

Article

Identifying Impacts of School-Escorted Trips on Traffic Congestion and the Countermeasures in Bangkok: An Agent-Based Simulation Approach

Titipakorn Prakayaphun ^{1,*} , Yoshitsugu Hayashi ² , Varameth Vichiensan ³  and Hiroyuki Takeshita ² 

¹ Department of Constructional Engineering, Graduate School of Engineering, Chubu University, Kasugai 487-8501, Aichi, Japan

² Center for Sustainable Development and Global Smart City, Chubu University, Kasugai 487-8501, Aichi, Japan; y-hayashi@isc.chubu.ac.jp (Y.H.); htake@isc.chubu.ac.jp (H.T.)

³ Department of Civil Engineering, Faculty of Engineering, Kasetsart University, Bangkok 10900, Thailand; fengvmv@ku.ac.th

* Correspondence: tc21801-6188@sti.chubu.ac.jp

Abstract: The often-discussed issue of parental escorting of children to school and its potential disruption of traffic flow has been extensively examined in the literature. Still, the specific effects of traffic congestion remain understudied. To fill this gap, this study addresses the impacts of school trips on traffic congestion. An agent-based model is applied to simulate various scenarios and assess their impact. Our findings indicate that the traffic speed without school trips is higher speed during peak hours by around 8% and average travel time in the city is reduced significantly. We examine countermeasures: Firstly, flexible working hours can lead to a morning traffic speed improvement of approximately 1.9%. Secondly, staggered school schedules can result in a 6.9% increase in traffic speed at 7 a.m. Optimizing school loading spaces can also enhance road capacity, mitigating road lane blockages during drop-off and pick-up periods. This research sheds light on the impact of parent-escorting travel existence and offers potential solutions to alleviate traffic congestion.

Keywords: education trip; agent-based model; traffic assignment; trip chain; MATSim; Bangkok



Citation: Prakayaphun, T.; Hayashi, Y.; Vichiensan, V.; Takeshita, H. Identifying Impacts of School-Escorted Trips on Traffic Congestion and the Countermeasures in Bangkok: An Agent-Based Simulation Approach. *Sustainability* **2023**, *15*, 16244. <https://doi.org/10.3390/su152316244>

Academic Editor: Victoria Gitelman

Received: 31 October 2023

Revised: 17 November 2023

Accepted: 21 November 2023

Published: 23 November 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Traffic congestion poses a significant and widespread challenge. Bangkok, as the bustling capital of Thailand is no exception. The city's rapid growth and economic development have led to a notable increase in vehicle ownership, outpacing the expansion of road infrastructure [1]. As a result, Bangkok's streets frequently experience extreme traffic jams during peak hours, resulting in delays, frustration, and environmental concerns.

A key contributor to this congestion is the limited availability of public transportation services in certain parts of the city. Despite the substantial improvements in Bangkok's urban rail transit system extended to a substantial 291 km [2], which has been remarkably extended during the past 20 years, it still struggles to meet the high transport demand. Consequently, many areas of the city face inadequate accessibility, forcing residents to rely heavily on private vehicles for their daily commutes [3].

The issue of parents escorting their children to school has become a significant concern in recent years which consists of three factors. (1) A key factor in this problem is the rapid increase in car ownership. As more families own vehicles, the roads leading to schools have become increasingly congested during drop-off and pick-up times [4,5]. This congestion exacerbates traffic-related issues and negatively impacts the environment due to increased emissions. (2) Another aspect is the inadequacy of public transport (PT) services, such as low-frequency services, no coverage area, and fully occupied coaches. This lack of convenient public transportation options places a heavy burden on parents who must

arrange daily transportation for themselves and their children, further contributing to the escorting problem. (3) Additionally, suitable schools are not located close to their houses, and their accessibility by walking or biking is impossible for long distances. Parents understandably opt to drive their children to ensure their safety, even if it contributes to traffic congestion and discourages active transportation [6–8].

This study aims to examine and assess policies to ease traffic congestion caused by school-related travel. From the viewpoint of “Physical Urban Design”, changing the locations of schools or restricting school selection to within walking distance from home would be effective in substantially reducing school trip distance. However, it would be quite challenging to implement due to the cost of removal, change of habits, and preferences of parents on prestigious schools that may not be close to home. Additionally, schools in suburban areas may be located beyond the distance reachable by active transport either on foot or by bicycle. To address these challenges, we look into another dimension, “Time Urban Design”, an essential aspect of urban planning, to influence behavior without costly infrastructure improvement. By strategically managing the timing of activities, existing transport infrastructure should be efficiently used, but how?

“Time Urban Design” means shifting the time of activities under the severe constraints of existing infrastructure capacity. In other words, we must strategically redistribute activities and encourage off-peak utilization. Adjusting daily routines can also improve overall quality of life, illustrating that “Time Urban Design” is cost-effective for shaping behavior and promoting sustainable urban development. To analyze the effectiveness of “Time Urban Design”, we introduce an agent-based model to simulate individual behaviors. This study aims to discuss the transportation policies, such as flexible work and school time, that can alleviate traffic congestion based on the agent-based simulations.

The remaining part of the paper comprises a literature review of related studies in Section 2, followed by the methodology and data in Section 3. Section 4 compares alternative policy cases such as (a) case of no school trip, (b) work starting time shift, and (c) school starting time shift compared with the Business as Usual (BAU) case. Finally, Section 5 concludes the paper by summarizing key findings and acknowledging limitations.

2. Literature Review

Over the past decade, agent-based modeling and simulation have emerged as invaluable tools for observing and analyzing the intricate interactions between agents and regulatory mechanisms. Leveraging the granular unit of individual movement, these models can capture an exhaustive array of details within network simulations, enabling precise calculations of metrics such as commuter volumes and average speeds for specific network segments across various periods. Numerous studies have harnessed MATSim’s power to address diverse research questions, from autonomous vehicles to traffic signal optimization.

In this section, we explore research on school trips within urban areas and their environmental impact, emphasizing the utility of agent-based modeling and introducing relevant tools. Within the context of Bangkok, we also investigate studies employing time shift scenarios, offering valuable insights into the temporal variations shaping transportation dynamics in this bustling metropolis.

2.1. School Trips on Urban Congestion and Pollution

School trips significantly contribute to urban traffic congestion and pollution, as evidenced by several studies in the literature. In a case study conducted in Beijing, Lu et al. [4] highlighted the adverse consequences of driving-to-school trips on the city’s congestion and environmental costs and emphasized the need for policymakers to optimize the spatial balance between school supply and demand to alleviate extra congestion and mitigate environmental impacts. Similarly, the longer school distance encourages the school escort trips from the households with car ownership [9].

Furthermore, the impact of school trips extends beyond traffic congestion to influence parental decisions and transportation practices. Yeung et al. [8] explored the factors

influencing parental decisions regarding their child's active transport to school. Their findings revealed that safe walking paths, adult supervision, commuting distance, and the child's age were among the frequently reported factors shaping parental choices. This insight underscores the importance of enhancing pedestrian-friendly infrastructure and implementing safety education to encourage active commuting options. Moreover, Rojas López and Wong [10] conducted a review and analysis of children's active trips to school, highlighting the benefits of such trips for both children and parents. By advocating for active school transportation, they emphasized its positive impact on physical health, environmental sustainability, and reduced traffic congestion. Overall, the literature consistently emphasizes the crucial role of school trips in shaping urban transportation patterns and the need for targeted interventions to address their impact on traffic congestion and pollution.

2.2. Agent-Based Model

The agent-based model (ABM) is a powerful and flexible simulation methodology that has found applications across a multitude of research domains, ranging from social sciences to environmental studies and healthcare systems. ABM allows for the representation of complex systems through the modeling of individual agents and their interactions within a simulated environment. Among the commonly used ABM platforms are NetLogo and AnyLogic, which are recognized for their versatility and applicability in various research areas. NetLogo, an open-source platform, offers a visually intuitive environment for creating agent-based models, which are widely used for general and transport purposes due to its flexibility [11]. Chiou and Bayer [12] applied NetLogo for microscopic modeling of pedestrian movements in Taiwan. AnyLogic, on the other hand, is a commercial simulation platform that extends ABM by incorporating discrete-event modeling to simulate dynamic systems. AnyLogic also can perform microscopic simulations with a high level of detail. The agent's behavior on these platforms is pre-defined with a set of rules in the form of a flowchart [13].

While these general-purpose ABM platforms have proven to be invaluable in diverse research contexts, our primary focus lies in the specialized domain of transportation analysis, where the Multi-Agent Transport Simulation (MATSim) [14] is the agent-based model tool inherited from Transportation Analysis and Simulation System (TRANSIMS) [15], which is the open-source software that many researchers adopt and developed modules to support their research and designed for large-scale scenarios due to its adaption of the computationally efficient queue-based approach. TRANSIMS, on the other hand, is an open-source microscopic simulation model used to model travel behavior in large-scale road networks and large populations due to the limitations of four-stage models that are unable to capture demand and supply variations in space and time within a day. However, MATSim is a mesoscopic simulation model and is faster than TRANSIMS. Its agent's behavior is based on a stochastic, co-evolutionary algorithm, which is optimized for the best score of agents' plans. MATSim is also the most popular agent-based simulation framework used in urban transport simulation [16].

