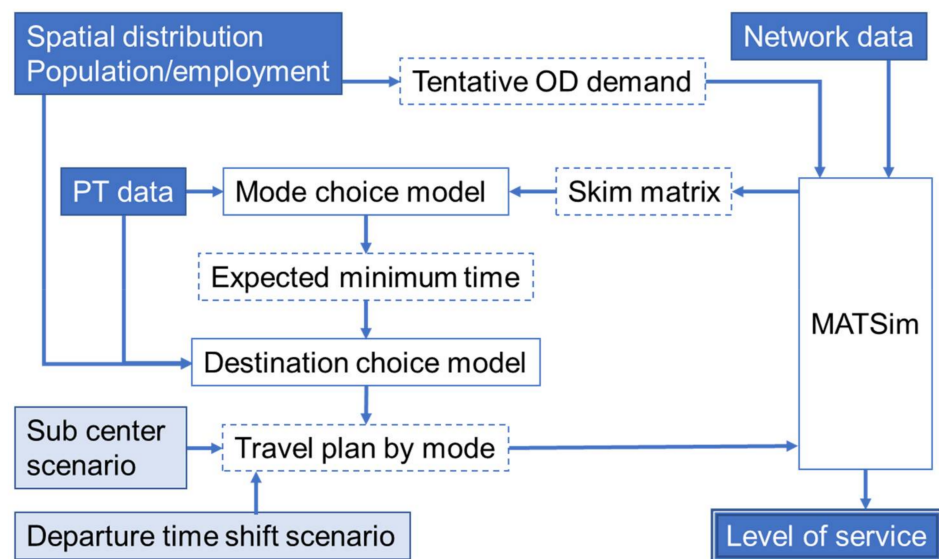

Figure 3. Analytical flow of the modeling and scenario impact assessment.

Second, we estimated the logit model parameters for mode choice by age class and gender using HTS data and the skim matrices. The explanatory variable of this model was travel time by mode only. We calculated the expected minimum time between OD using estimated parameters of the mode choice model, and this representative time between zones was used as the explanatory variable for the destination choice model.

Here, for the walking travel, the Manhattan distance can be a better approximation of the travel distance than the Euclidean distance in practice. Obviously, the Manhattan distance is larger than the Euclidean distance when the distance between origin and destination is long, and therefore it could overestimate the non-motorized travel share for short trips. Even though the model parameters were estimated under the assumed distance to represent the observation, so the bias caused by the assumed distance was expected to be corrected to some extent. Table 2 shows the estimated parameters of the mode choice model where the parameters for all the segments met the sign condition except for females less than ten years old and males more than or equal to 70. The *p*-values were almost zero except for the age class less than 10, more than or equal to 70, and males of 50–59. So, most of the models were statistically significant, although McFadden's R2 of all models was quite low, i.e., the representability of the mode choice model was poor. This is because the transportation mode choice is actually affected not only by travel time but also by various factors, such as availability of car, possibility to accompanied drive with a family member, fare, reliability on timetable, safety for public transport, etc. The mode choice decision is, therefore, affected by each individual's conditions. In this study, most of the mode choice model parameters satisfied the sign condition and were statistically significant. Thus, we assumed that the average behavior could be reflected by the model parameters, which were applied for the transportation mode choice estimation. The other studies applied alternative approaches to estimating the modal share under the data limitation, for example, modeling based on the expert survey [35] and statistical model using travel time ratio [36]. They can be candidates for the modal split analysis under the data limitation. However, we used the discrete choice model that was highly compatible with agent-based modeling.

<div align="center">Table 2. Mode choice model parameters.</div>

Age Class		Male			Female		
		Transit Dummy	Walk Dummy	Time Coefficient	Transit Dummy	Walk Dummy	Time Coefficient
<10	parameters	0.033	−2.279	−0.002	−0.021	−2.086	0.002
	t-value	0.140	−5.933	−0.616	−0.116	−7.025	0.820
	p-value		0.532			0.409	
	McFadden R2		0.001			0.001	
10–19	parameters	0.583	−1.600	−0.007	1.193	−1.067	−0.008
	t-value	7.316	−12.589	−5.498	15.931	−9.248	−6.555
	p-value		0.000			0.000	
	McFadden R2		0.012			0.014	
20–29	parameters	−0.168	−2.216	−0.009	0.571	−1.508	−0.010
	t-value	−3.869	−29.719	−11.188	16.229	−27.096	−15.663
	p-value		0.000			0.000	
	McFadden R2		0.014			0.019	
30–39	parameters	−0.864	−2.994	−0.010	−0.442	−2.624	−0.008
	t-value	−17.412	−31.305	−9.589	−10.450	−32.974	−9.566
	p-value		0.000			0.000	
	McFadden R2		0.013			0.010	
40–49	parameters	−1.250	−3.303	−0.011	−0.598	−2.427	−0.006
	t-value	−16.161	−23.823	−6.944	−9.872	−24.342	−6.001
	p-value		0.000			0.000	
	McFadden R2		0.015			0.008	
50–59	parameters	−1.601	−3.278	0.000	−0.107	−1.558	−0.005
	t-value	−14.968	−16.500	−0.176	−1.072	−11.761	−3.363
	p-value		0.860			0.000	
	McFadden R2		0.000			0.007	
60–69	parameters	−0.325	−2.248	−0.009	0.689	−0.762	−0.008
	t-value	−1.544	−8.498	−2.458	3.935	−4.050	−2.939
	p-value		0.007			0.002	
	McFadden R2		0.014			0.015	
≥70	parameters	−0.097	−3.343	0.003	0.956	−0.957	−0.006
	t-value	−0.280	−4.465	0.468	3.204	−2.637	−1.615
	p-value		0.641			0.079	
	McFadden R2		0.001			0.015	

Third, we estimated the destination choice model. Here the trip pattern of HTS survey and the estimation based on the gravity model were largely different due to the small sample of HTS. On the other hand, the HTS survey contained sample attributes information. To reflect both the information of HTS and crude estimate of OD pattern, we estimated the destination choice model parameters θ_k, and ρ_k that maximized the following log-likelihood function *LL*.

$$LL = LL1 + LL2 , \tag{1}$$

$$LL1 = \sum_d q_d \log \frac{\sum_k \widetilde{q}_{dk}}{\sum_k \sum_d \widetilde{q}_{dk}}, \tag{2}$$

$$\widetilde{q}_{dk} = \sum_{(i,j) \in \Omega_d} \frac{\exp\left(\theta_k T_{ijk}\right) N_{Ej}^{\rho_k}}{\sum_{j=1}^J \exp\left(\theta_k T_{ijk}\right) N_{Ej}^{\rho_k}} N_{Rik}, \tag{3}$$

$$LL2 = -\frac{n_z^2}{2} \log\left(2\pi\sigma^2\right)^2, \tag{4}$$

$$\sigma^2 = \sum_i \sum_j \left(Q_{ij} - \sum_k^K \frac{\exp\left(\theta_k T_{ijk}\right) N_{Ej}^{\rho_k}}{\sum_{j=1}^J \exp\left(\theta_k T_{ijk}\right) N_{Ej}^{\rho_k}} N_{Rik} \right)^2 \div n_z^2. \tag{5}$$

where q_d is the number of trips of distance class d, $\widetilde{q}_{dk}$ is the estimated number of trips of distance class d of traveler's attribute k by model, T_{ijk} is expected minimum travel time between zones i and j of attribute k, N_{Ej} is the number of the employee at zone j, N_{Rik} is the number of residents of attribute k at zone i, Ω_d is a set of OD pair belonging to distance class d, n_z is the number of zones, Q_{ij} is travel demand between i and j given by gravity model and Fratar method, σ^2 is the variance of OD demand model. By definition, $LL1$ is the log-likelihood of travel distance distribution, and $LL2$ is that of OD travel demand of the model.

Table 3 indicates the estimates of the destination choice model parameters. The parameters indicate that the choice probability of the destination zone was higher for shorter the access time to the zone and larger numbers of the employee at the zone. Most of the parameters were statistically significant, while some parameters did not have an adequate estimation of variance; therefore, we could not determine the significance of those parameters. As formulated in the likelihood function, the parameters for all segments were estimated simultaneously. There might be correlations between the explanatory variables among segments that would cause the failure to estimate the variance of some parameters. Merging the age class may improve the estimation stability. The destination choice model was statistically significant according to the likelihood ratio.