The conventional and widely used four-step model considers aggregate data, makes assumptions about traveler behavior, and provides a macroscopic overview of travel demand and distribution [17]. It is suitable for regional planning and forecasting but often lacks the fine-grained detail required to understand individual-level decision-making and interactions within the transportation system. On the other hand, the agent-based model focuses on individual travel behaviors with unique personal attributes and interactions within the transportation system [18]. This level of detail is crucial in capturing the complexity of school commute behavior, as it accounts for the diverse motivations and constraints that different commuters face.

MATSim is used to analyze the effects of traffic management policies such as road tolls or introducing a new travel mode. He et al. [19] proposed a test bed to evaluate congestion pricing policies on population segments in New York City, and car trips have significantly fallen after the congestion policy. The population within Manhattan mainly benefits from the policy. The agents with demographic attributes react to the test policies and adapt their dynamic movement. Kii et al. [20] investigated two demand management scenarios which are peak time shift and workplace decentralization, and found that travel distances declined by 1% for cars but inclined by 0.7% for public transport in the time shift scenario. Hörl et al. [21] implemented the automated taxi services in the MATSim to identify different operational policies and their advantages in Zurich city. Ciari et al. [22] introduced a methodology for estimating travel demand for car-sharing within MATSim. The model is validated by using customer data from a car-sharing operator in Zurich, and the results show that it can accurately capture the distribution of distances, mode choice, and destination locations for car-sharing trips. To our knowledge, applications of an agent-based model to studying school travel-related policies remain limited and have not yet focused on the impact of school trips.

2.3. Time Shift Scenario

Urban transportation reaches its limit, and transportation experts realize that more transport facilities are not always the best solution. Goodman [23] proposed a non-capital improvement, the concept of time shift. The timeshift scenario is a strategy to alleviate congestion by encouraging individuals and businesses to adjust their travel times to off-peak hours. The potential benefits of implementing staggered working hours include reducing traffic congestion during peak hours [24]. It increases traffic speed by spreading out the demand for transportation services more evenly throughout the day. Yildirimoglu et al. [25] proposed the optimal staggered work schedules strategy accounting for commuters' departure trip time choice, and it can significantly reduce traffic congestion in urban networks. Motivated by prior works, this approach is low in cost and offers promising results theoretically for reducing peak congestion. We will apply this concept in our study to examine the effectiveness of the time shift scenario.

3. Methodology and Data

This section outlines the key elements of our work, detailing the data requirements and our workflow. We employ MATSim as our agent-based simulation model, which relies on several essential environmental components such as network data, vehicle specifications, facilities, and agent travel plans. Since these data are not publicly available, we are responsible for generating our dataset and leveraging any accessible resources to configure our simulation model accurately. Following the meticulous setup, a critical phase entails calibrating our simulation results to match the actual data on our network closely. This calibration step assumes a pivotal role in ensuring the confidence of our model, allowing it to represent the real-world scenario. Such alignment between simulation outcomes and empirical data is essential, as it supports the credibility and relevance of our computational approach, ultimately enriching its applicability within the scope of our academic research.

3.1. Methodology

In this study, an agent-based model was employed to assess the effect of school trips on traffic congestion. We generated the synthetic population, including household, personal attributes, dwelling locations, and job locations. The travel plans were generated based on their household conditions, such as vehicle ownership, age, and gender. The resulting travel plans were then delegated onto a road network using MATSim, as shown in Figure 1.

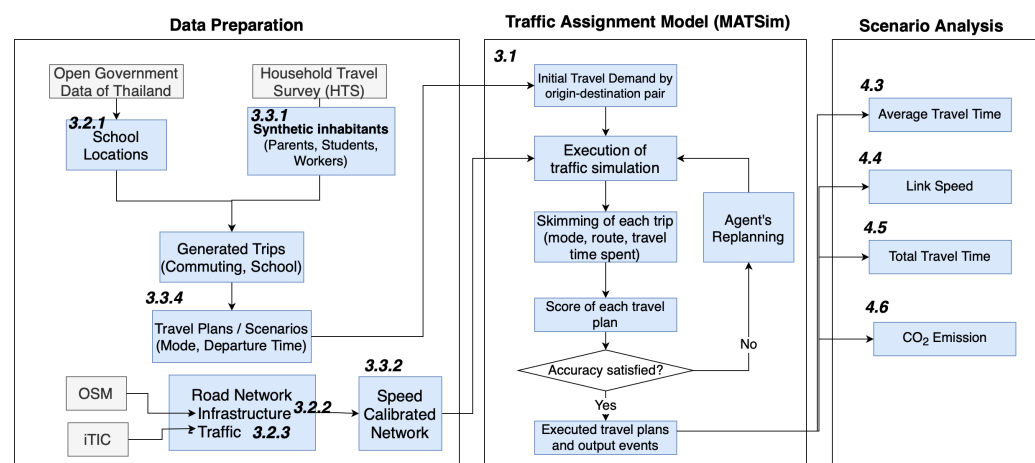


Figure 1. Flow chart of the workflow of MATSim simulation in this study.

MATSim is a micro-level, agent-based transportation simulation and analysis platform. Unlike trip-based aggregation techniques, travel demand in MATSim is derived from agents' simulated daily activities. It uses a co-evolutionary approach to reach an equilibrium state where each agent aims to optimize their score by adapting to current transportation conditions. Agents earn higher scores by spending time on planned activities and lower scores by traveling or waiting. The simulation is iterative and requires initial demand, modeled as a collection of individual agents with daily activities and plans as shown in Figure 1.

Demand generation options are available, but each agent must have at least one plan specifying activity durations and locations. During the assignment phase, each agent executes its selected plan, and the resulting demand is loaded onto the network. For explicitly simulated modes, MATSim uses a queue-based traffic flow simulation that tracks the number of cars waiting at a link and limits the resultant volume based on the link's capacity. Upstream congestion spillback can be detected if the storage capacity is exceeded. The queue-based approach enables the simulation of large numbers of agents efficiently but does not consider detailed intersection logic or car-following behavior. MATSim calculates travel times for each trip and each plan and uses them to score operations. Scores are determined based on a utility function [26]. A plan's utility score decreases if the activity duration decreases and travel time increases. In the next round, some agents modify their plans by changing transport mode, route, departure time, or activity duration. Finally, MATSim's co-evolutionary algorithm selects plans based on predefined strategies. The number of iterations is also predefined and resulted from many trials when validating with the reference data. The results of the simulation include final travel plans, activity events for agents, mode distribution, average plan scores, and total passenger kilometers and hours traveled per mode.

In this simulation, we have opted for a scaled sample population size of 1% to get a balance between computational efficiency and accuracy [27]. This judicious choice ensures that our computational resources are used efficiently while still providing meaningful insights into network congestion dynamics. To mitigate congestion effectively within this 1% scaled population, we meticulously fine-tuned two critical factors: the flow and storage capacity factors. Various experiments were conducted using factor values of 0.01, 0.10, 0.15, 0.20, and 0.30. Among these numbers, the factor of 0.15 emerged as the best option for our simulation since the average travel time of agents is roughly 34.2 min. In comparison, the reported travel time by OTP is about 36 min [28]. Therefore, the simulation result has a 5% deviation, which is an acceptable disparity. In Table 1, QSim is the default mobility simulation of MATSim. In order to compare between scenarios, the agent activity plan should remain unchanged. We adopted the "KeepLastSelected" strategy at about 95%. The re-routing strategy is 30% to ensure their travel route alteration. Our traffic model is predicated on the queue traffic dynamic, where vehicles operate at their free-flow speeds

until they encounter a queue. When a vehicle reaches the end of a queue, it transitions to the subsequent link. This dynamic modeling approach aligns with actual traffic behavior, enhancing the authenticity of our simulation by accounting for the interplay between unobstructed traffic flow and queuing phenomena.

Table 1. Configuration parameters for MATSim simulation.

Modules	Parameters	Values
QSim	Flow capacity factor	0.15
	Storage capacity factor	0.15
	Traffic dynamics	queue
Strategy	Keep-last-selected probability	0.95
	Re-route probability	0.3

3.2. Spatial Data

3.2.1. School Locations

School data from 1277 locations, including name, address, and geographical location, was recorded in 2020 and provided by the Open Government Data of Thailand. The school location is categorized into primary school, high school, and university. The spatial distribution of school locations is shown in Figure 2 with their respective Traffic Analysis Zone (TAZ). In this study, the primary school is for students ranging from 3 to 11, while the high school is starting from 12 up to 18. The university is for students over 18. The school locations are used to assign the school trips to the agents with respective ages.