Table 3. Destination choice model parameters.

Age Class	Parameters	Male				Female			
		Estimate	Std. Error	t Value	Pr (>t)	Estimate	Std. Error	t Value	Pr (>t)
<10	θ	−0.923	0.0078	−18.9	0	−1.066	0.0104	−102.5	0
	ρ	1.476	0.0089	166.0	0	1.882	NA	NA	NA
10–19	θ	−0.818	0.0064	−127.2	0	−1.020	NA	NA	NA
	ρ	1.675	0.0100	167.6	0	2.595	0.0070	372.6	0
20–29	θ	−0.086	0.0004	−222.3	0	−0.881	0.0142	−61.9	0
	ρ	0.340	NA	NA	NA	1.775	0.0123	144.5	0
30–39	θ	−0.090	0.0004	−249.6	0	−0.745	0.0075	−99.1	0
	ρ	0.000	NA	NA	NA	1.408	NA	NA	NA
40–49	θ	−0.006	0.0001	−85.6	0	−0.087	0.0003	−270.6	0
	ρ	0.059	0.0024	24.7	0	0.621	0.0107	57.7	0
50–59	θ	−0.087	0.0004	−235.7	0	−1.143	0.0105	−109.3	0
	ρ	0.334	0.0139	24.1	0	1.662	0.0077	215.4	0
60–69	θ	−0.080	0.0005	−159.9	0	−0.266	0.0029	−90.5	0
	ρ	0.629	NA	NA	NA	1.492	0.0072	208.2	0
<70	θ	−0.072	0.0007	−100.6	0	−0.725	0.0048	−151.3	0
	ρ	2.489	0.0052	474.7	0	1.871	0.0071	263.3	0

Table 3. *Cont.*

Age Class	Parameters	Male				Female			
		Estimate	Std. Error	t Value	Pr (>t)	Estimate	Std. Error	t Value	Pr (>t)
Log-likelihood					-3.1×10^7				
Initial log-likelihood					-6.7×10^7				
Likelihood ratio test statistics					7.099×10^7				
Prob>chi2					0				

4. Scenarios for Transport Policy Measures

Using the models estimated in the previous section, we estimated the OD travel demand by transport modes and generated agents' initial daily travel behavior. We generated the coordinates of origin and destination randomly within the geographical extent of the origin and destination zones. The agents were assumed to make two trips a day. The departure time of the two trips was sampled from the HTS. Here, we input these initial travel behaviors to MATSim by mode separately, and the mode choice module of MATSim was not applied afterward. In other words, the modal share was fixed to the initial estimation by the mode choice model and did not feedback the MATSim simulation results to the mode choice and destination choice behavior. As a result, each agent's travel time and distance were simulated for each demand management scenario.

In this study, the decentralization of employment places and the time shift of peak hours were analyzed as the demand management scenarios. Compared with the business as usual (BAU) case representing the current employment and departure time, we estimated the impact of these scenarios. The time shift impacts combined with mobility as a service (MaaS) system in Bangkok have already been analyzed in the other article [37], but we analyzed the impact of combination with the decentralization. To focus on the impact analysis, we fixed the other factors, such as population, road infrastructure, and public transport level of service, to the current level.

As a decentralization scenario, 30% of employees of the zones ranked as top 10% in terms of density (i.e., these were the CBD where the employment density is very high) moved into the zones ranked as top 10–20% (i.e., these are potential urban subcenters in the less-dense area that are being connected or soon to be connected by urban railway lines). Such employment decentralization will change the destination choice probability and relieve the traffic congestion in the city center. That will affect the trip length, travel time, and road speed. Figure 4 shows the location of the zone with changed comparing with the BAU case: decreased zones displayed in blue and increased zones in reds.