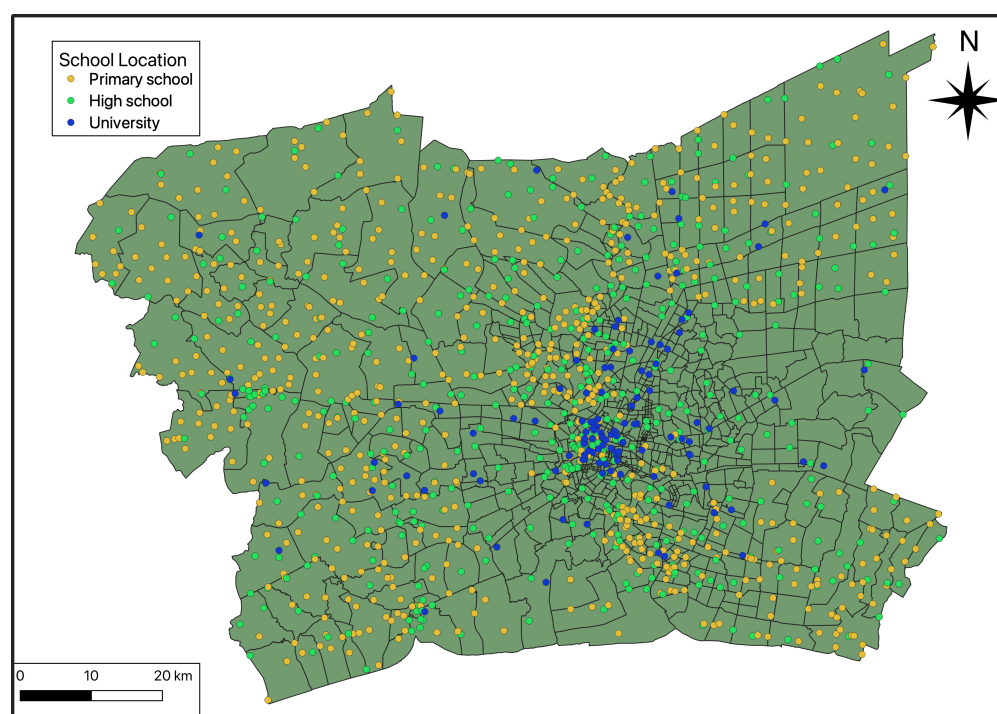


Figure 2. TAZs and spatial distributions of school locations.

The unequal distribution of schools in certain areas has significant consequences, posing challenges to students and families. Limited access to education due to the scarcity of nearby schools can lead to long-distance commutes. For some families, renting rooms near institutions or relocating becomes necessary, incurring additional financial burdens. Overcrowding in certain schools can lead to excessive demand, while disparities can widen

between those who can afford to relocate and those who cannot. Moreover, students may face social isolation if they must live near their school, resulting in parents preferring to escort their children to school instead.

3.2.2. Road Network

The study area is the Bangkok metropolitan region (BMR), which consists of Bangkok, Nakhon Pathom, Pathum Thani, Nonthaburi, Samut Prakan, and Samut Sakhon. The total area is about 7762 km². The network data are derived from OpenStreetMap (OSM) within the region of BMR. It is crucial to recognize the inherent incompleteness within the OSM network dataset. As a result, there is a clear need for manual intervention to improve the accuracy and completeness of the network data. Figure 3 shows our network data with the free flow speed highlight on the road link.



Figure 3. Road network of the study area.

The MATSim network is characterized by several attributes associated with its links, including link length, capacity, free flow velocity, lane count, and available transportation modes. Additionally, the network's links have been categorized into two distinct classes: express links and ordinary links. This classification is based on the unobstructed velocity attributed to each link. Specifically, if a particular link's unobstructed velocity exceeds 80 km/h, it is appropriately designated as an express link. Conversely, if the free flow velocity falls below this threshold, the link is classified as an ordinary link. In this road network, there are 886 express links and 35,972 ordinary links.

3.2.3. Traffic Data

In 2018, Thailand's historical traffic information was sourced from the Thai Intelligent Traffic Information Center (iTIC), offering invaluable insights into the state of traffic during that period. This dataset consists of an array of traffic-related parameters, such as traffic speed and estimated capacity, ranging from unobstructed traffic flow (1) to congested conditions (3) as shown in Table 2. The frequency of this data is at a 5-min interval; however, it is imperative to note that not all traffic links are reported at each time point.

Table 2. Data example of traffic information from iTIC.

From	To	Link Speed	Quantity
1506	1507	47.3	1
3222	3223	30.88	2
3223	3222	10.2	3

To derive meaningful insights, a careful approach is undertaken. Specifically, each traffic link undergoes sampling at hourly intervals, allowing for calculating the mean average speed. This process ensures a robust and representative depiction of traffic conditions. Furthermore, data points with frequencies falling below the mean frequency are filtered out, resulting in a trustable dataset that prioritizes the most reliable resources for each road.

For analytical purposes, the weekday data in December 2018 are aggregated, yielding an average speed value. The statistics of these data are shown in Table 3, and the minimum and maximum values are within acceptable ranges, indicating no outliers in the dataset. The decreasing trend in mean values suggests a consistent pattern of traffic congestion during peak hours. This average speed is a crucial reference point for subsequent comparisons between the iTIC data and the simulation results. Such a comparative analysis holds significant academic value in assessing the accuracy and applicability of the iTIC dataset within the context of traffic simulations.

Table 3. Statistics of hourly iTIC network speed in km/h.

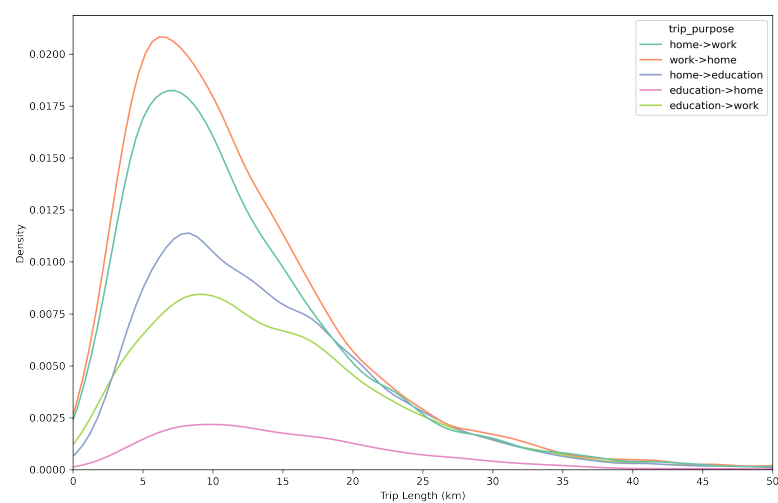
Hour	Std	Mean	Min	Max
6	13.50	40.47	12	98
7	14.28	36.41	11	93
8	14.08	35.99	10	91
16	14.02	35.14	9	92
17	13.79	32.97	8	90
18	13.81	31.89	8	89

3.3. Preparation for MATSim Simulation

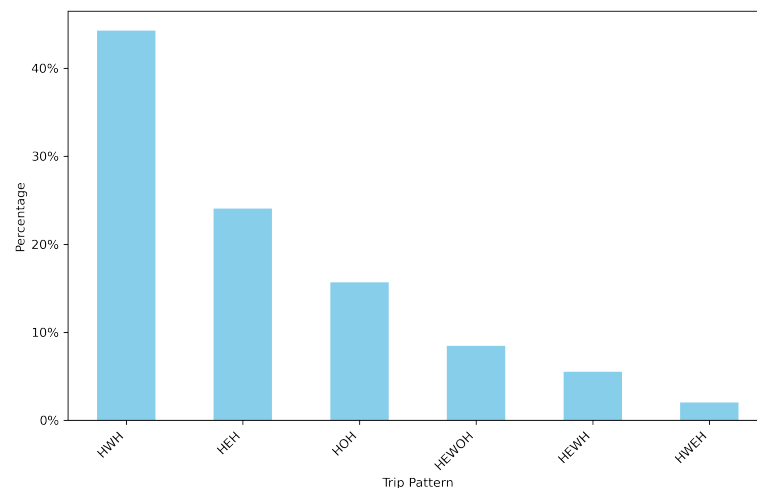
3.3.1. Generating Agents

Initially, we created the synthetic population for the BMR by using a survey sample of households with attributes at the household level, such as household size and number of vehicles, or at the person level, such as gender, age, role, and employment status. The control attributes, such as the number of population, households, and employment, are required for each zone. In Figure 1, we used the household travel survey (HTS) as a foundation to create travel plans for our synthetic population. This HTS consists of 18,833 households accounting for 38,054 people conducted in 2017 and provided by the Office of Transport and Traffic Policy and Planning (OTP). The data records contain each household profile and each person's daily trip behavior including origin zone, destination zone, departure time, duration, and transportation mode. Since our synthetic population lacked travel plans at this stage, we aligned the HTS data with our target population by identifying similarities in attributes like age, gender, and income levels. We employed the Iterative Proportional Fitting (IPF) method [29] to assign appropriate weights to individuals within the survey data. This ensured that the weighted population distribution matched the marginal distributions of key attributes. Consequently, we integrated the complete daily activity schedules and trip chains from the HTS data into our synthesized population. This approach leveraged the assumption that sociodemographic attributes correlate with daily activity patterns, thus enriching our synthetic population with realistic and behaviorally

consistent travel plans. The trip length distribution by kernel density estimation (KDE) in Figure 4a shows that the average trip length for the variability of education trips is high, which indicates that people who live in suburban need to move into the city to go to school due to the school site limitation. While in developed countries like Japan, the school site is available within the district area. The peak value of all trip purposes is located around 7.5 km. However, the peak value of the education trip is a little bit higher, which means that the education trip's distance is quite far. There are four activity types defined: Home (H), Work (W), Education (E), and Other (O), as seen in the trip pattern distribution in Figure 4b. Home-based work trip (HWH) is the most common trip in the simulation. Home-based education trip (HEW) contains both students and parents. Trip chaining, such as going from home to school to work to other to home (HEWOH) or going from home to school to work to home (HEWH), is also included in agent plans.



(a)



(b)

Figure 4. Trip characteristics of the synthetic population: (a) trip length distribution by trip purpose and (b) distribution of top 6 trip patterns.