As a time shift scenario, we arbitrarily shifted the departure time of 30% of agents at peak time. The morning peak hour was 7:00–9:00 and the evening peak hour was 16:00–18:00. In this scenario, the sampled 30% of agents departing at the morning peak hour were forced to depart 2 h later, and the sampled 30% departing at the evening peak hour was made to depart 2 h earlier. This scenario will affect the road congestion and may change the travel time and shift the route. It was also expected to affect the public transport travel time and route because these factors were different time by time depending on the time schedule of public transport. Figure 5 shows the departure time distributions of BAU and time-shift scenarios.
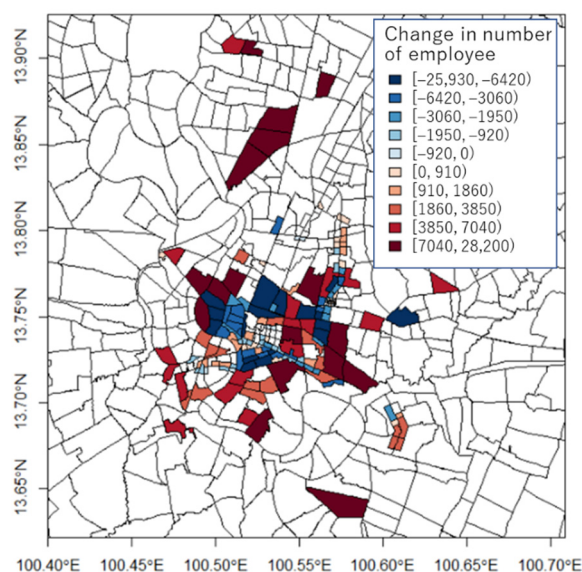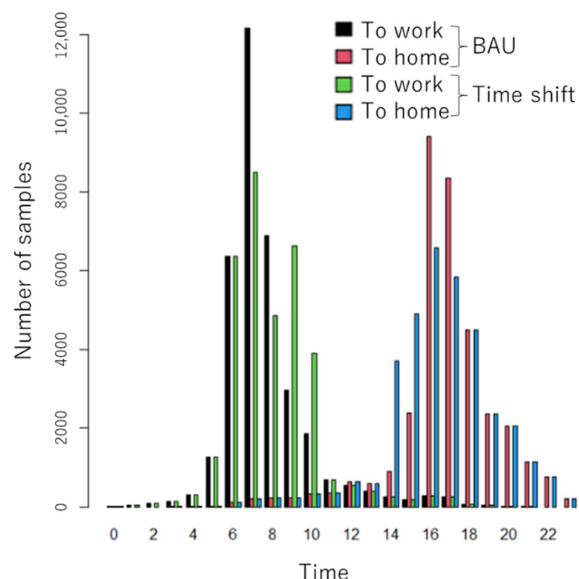
Figure 4. Employment place dispersion scenario.

Figure 5. Departure time distribution (BAU case and time-shift case).

5. Results

We applied these scenarios with MATSim and compared their simulated travel times and distances. The sample rate was chosen to be 5% for road transport and 1% for public transport in the simulation, which is a reasonable approach in agent-based modeling to economize on runtime [38]. The total volumes indicated in the results were scaled back to 100% to be consistent with observed demand volumes. In this section, first, we validate the model, and then we present the simulated results of the scenarios.

5.1. Validation

The simulation results were compared with the observed data. Table 4 shows the key travel demand indices of the HTS 2017 and the simulation results produced by MATSim. The HTS estimation of car travel demand 2qw 14.9 million trips/day, and 9.1 million trips/day for motorcycles. Our estimation did not distinguish cars from motorcycles, and the total demand was calculated to be 17.5 million trips/day. Assuming the passenger car equivalent value (PCE) of a motorcycle was 0.33, the travel demand of the HTS was equivalent to 17.9 million PCE-trips/day. The difference of this volume to our estimate was

2%. The number of trips by public transport in our simulation was smaller than that in the HTS. In MATSim, the public transport module simulated the agent's behavior to use public transport and walk. If the travel time of public transport was too long, the agents did not use public transport but traveled on foot. In the simulation, a substantial number of agents were estimated to travel only by walking, reflecting a bias of level of service estimation due to the small sampling.

Table 4. Observed and simulated transportation indices.