3.3.2. Network Calibration

As the simulation network model relies on the free flow speed and these network data are already simplified to support our computation resources, we need to calibrate the network data to match the actual traffic conditions. We also observed that the traffic congestion in the BMR has characteristics of traffic speed depending on the regional area starting from the city center. Within our network framework, we decided to classify network links into inner, intermediate, and outer categories to reflect that relation. Each link type is associated with a specific factor number, serving as a control parameter to regulate traffic speed during designated time periods as Equation (1).

$$fv_f = v_o \quad (1)$$

where v_f is the free flow speed, v_o is the observed speed, and f is the factor number. These factor numbers come into play during the morning and evening peak hours, effectively scaling down the free flow speed of the respective network links. The morning peak hours start from 7 a.m. to 8 a.m., and the evening peak hours begin from 4 p.m. to 6 p.m.

The implementation of these adjustments occurs through the activation of a time-variant network configuration within the MATSim platform. This dynamic approach empowers us to manipulate essential link attributes, including flow capacity, free speed, and the number of lanes. Through this method, we gain precise control over the network's characteristics, allowing us to simulate and analyze traffic conditions under varying scenarios with high accuracy and granularity.

The queue-based traffic flow simulation involves treating a network link as a discrete point queue. Upon a vehicle's entry into a link, it is appended to the tail of a waiting queue situated at the link's initiation. The travel duration along this link is established on the free flow speed. In addition, the queue-based model streamlines computational processes by neglecting intra-link interactions. In instances of link saturation, the flow within MATSim remains constant, contingent upon the downstream link being unobstructed. This contrasts with real-world scenarios where flow diminishes with increasing density. The underlying assumption is that MATSim equilibrium unfolds within a persistent state devoid of traffic oversaturation. It is imperative to acknowledge that additional variables, such as traffic volume and non-residential excursions, have been omitted due to data limitations. The calibration of road free flow speed becomes imperative in light of these considerations.

The calibration was run for ten iterations, and the standard deviation was around 0.001 km/h. The average results presented in Figure 5 show a comparison of iTIC and our network speed with calibration for both express and ordinary links during peak hours. For the express links, the relative error of the model with calibration is equivalent to 3.54% on average, with the highest at 7.13%. In the case of the ordinary links, the relative error is 3.74% on average, with the highest at 5.81%. The average speed of both iTIC and the model shows that the speed patterns during evening peak hours exhibit a consistent trend of lower speeds compared to the morning peak hours. This phenomenon is observed for both express and ordinary links. Such a pattern aligns with typical traffic behavior in urban areas, where traffic congestion intensifies during evening rush hours due to increased travel demand.

3.3.3. Model Validation

The BAU scenario's result was compared with the observed data from OTP's HTS data to ensure the accuracy of our modeling. Table 4 shows the travel statistics of the observation and simulated data [30]. It is crucial to note that the average trip length in the model was smaller by 20% compared to the observation. This discrepancy is attributed to the combination of car and motorcycle modes and the simplification of the network structure. Furthermore, the travel time in our simulation was found to be lower than that observed in the HTS dataset. This variance can be attributed to the model's higher average speed, exceeding the HTS average by 16%, influenced by the integration of iTIC

traffic data. The model validation process underscores the effectiveness of our simulation in capturing the essence of travel patterns within the study area. The slight disparities observed in trip length and travel time are justifiable, given the complexities involved in merging distinct modes of transportation and the influence of external traffic data. The overall alignment of trip numbers and age distribution reaffirms the reliability of our model, providing confidence in its utility for further analyses and scenario evaluations.

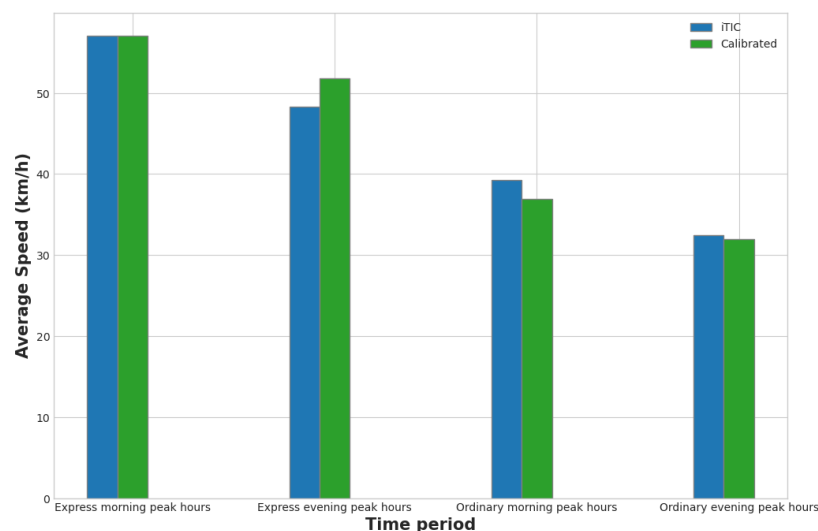


Figure 5. Comparison of iTIC and calibrated network on express and ordinary links in peak hours.

Table 4. Comparison of travel statistics between observation and simulation.

Travel Statistics	Observation		Simulation
	Car	Motorcycle	Car
Average trip length (km/trip)	16	10	12.9
Travel time (min)	36	24	34.2
Average Speed (km/h)	26	25	30.4

4. Comparison of Alternative Scenarios

4.1. Setting up Scenarios

We observed the travel plans in the HTS, which consist of trip chain activities, such as home, work, education, and other activities. The education activity is the school trip, which is the focus of this study. The escorted trip chain is the shared mobility from home; the next destination is the school, and its following destination is the workplace. The trip solely made for escorting students also indicates the necessity of accompanying trips. Therefore, we designed the following cases to analyze the impact of school trips: (1) BAU is the baseline scenario consisting of working, education, and other trip activities. (2) School Trips Elimination is the scenario that excludes the education activity for analyzing the impact of school trips. (3) Work Time Shift is the scenario that randomly adjusts the schedules of half of the workers by moving their daily activities 25% earlier or 25% later in many consecutive iterations to diversify their commuting times. For example, if the usual departure time was around 6 a.m., that individual's departure will be shifted to either 5 a.m. or 7 a.m. (4) School Time Shift is the scenario that changes schools' starting times later and results in a need for students and their parents to adapt their schedules to match the new school start times. By allowing flexible work for their parents, parents' and students' departure times are shifted to compromise the school starting time. (5) Work From Home (WFH) is the scenario that allows a particular portion of workers to do their work at home.

4.2. Effects of School Trip Reduction on Urban Traffic Congestion

Figure 6 presents school locations and the road average speed difference between the BAU and the BAU without school trips. It is evident from Figure 6a in the morning peak that, on average, the traffic speed gets higher in almost all areas close to the school locations. Around the border of the inner area, the average speed is higher than 20 km/h, which is significantly higher than the BAU case. This highlights the effects of school trips on traffic congestion.

Figure 6b shows the evening peak period; the average speed is higher than 20 km/h in the inner area and the intermediate area. This result is consistent with the morning peak hour. The absence of school trips has a positive impact on traffic congestion, even in the most congested period, because workers finish their jobs around 5 p.m. and start to commute back home. Therefore, it marked a more remarkable improvement compared to the morning peak hour and the substantial role of school trips in shaping traffic.

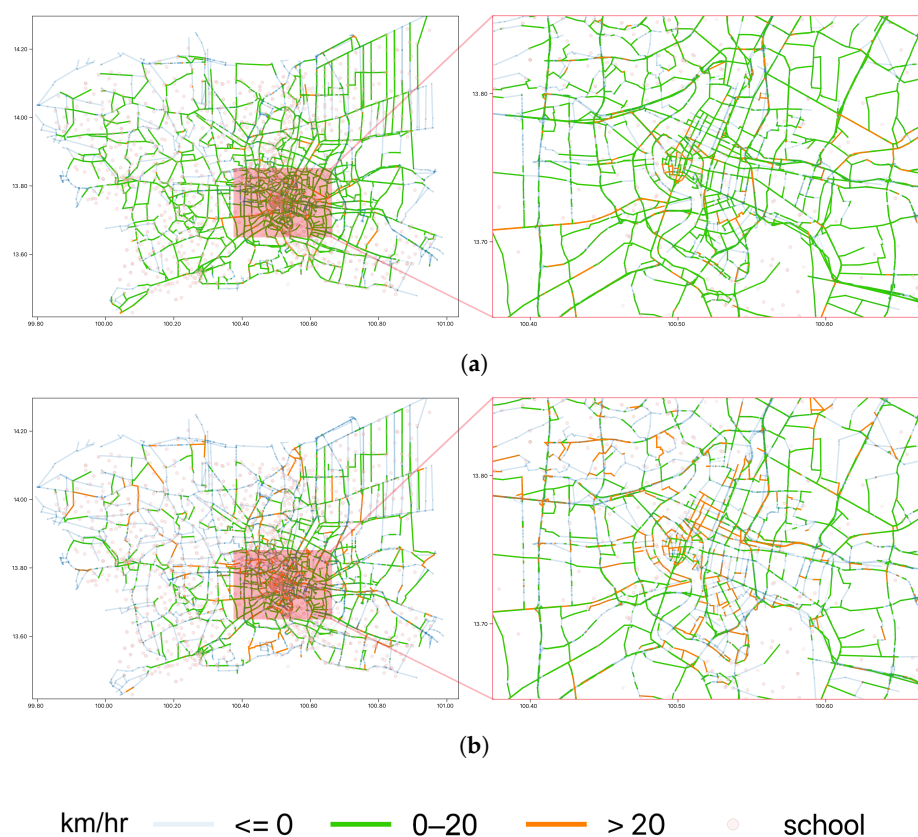


Figure 6. Spatial distribution of road network speed difference between BAU with school trips and BAU without school trips: (a) average road network speed on 7 a.m. and (b) average road network speed on 6 p.m. School locations are shown in pink dots.