	Observation (Household Travel Survey, HTS 2017)			Simulation by MATSIM	
	Car	Motorcycle	Public Transport	Car	Public Transport
Number of trips (million trips/day)	14.9	9.1	9.9	17.5	7.1
Total trip length (million p-km)	201.6	82.7	116.7	329.1	67.2
Average trip length (km/trip)	13.5	9.1	11.8	18.8	9.4
Beeline trip length (km)				9.6	5.9
Travel time (min)	36.0	28.0	68.1	49.5	65.2
Waiting time (min)			8.1		9.9
Average speed(km/h)	22.5	19.5	10.4	22.8	8.6

The total and average trip length of the car in our estimation was much longer than those of HTS. The simulated trip length was almost double the average Euclidean distance between ODs. This trip length reflects the network topology and the detouring behavior to avoid traffic congestion in the simulation. The simulated total trip length of public transport was much shorter than that of HTS. The simulation underestimated both the number of trips and the average trip length of public transportation as well. The car travel time of our estimate was much longer than the HTS, reflecting the estimation of the longer trip length. The average travel speed was almost the same level as HTS because the model was calibrated to fit with the average speed. The estimated travel time of public transport was relatively close to the HTS data, but the estimated travel speed was slower by about 20% because of the shorter trip length in our estimation. While these differences deserve further investigation, it should be noted that HTS was a comparatively small survey with a certain level of uncertainty. The resulting traffic flows appear to be sufficient for scenario analysis.

Figure 6 plots the observed and estimated hourly average link speed. From the observed data panel (a), the speed declined during the morning peak hours. During the daytime, the traffic speed was fairly low and stable at the same level as the morning peak hour. In the evening peak-hour, the average speed became lower and reached the bottom between 19:00 and 20:00. After that time, the speed recovered to free flow toward midnight. While our estimation shown in panel (b) indicates that the average speed was too low in the morning and evening peak hours, the midday speed recovered nearly to the free-flow speed. Such a difference between the observed situation and the model estimation is probably because we did not have business trips or logistics in the simulation, resulting in the total traffic volume being underestimated. However, when considering the acceptable morning and evening peak pattern, we decided to calibrate the MATSim to fit with the daily average speed.

Even though there were biases in traffic flow and speed estimation, we applied this model to the sensitivity analysis of the scenarios. The discussion section will address the issues related to estimation bias.
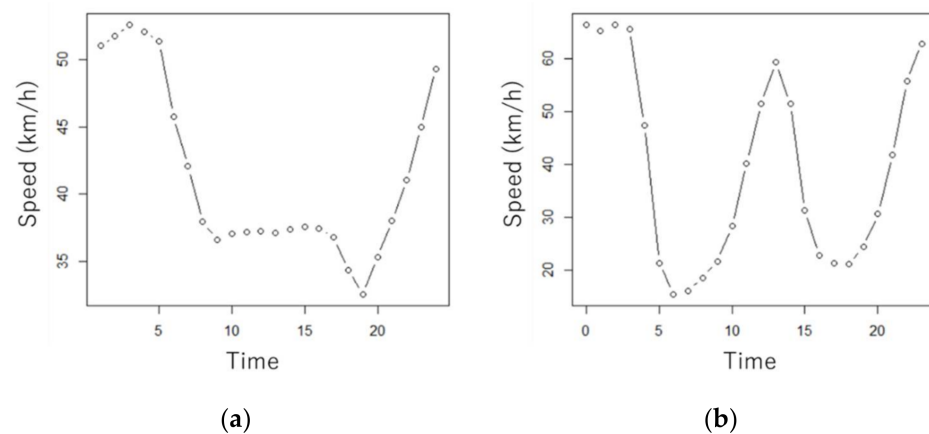
(**a**)　　　　　　　　　　　　　　　　　　　　　　　　(**b**)

Figure 6. Hourly average link speed: (**a**) observed data by iTIC (Intelligent Traffic Information Center Foundation); (**b**) estimation in this study; iTIC collects the data from probes on taxis, buses, logistic vehicles, and mobile phones. We compiled the data using the raw data from 15 to 24 November 2020 in the TAZ region and calculate hourly average link speed on weekdays. Panel (**b**) shows the average speed trajectory of simulated road travel aggregated by departure time.