4.3. Average Travel Time per Trip among TAZs

In the BAU, the average travel time's high-value areas are located around the suburban areas of the city, as shown in Figure 7a. The red areas are pretty far away in suburban areas, indicating that commuters must move to the central areas. People in the city area are not always long-distance travelers, but suburban people move towards the city center since school locations are not around their residences. The BAU excluding school trips in Figure 7b shows that almost all suburban long-distance trips have disappeared, which leads to the average travel time reduction from this comparison. This finding is consistent with the travel distance distribution, where the school areas are primarily located in the inner area. This phenomenon can be attributed to the high demand for travel in the outer area,

leading to traffic congestion. Conversely, in the BAU excluding school trips, the average travel time in the inner area is relatively lower, as the school trips are missing. This finding corroborates the relationship between traffic congestion and school trips because school trips compete mainly with work trips during peak hours.

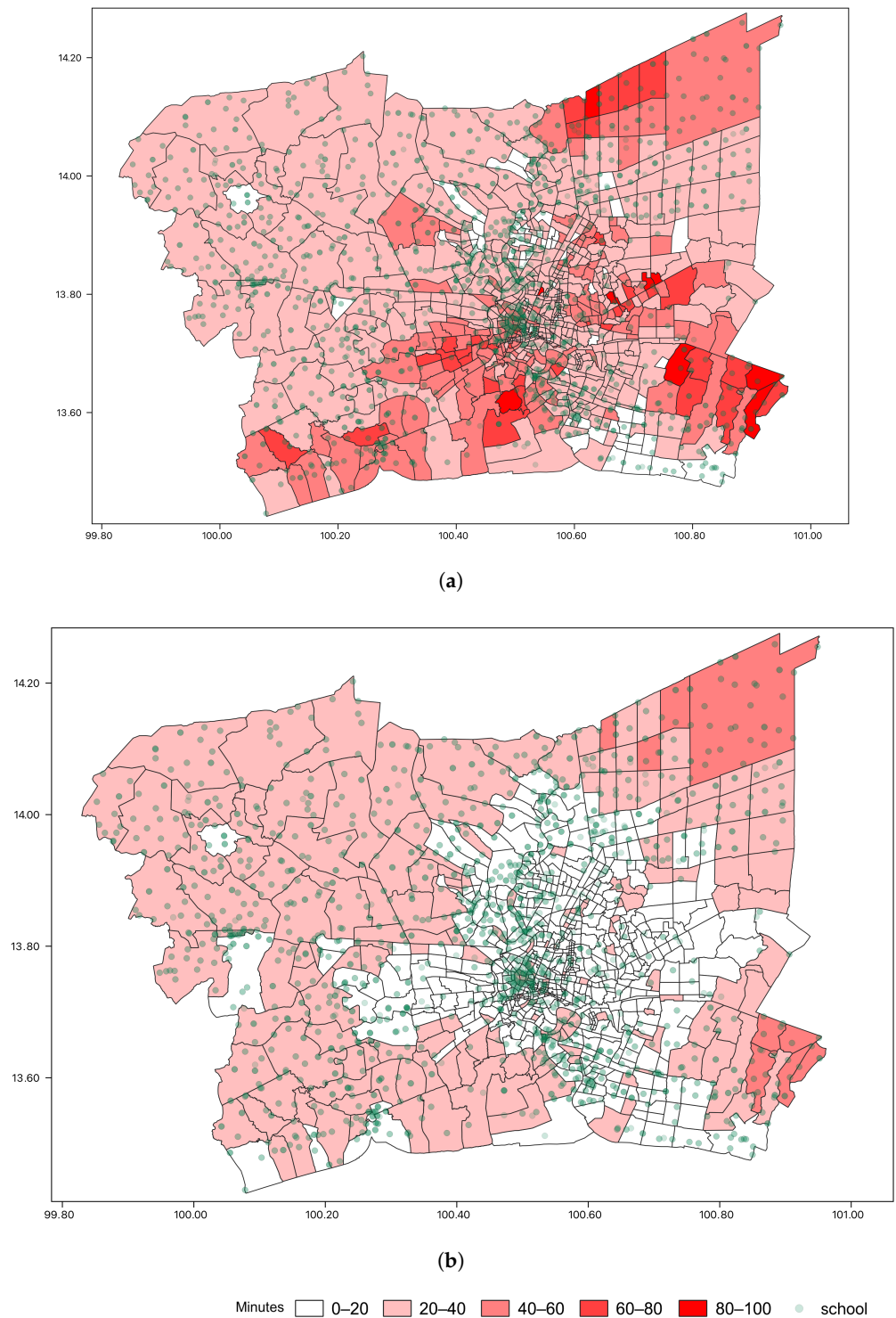


Figure 7. Average travel time per trip in minutes for all travelers in the TAZs for each scenario: (a) BAU and (b) BAU excluding school trips. School locations are shown in green dots.

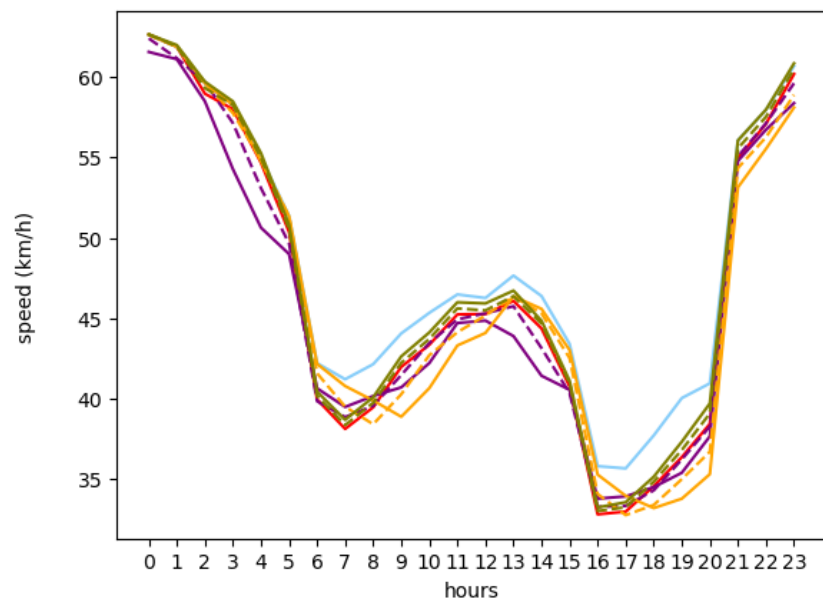
4.4. Comparison of Average Speed over All Links between Scenarios

Figure 8 presents a detailed overview of average speed over all links variations throughout a day, offering insights into the effects on traffic congestion of eight scenarios as follows: (1) in the BAU case, the average speed on 7 a.m. is 38.11 km/h, and the average speed on 6 p.m. is 34.55 km/h. (2) in the BAU without school trips, the average 7 a.m. and 6 p.m. speed is 41.20 km/h and 37.70 km/h, respectively. This clearly shows the effectiveness of school trip absence due to the speed increment at 7 a.m. and 6 p.m., about 8.1% and 9.1%, respectively, over the baseline. (3) in the Work Time Shift one-hour scenario, the average speed at 7 a.m. and 6 p.m. is 38.85 km/h and 34.29 km/h, respectively, and its differences to the baseline are 1.9% and −0.7%. (4) in the Work Time Shift two-hour scenario, the average 7 a.m. and 6 p.m. speed is 39.48 km/h and 34.49 km/h, respectively, and its differences to the baseline are 3.5% and −0.1%. (5) in School Time Shift one hour, the average 7 a.m. and 6 p.m. speed is 39.49 km/h and 33.38 km/h, respectively. The speed difference compared to the baseline at 7 a.m. and 6 p.m. is around 3.6% and −3.3%. (6) in the School Time Shift two-hour scenario, the average speed at 7 a.m. and 6 p.m. is 40.78 km/h and 33.18 km/h, respectively, and its differences to the baseline are 6.9% and −3.9%. (7) in WFH 10%, the average 7 a.m. and 6 p.m. speed is 38.35 km/h and 34.83 km/h, respectively. The speed difference compared to the baseline at 7 a.m. and 6 p.m. is around 0.6% and 0.8%. (8) in the WFH 20% scenario, the average speed at 7 a.m. and 6 p.m. is 38.68 km/h and 35.14 km/h, respectively, and its differences to the baseline are 1.4% and 1.7%.