5.2. Effect of Policy Scenarios

Figure 7 shows the rate of change in total travel time and distance for the scenarios of time shift, decentralization, and their combination compared with the BAU. The travel time of car was reduced for all scenarios, while that of public transport increased. Car travel time was reduced by 10.5% by the time shift scenario, reflecting the alleviation of congestion by avoiding the peak hour. The decentralization scenario reduced travel time by 2.4% and alleviated the congestion by shifting the traffic concentration from the center to the near suburbs. The combined scenario reduced travel time by a car by 13.4%, which was more than the sum of the two scenarios. That implies synergies in the spatiotemporal transportation demand management measures.
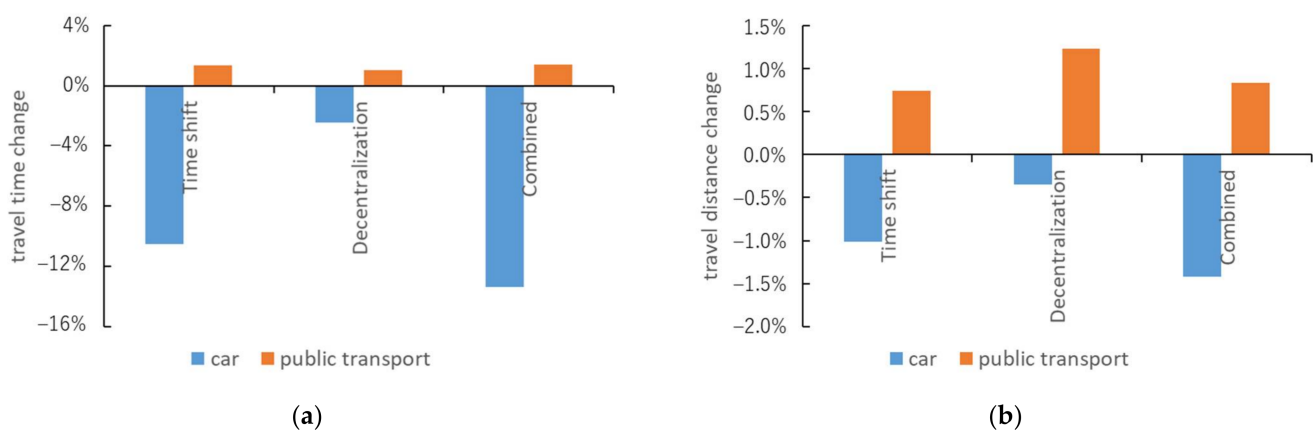

(**a**)　　　　　　　　　　　　　　　　　　　　　　　　(**b**)

Figure 7. Estimated change rate of (**a**) Travel time; (**b**) Distance.

On the other hand, the travel time of public transport slightly increased for all scenarios. All scenarios had the same timetable for public transport. In other words, the supplied level of service was unchanged. The results indicate that a simple departure time shift would cause an increase in waiting time or a detour depending on the public transport service level. In this case, the average travel time increased by 1.3% by the time shift scenario. The decentralization scenario increased the travel time by 1.1%. This scenario did not necessarily move the employment to places that were accessible by public transport. The combined scenario increased travel time by 1.4%. Spatiotemporal demand management measures did not necessarily have a uniform effect on public transportation travel.

Travel distances declined in the time shift scenario by 1.0% for cars and inclined by 0.7% for public transport. In the simulation, car users could choose shorter routes when road congestion was reduced. In contrast, the travel distance of public transport increased probably due to the timetable and change in routes. The decentralization scenario decreased the travel distance of cars by 0.3% and increased that of public transport by 1.2%. Dispersion of employment to near suburbs may reduce the distance between home and workplace or avoid the detour by congestion for car users. Meanwhile, decentralization may affect the route choice of public transport or increase the egress distance. The combined scenario decreased the travel distance of a car by 1.4% and increased that of public transport by 0.8%.

Figures 8 and 9 show the spatial distributions of the rate of change in travel time by departure zones for car and public transport, respectively. Panel (a) in Figure 8 indicates that the time shift scenario decreased the car travel time for most zones but increased for a few zones. The decentralization scenario shown in panel (b) had many zones where the travel time increased. This result implies that the spatial dispersion of the urban core function possibly causes longer travel for some departure zones. From this panel, we can find that zones in the central area, and inner suburbs tended to decrease the travel time. On the other hand, outer suburbs had relatively more zones that increased the travel time. Thus, possibly decentralization will increase the congestion in the outer area even though it reduces the congestion in the central area. The combined scenario shown in panel (c) decreased the travel time for more zones, and the decreasing rates were larger than the time shift solely.
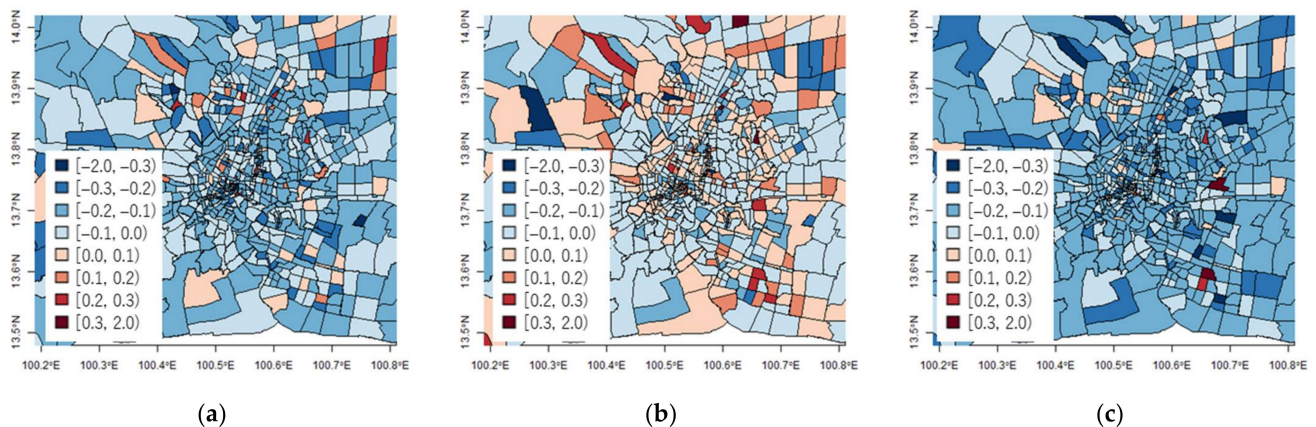

(a) (b) (c)

Figure 8. Spatial distribution of car travel time change rate by departure zones: (**a**) Time shift scenario; (**b**) Decentralization scenario; (**c**) Combined scenario.
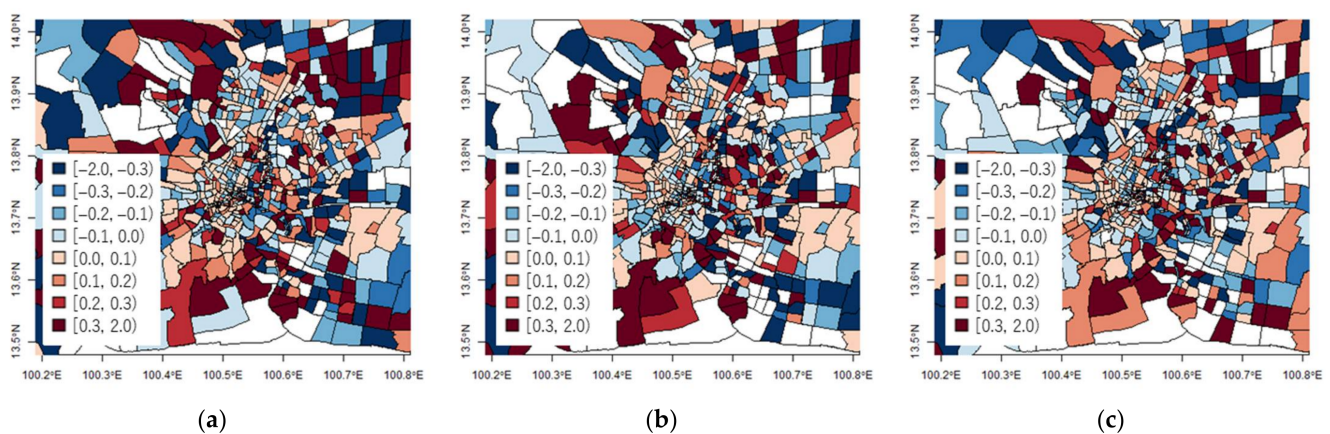

(a) (b) (c)

Figure 9. Spatial distribution of public transport travel time change rate by departure zones: (**a**) Time shift scenario; (**b**) Decentralization scenario; (**c**) Combined scenario.