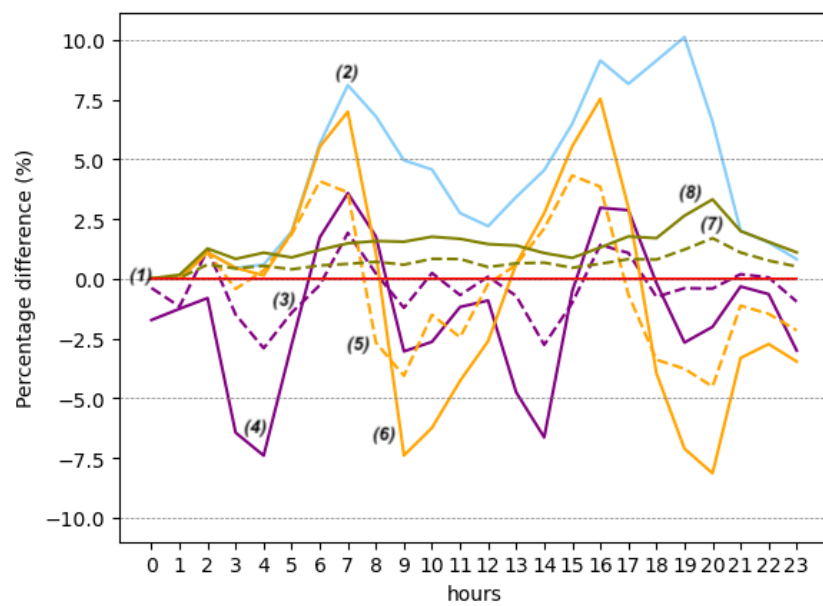
In the morning peak hours, we observe that the BAU case has the lowest speeds, while the BAU case, excluding school trips, records the highest speeds in the morning and evening peaks. This highlights an 8.1% and 9.1% reduction in congestion when school-related travel is absent. The WFH cases have a higher speed than the BAU cases during the whole day. This reflects the importance of demand reduction, which is the best practical solution against congestion. However, during the evening peak hours, the “School Time Shift” scenarios consistently exhibit a slow speed with −3.3%.

In the School Time Shift scenarios, the traffic speed is improved during non-peak hours by around 4.32%. This emphasizes the significance of the timing of school-related travel in influencing evening traffic congestion. The “Work Time Shift” scenarios demonstrate a unique traffic pattern with 1.9% and 1.0% improvement during the morning and evening peak hours, respectively. While these scenarios experience improved speeds during peak hours, they concurrently witness reduced speeds during other times of the day. This trade-off underscores the complexity of traffic management, where attempts to alleviate congestion during specific hours can impact traffic conditions at different times.

With results from various scenarios, the time shift scenario alone is not as effective as the combination of the work-from-home scenario and the time shift scenario. When applying a time shift scenario, traffic in a specific timeframe tends to flow more smoothly, while later, it becomes congested. Contrastingly, the work-from-home scenario has the most impact on overall timelines. Reducing the demand for physical commuting by enabling remote work has a noticeable effect on mitigating traffic congestion across multiple periods. Therefore, when proposing a flexible working time policy, it is crucial to consider the location of workplaces and school timing because they proved to be a more comprehensive and practical approach for addressing and alleviating traffic congestion issues.



(a)



(b)

- | | |
|----------------------------|------------------------------|
| 1.BAU | 5.School Time Shift 60 mins |
| 2.BAU without School | 6.School Time Shift 120 mins |
| 3.Work Time Shift 60 mins | 7.WFH 10% |
| 4.Work Time Shift 120 mins | 8.WFH 20% |

Figure 8. Comparison of average speed over all links in BMR between scenarios for each hour in a day: (a) speed and (b) percentage difference compared with the BAU case.

4.5. Total Travel Time

The comparison of total travel time is a critical indicator in assessing the efficiency and effectiveness of various scenarios to alleviate traffic congestion. The result presented here reveals compelling insights into the potential impact of different strategies on reducing total travel time within the metropolitan road network. First and foremost, the BAU scenario, representing the typical traffic conditions, demonstrates a total travel time of approximately

243,419 h, as shown in Figure 9. This baseline scenario serves as a crucial reference point for evaluating the effectiveness of proposed interventions. Notably, when school trips are excluded, the total travel time falls 72.78% to roughly 66,260 h, underscoring the significant influence of school-related travel on congestion.

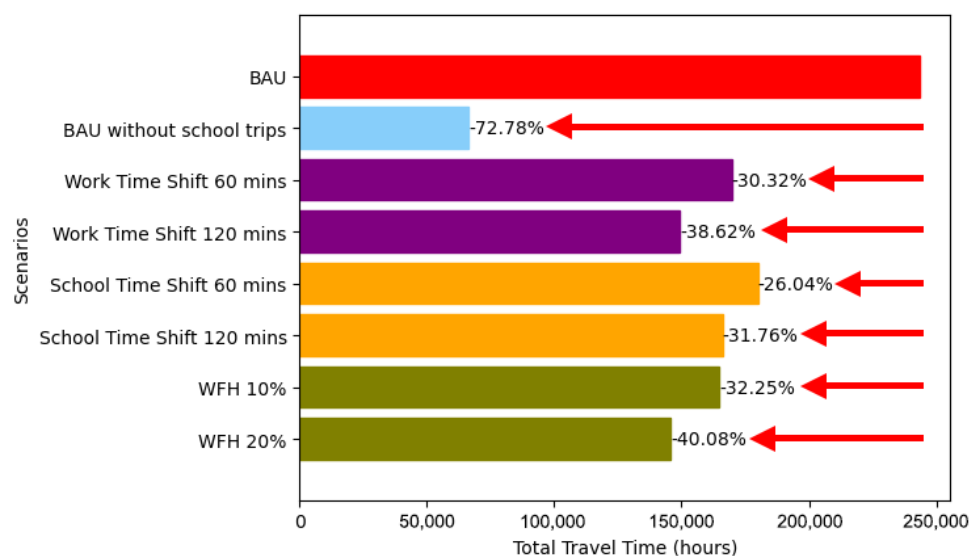


Figure 9. Comparison of total travel time in minutes between scenarios.

On the other hand, the introduction of work time shifts, whether by one or two hours, results in 30.32% and 38.62% reductions in total travel time. The “Work Time Shift 1 h” scenario, for instance, demonstrates a marked decrease to approximately 169,626 h, suggesting that staggered work hours have the potential to alleviate congestion during peak hours. Similarly, the “School Time Shift 1 h” and “School Time Shift 2 h” scenarios illustrate 26.04% and 31.76% reductions in total travel time, highlighting the importance of adjusting school start times to optimize traffic flow. Lastly, the “WFH 10%” and “WFH 20%” scenarios yield reductions of 32.25% and 40.08% in total travel time. These findings underscore the potential benefits of time-based interventions and location-based interventions in reducing traffic congestion and enhancing urban mobility.

4.6. CO₂ Emission

This result comprehensively compares carbon dioxide (CO₂) emissions as shown in Figure 10, measured in kilograms, across scenarios to mitigate emissions in the urban environment. Each scenario represents distinct strategies to address emissions, offering valuable insights into their potential environmental impact.

$$\text{CO}_2 = \frac{d}{s \times 10} 2.007 \quad (2)$$

where d is the distance in kilometers, s is the speed in km/h, 10 is the assumed kilometers per liter, and 2.007 is the fuel consumption rate in kgCO₂eq/L [31]. The individual traveler’s distance and travel time are calculated with Equation (2) from the simulation results to get each commuter emitted CO₂ emission.

The BAU scenario, serving as the baseline, reveals substantial CO₂ emissions of approximately 2.23 kilotonnes. It underscores the significance of emissions in typical traffic conditions, framing subsequent comparisons. When school-related travel is excluded, CO₂ emissions decrease 77.08% to about 0.5 kilotonnes. It also highlights the substantial contribution of school-related commuting to urban CO₂ emissions, pinpointing a key focus area for emission reduction.

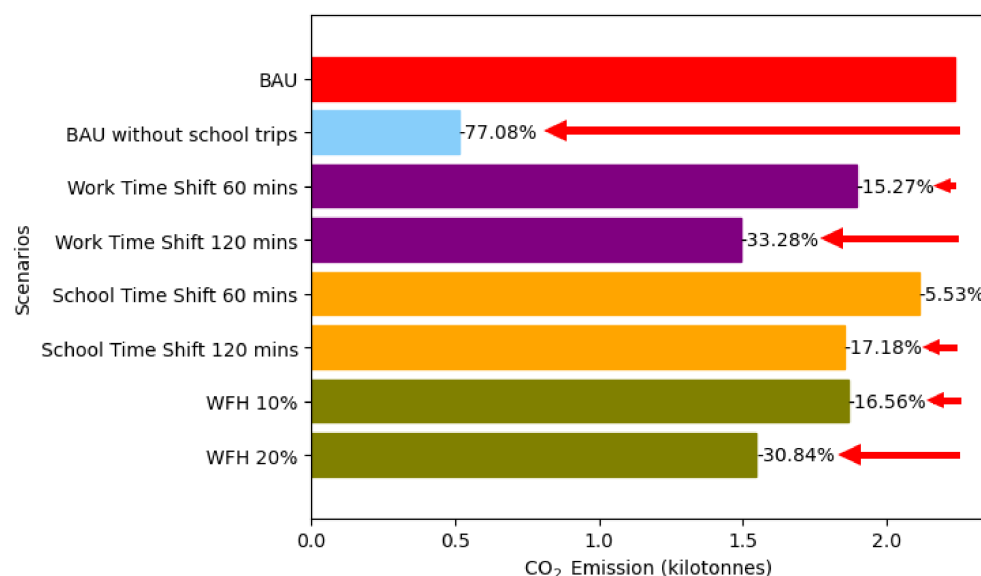


Figure 10. Comparison of CO₂ emission between scenarios.

Promisingly, alternative strategies yield noteworthy reductions in CO₂ emissions. “Work Time Shift 1 h” and “Work Time Shift 2 h” scenarios demonstrate 15.27% and 33.28% reductions of CO₂ emissions, emphasizing the potential of staggered work hours in reducing greenhouse gas emissions. Similarly, scenarios involving adjustments to school start times, such as “School Time Shift 1 h” and “School Time Shift 2 h”, exhibit 5.53% and 17.18% CO₂ reductions, underlining the environmental benefits of these interventions. “WFH 10%” and “WFH 20%” scenarios yield CO₂ reductions of 16.56% and 30.84%. Surprisingly, the reduction amount of “School Time Shift 2 h” and “WFH 10%” is very close. These findings underscore the feasibility of a comprehensive strategy that combines both time-based strategies and location-based strategies in mitigating CO₂ emissions within urban transportation towards sustainability, offering a more robust and adaptable strategy.

5. Conclusions

5.1. Effects of Alternative Scenarios

In this study, as a metropolitan comprehensive scenario, we look into the time design dimension to explore its potential in distributing travel demand. As a local scenario, we also examine the effect of preparation of unloading spaces inside school sites and the benefit of working from home.

According to the results of Section 4 and Figure 8, we conclude this research as follows:

5.1.1. Flexible Working Time (Time Design, Scenario 3 and 4)

Several policy measures can be proposed to alleviate congestion resulting from school trips. One effective solution is the implementation of flexible work hours for parents. By allowing parents to adjust their work schedules by one hour (Scenario 3), the traffic speed can be increased by 1.9% at 7 a.m. and 1.0% at 6 p.m. While adjusting their work schedules two hours (Scenario 4) has the traffic speed at 7 a.m. and 6 p.m. as 3.5% and −0.1% compared to the baseline. These effects are limited.

5.1.2. Staggered School Start Times (Time Design, Scenario 5 and 6)

The introduction of staggered school start times and corresponding parent working hours can help distribute traffic more evenly than Scenarios 3 and 4 throughout the morning and evening, diminishing the stress on road infrastructure during rush hours. Scenario 5 (students commuting to school later one hour) can lead to an even more congested situation during peak hours. Still, the traffic speed during off-peak hours is 4.3%, increased from the

BAU, which is higher than in other cases. Scenario 6 (students commuting to school later two hours) has the same effect as Scenario 5 but better speed improvement at 7 a.m.

5.1.3. Work from Home (Physical Urban Design, Scenario 7 and 8)

The introduction of the work-from-home scenario not only reduced the travel demand in the network but also shed light on remote working benefits. The flexible working location was proved to be eligible for most employers due to the pandemic. With only 10% of workers applying this policy, the improvement in road network speed and total travel time for commuters in the network prevailed. Even though the staggered activity time scenario is efficient, the unchanged activity location will hinder its effectiveness. Therefore, remote working will be possible if work from home is allowed, and it can empower another policy greatly.

5.1.4. Local Physical Design

School escorting cars surge in traffic is primarily attributed to parents dropping off their children on the road in front of schools, causing road demand to spike and often leading to road lane blockages. This evidence is shown in our result when comparing the average road network speed. The network speed is significantly increased around the school locations during both morning and evening peak hours in case of excluding school-related trips (Scenario 2). This reminds us that schools have to prepare adequate loading spaces inside their sites. This is the matter on roadside sites. Local design modifications should be explored to facilitate seamless drop-off and pick-up points at schools. For example, if the school site has access from at least two adjacent roads, it can distribute the traffic entering and exiting the site. An adequate driveway on site is also an important factor to support stacking cars which should be able to support the maximum queue lengths during drop-off and pick-up periods to prevent spillback on adjacent roads.

5.2. Policy Implication

The Bangkok Metropolitan Administration (BMA) ordered officers of around 20,000 to utilize staggered working hours to start their work at 10 a.m. instead of 8 a.m. BMA suspended education classes due to unhealthy smog levels in Bangkok. BMA believed that staggered working hours would lead to a reduction of vehicles during rush hours and the use of private cars by parents [32]. Flexible working time policy was already implemented in the government and widely adopted in the private sector by counting the required number of working hours regardless of their starting time. Cabinet approved working guidelines to support the new way of living and working as a result of the pandemic period [33]. The guidelines contain three topics: staggered working hours, dynamic working hours, and remote working. Firstly, the operating hours are divided into four options: 7:30 a.m. to 3:30 p.m., 8:00 a.m. to 4:00 p.m., 8:30 a.m. to 4:30 p.m. and 9:30 a.m. to 5:30 p.m. Secondly, the total working hours within a week must be at least 40 h. Thirdly, working outside the working office is allowed.

As mentioned earlier, the Thai government recognized the potential benefits of these interventions in the short and long term. However, workers who have children still need to work on their limitations since the school starting time is fixed. Most of them followed their usual behavior, which led to the same congestion. The integration of staggered school times should also be considered since it aligns with the goal of reducing vehicles during peak hours. Moreover, remote working would have significant benefits to the parents since the school may be located in the opposite direction of the work office, and they need to detour across the city. Achariyaviriya et al. [28] simulated the space-time distribution with the idea of introducing co-working spaces and flexible working hours, which proved to be effective in reducing traffic congestion during peak hours. Therefore, as seen in the result of this study, the combination of space and time design is very crucial even though they are separated, but considering these two matters can shape the final policy to be as effective as possible to overcome these persistent challenges.

The advantage of staggered working and school hours is to reduce congestion during peak hours and lower levels of CO₂ emissions. Workers who value flexibility and understand the benefits of reduced commute times might appreciate the changes. Citizens who suffer from daily traffic jams and consider consequences as a positive step toward improving the quality of life will likely support these policies. However, individuals with a conservative mindset, those resistant to change or affected negatively, may oppose these measures. Workers or students who have established routines may find it challenging to adapt to flexible hours, leading to dissatisfaction and potential disruptions to productivity. Working parents and single individuals may be concerned about fairness regarding individual circumstances and work balance. Therefore, the policymaker should implement these measures within a controlled environment to identify potential challenges and make necessary adjustments.

To effectively alleviate traffic congestion more sustainably, it is imperative to reduce excessive car traffic significantly. This study revealed the significant contribution of education-related escorted trips to congestion. While young children still require parental accompaniment, encouraging higher-level students to use public transport, particularly urban railways, is crucial. This shift aligns with Bangkok's evolution into a polycentric city, anticipating the emergence of employment and education hubs around subcenters connected by railways [34].

5.3. Study Limitation and Future Research

Our study confronts several limitations that impact the depth and precision of our analysis, primarily stemming from data scarcity. The reliance on traffic counter data for benchmark road analysis in our simulation model is hindered by the limited availability of such data. The number of survey samples is also a small portion compared to the whole population number, which needs more trip diversity and business-to-business trips. To calibrate the model, we are constrained to using traffic speed data solely from the iTIC dataset, which is not exhaustive. The iTIC dataset's collection is restricted to a specific number of traffic links, and the inconsistent frequency of data collection further compounds this limitation. Crucially, the absence of data on critical metrics, such as traffic volume and vehicle composition in link data, impedes a comprehensive validation of our simulation model.

We employed the synthetic population method, incorporating survey data to deal with data availability. For travel mode choice and activity planning, we aligned our synthetic population with travel plans from the HTS, leveraging sociodemographic attributes to enhance consistency. However, a limitation arises from the fact that HTS data is derived from a limited number of respondents, and its sample size only offers a representative cross-section of the entire population. Additionally, the temporal focus of HTS data on daily commuter activities from morning to evening raises concerns about the limited diversity in travel patterns. As noted by Ramadan and Sisiopiku [35], these limitations can potentially impact the accuracy of our simulation model, limiting its ability to capture the complexities of real-world scenarios fully and consequently affecting the generalizability of our results.

In light of these limitations, it is imperative to shape policies that address the challenges associated with traffic congestion, particularly concerning school-escorted trips. Local authorities should consider amending the regulation to allow the usage of mobile phone data, especially in the context of research. Bassolas et al. [36] reconstructed the activity plans from the mobile phone records in Barcelona. With the usage of mobile devices, the mobile application can track personal movements through a global positioning system (GPS) and local interaction by Bluetooth. If the local authorities utilized the collection of mobility information, the big data would be available in each district to be analyzed. Simultaneously, qualitative data on travel behavior can be enriched through more extensive and representative surveys. By enhancing the quality and quantity of available data, these measures can contribute to more robust and precise findings. The development of mobility

simulation in the context of Bangkok is also crucial to emphasize the travel characteristics and structures that ensure the actual traffic situation in the simulation.

In our future studies, we want to investigate the impact of both staggered activity time and remote working and the introduction of transport modes such as public transport or school bus service. With the integration of public transport, bus services in Bangkok run on the road network, while in developed countries, the bus has its dedicated road. Bus routes need to be mapped into the current road network to experience the congestion. The school bus is not common in Bangkok due to its cost of operation, but it is also one of the mass transport vehicles to escort children to school, which can reduce the usage of private vehicles directly.