As shown in Figure 8, there was no clear pattern in the spatial distribution of travel time change for public transport. The zones where the travel time increases or decreases seem to be mixed geographically, and many zones had a larger rate of change than car travel. Smaller differences were likely to be caused by the random variation of different model runs. Public transport users may be affected more by a change in departure time or destination place than car users because the travel time and optimal route are sensitive to the timetable and transit route connections. This result indicates that the spatiotemporal measures of transportation demand management have to be coordinated carefully for public transport operations.

6. Discussion and Conclusions

In this study, we applied MATSim to the Bangkok metropolitan region in Thailand. Even with access to the data provided by government authorities through the government-supported project and complemented by private companies' data, the input information was insufficient for an agent-based model. Therefore, we developed an estimation method of travel patterns and synthesized the input data for MATSim. On the other hand, we used GTFS data for the entire Bangkok metropolitan area for public transportation analyses, which is still not applied in many studies in transportation research in developing countries.

Applying this model, we analyzed the impact of employment decentralization and peak time shift on transportation. These spatiotemporal peak shift measures were effective for road transport to alleviate congestion and reduce travel time. However, the effect of those measures on public transport was not uniform but different by users' circumstances. On average, the simulated results indicate that those measures increased the average travel time.

The effects of peak time shift measures on public transport were different depending on the timetable and routes. There was no clear spatial pattern of the travel time change. These results suggest that demand management policy measures for public transport require consideration of more detailed conditions to improve usability. For instance, the employment dispersion should be incorporated with transit-oriented development plans to improve the access and egress to and from public transport. The time shift measures may need to be tailored to reflect the individual travel circumstances to reduce the travel time and congestion for the public transport system. Potentially, MaaS systems may be an effective tool, especially for the demand management of public transport.

This study conducted the analysis for the base year population in 2015. In practical transportation planning, population forecasts are required. Some studies projected the depopulation of Asian cities in the latter half of this century [39]. We need to reflect on the future population and its spatial distribution in the simulation. The spatial distribution of the urban population is also known to be affected by the transport system [3,40]. For future studies, we need to incorporate this interaction between transport and land use. In the decentralization scenario, we arbitrarily dispersed the employment from the center to near suburbs. However, more precise scenarios are required to coordinate with transit and urban development policies.

The model output can be used not only for estimation of travel time and distance but also for the other various analysis, such as environmental load, energy efficiency and consumption [41], effective land use and land value, value capture for transportation investments, and social disparities. For instance, based on a statistical model, urban structure and road congestion reduction were demonstrated to have only a limited impact on CO_2 emission reduction in the transport sector [42] using aggregated analysis. Microsimulation models can analyze more detailed spatiotemporally policy measures that cannot be analyzed by conventional models. Such microsimulation models may provide in-depth knowledge in policy practice. In particular, agent-based models are known to be superior in pricing studies and equity analyses.

Another study integrated MATSim with an agent-based land-use model [43] to analyze whether SDGs may be achieved by urban and transport policies [44]. Our study will

incorporate the land-use model to reflect the population dynamics in Bangkok and will be able to analyze urban and transportation sustainability.

As mentioned above, this model has some considerable biases. Our analysis did not include business travel and goods transport. That a major reason for the bias in road speed estimation, congestion, subsequent detour trips, trip length, and travel time. That requires improving the accuracy and stability of mode choice and destination choice models. Furthermore, motorcycles were currently not represented in the simulation explicitly. Given the relevance of this mode in Bangkok, we may need to distinguish motorcycles from cars in the traffic simulation appropriately. It should also be noted that potentially induced travel was not represented here. It is conceivable that some trips that were suppressed due to high levels of congestion would be added if congestion was reduced. The model was not able to quantify this latent demand, as it was not observed in current traffic volumes.

There are various urban problems in Bangkok, including air pollution, rapid aging of society, securing mobilities for vulnerable people, suburban development on transportation, gentrification by inner-city development, the fiscal balance of the urban railway project, and induced urban development by transportation provision. Our model can be applied to a wide range of urban transport policy problems combined with the land-use model. Data limitation, however, requires various assumptions in modeling, which may explain at least in part the estimation bias. Our future studies will address these modeling issues.

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