Author Contributions: Conceptualization, V.V., T.P. and Y.H.; methodology, V.V. and T.P.; data preparation, T.P. and V.V.; validation, T.P.; data analysis, T.P.; writing—original draft preparation, T.P. and Y.H.; writing—review and editing, T.P., Y.H., V.V. and H.T.; visualization, T.P.; supervision, Y.H. and V.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Science and Technology Research Partnership for Sustainable Development (SATREPS) (JST/JICA JPMJSA1704).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors affirm no conflict of interest. The funders played no part in the study's design, data collection, analysis, interpretation, manuscript preparation, or the decision to publish the study's findings.

Abbreviations

The following abbreviations are used in this manuscript:

MATSim	Multi-Agent Transport Simulation
TAZ	Traffic Analysis Zone
BAU	Business As Usual
HTS	Household Travel survey
iTIC	Intelligent Traffic Information Center
BMR	Bangkok Metropolitan Region

References

1. Vongpuapan, S.; Latchford, J. Traffic Management in Bangkok. In Proceedings of the Transportation Research Record, Washington, DC, USA, 14–17 January 1985.
2. Vichiensan, V.; Wasuntarasook, V.; Hayashi, Y.; Kii, M.; Prakayaphun, T. Urban Rail Transit in Bangkok: Chronological Development Review and Impact on Residential Property Value. *Sustainability* **2022**, *14*, 284. [\[CrossRef\]](#)
3. Ayaragarnchanakul, E.; Creutzig, F. Bangkok's locked-in traffic jam: Price congestion or regulate parking? *Case Stud. Transp. Policy* **2022**, *10*, 365–378. [\[CrossRef\]](#)
4. Lu, M.; Sun, C.; Zheng, S. Congestion and pollution consequences of driving-to-school trips: A case study in Beijing. *Transp. Res. Part D Transp. Environ.* **2017**, *50*, 280–291. [\[CrossRef\]](#)
5. Rothman, L.; Buliung, R.; Howard, A.; Macarthur, C.; Macpherson, A. The school environment and student car drop-off at elementary schools. *Travel Behav. Soc.* **2017**, *9*, 50–57. [\[CrossRef\]](#)
6. McMillan, T.E. The relative influence of urban form on a child's travel mode to school. *Transp. Res. Part A Policy Pract.* **2007**, *41*, 69–79. [\[CrossRef\]](#)
7. Curtis, C.; Babb, C.; Olaru, D. Built environment and children's travel to school. *Transp. Policy* **2015**, *42*, 21–33. [\[CrossRef\]](#)
8. Yeung, J.; Wearing, S.; Hills, A. Child transport practices and perceived barriers in active commuting to school. *Transp. Res. Part A Policy Pract.* **2008**, *42*, 895–900. [\[CrossRef\]](#)
9. Zhang, R.; Yao, E.; Liu, Z. School travel mode choice in Beijing, China. *J. Transp. Geogr.* **2017**, *62*, 98–110. [\[CrossRef\]](#)
10. Rojas López, M.C.; Wong, Y.D. Process and determinants of mobility decisions—A holistic and dynamic travel behaviour framework. *Travel Behav. Soc.* **2019**, *17*, 120–129. [\[CrossRef\]](#)
11. Wilensky, U.; Rand, W. *An Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo*; The MIT Press: Cambridge, MA, USA, 2015.

12. Chiou, Y.S.; Bayer, A.Y. Microscopic Modeling of Pedestrian Movement in a Shida Night Market Street Segment: Using Vision and Destination Attractiveness. *Sustainability* **2021**, *13*, 8015. [\[CrossRef\]](#)
13. Borshchev, A. Multi-method modelling: AnyLogic. In *Discrete-Event Simulation and System Dynamics for Management Decision Making*; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2014; pp. 248–279. [\[CrossRef\]](#)
14. Horni, A.; Nagel, K.; Axhausen, K., Eds. *Multi-Agent Transport Simulation MATSim*; Ubiquity Press: London, UK, 2016; p. 618. [\[CrossRef\]](#)
15. Smith, L.; Beckman, R.; Baggerly, K. *TRANSIMS: Transportation Analysis and Simulation System*; U.S. Department of Energy: Washington, DC, USA, 1995. [\[CrossRef\]](#)
16. Bastariento, F.; Hancock, T.; Choudhury, C.; Manley, E. Agent-based models in urban transportation: Review, challenges, and opportunities. *Eur. Transp. Res. Rev.* **2023**, *15*, 19. [\[CrossRef\]](#)
17. McNally, M.G. The Four Step Model. In *Handbook of Transport Modelling*; Emerald Group Publishing Limited: Bingley, UK, 2007.
18. Bonabeau, E. Agent-based modeling: Methods and techniques for simulating human systems. *Proc. Natl. Acad. Sci. USA* **2002**, *99* (Suppl. S3), 7280–7287. [\[CrossRef\]](#) [\[PubMed\]](#)
19. He, B.Y.; Zhou, J.; Ma, Z.; Wang, D.; Sha, D.; Lee, M.; Chow, J.Y.; Ozbay, K. A validated multi-agent simulation test bed to evaluate congestion pricing policies on population segments by time-of-day in New York City. *Transp. Policy* **2021**, *101*, 145–161. [\[CrossRef\]](#)
20. Kii, M.; Goda, Y.; Vichiensan, V.; Miyazaki, H.; Moeckel, R. Assessment of Spatiotemporal Peak Shift of Intra-Urban Transportation Taking a Case in Bangkok, Thailand. *Sustainability* **2021**, *13*, 6777. [\[CrossRef\]](#)
21. Hörli, S.; Ruch, C.; Becker, F.; Frazzoli, E.; Axhausen, K. Fleet operational policies for automated mobility: A simulation assessment for Zurich. *Transp. Res. Part C Emerg. Technol.* **2019**, *102*, 20–31. [\[CrossRef\]](#)
22. Ciari, F.; Balac, M.; Axhausen, K. Modeling Carsharing with the Agent-Based Simulation MATSim: State of the Art, Applications, and Future Developments. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2564*, 14–20. [\[CrossRef\]](#)
23. Goodman, W.D. Transportation and Staggered Work Hours. *Transp. Law J.* **1972**, *4*, 157.
24. D'Este, G. The effect of staggered working hours on commuter trip durations. *Transp. Res. Part A Gen.* **1985**, *19*, 109–117. [\[CrossRef\]](#)
25. Yildirimoglu, M.; Ramezani, M.; Amirgholy, M. Staggered work schedules for congestion mitigation: A morning commute problem. *Transp. Res. Part C Emerg. Technol.* **2021**, *132*, 103391. [\[CrossRef\]](#)
26. Charypar, D.; Nagel, K. Generating complete all-day activity plans with genetic algorithms. *Transportation* **2005**, *32*, 369–397. [\[CrossRef\]](#)
27. Ben-Dor, G.; Ben-Elia, E.; Benenson, I. Population downscaling in multi-agent transportation simulations: A review and case study. *Simul. Model. Pract. Theory* **2021**, *108*, 102233. [\[CrossRef\]](#)
28. Achariyaviriya, W.; Hayashi, Y.; Takeshita, H.; Kii, M.; Vichiensan, V.; Theeramunkong, T. Can Space–Time Shifting of Activities and Travels Mitigate Hyper-Congestion in an Emerging Megacity, Bangkok? Effects on Quality of Life and CO₂ Emission. *Sustainability* **2021**, *13*, 6547. [\[CrossRef\]](#)
29. Lomax, N.; Norman, P. Estimating Population Attribute Values in a Table: “Get Me Started in” Iterative Proportional Fitting. *Prof. Geogr.* **2016**, *68*, 451–461. [\[CrossRef\]](#)
30. Office of Transport and Traffic Policy and Planning. Results of a Travel Demand Survey in BMR. Available online: https://otp.gdcatalog.go.th/dataset/otp_66_02 (accessed on 10 November 2023).
31. Achariyaviriya, W.; Suttakul, P.; Fongsamootr, T.; Mona, Y.; Phuphisith, S.; Tippayawong, K.Y. The social cost of carbon of different automotive powertrains: A comparative case study of Thailand. *Energy Rep.* **2023**, *9*, 1144–1151. [\[CrossRef\]](#)
32. Bangkok Post. City Hall Orders Staggered Hours in Fight against Smog. Available online: <https://www.bangkokpost.com/business/1840579/city-hall-orders-staggered-hours-in-fight-against-smog> (accessed on 10 November 2023).
33. Thai PBS. Cabinet Approved 3 Forms of Government Service for New Normal. Available online: <https://www.thaipbs.or.th/news/content/319628> (accessed on 10 November 2023).
34. Vichiensan, V.; Wasuntarasook, V.; Prakayaphun, T.; Kii, M.; Hayashi, Y. Influence of Urban Railway Network Centrality on Residential Property Values in Bangkok. *Sustainability* **2023**, *15*, 16013. [\[CrossRef\]](#)
35. Ramadan, O.E.; Sisiopiku, V.P. A Critical Review on Population Synthesis for Activity- and Agent-Based Transportation Models. In *Transportation Systems Analysis and Assessment*; Luca, S.D., Pace, R.D., Djordjevic, B., Eds.; IntechOpen: Rijeka, Croatia, 2019; Chapter 1. [\[CrossRef\]](#)
36. Bassolas, A.; Ramasco, J.J.; Herranz, R.; Cantú-Ros, O.G. Mobile phone records to feed activity-based travel demand models: MATSim for studying a cordon toll policy in Barcelona. *Transp. Res. Part A Policy Pract.* **2019**, *121*, 56–74. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.