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Creating and Validating Hybrid Large-Scale, Multi-Modal Traffic Simulations for Efficient Transport Planning

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Highlights:

What are the main findings?

- With the proposed hybrid toolchain, a seamless transfer from the globally assigned meso-demand to a smaller, locally simulated micro-network has been successfully applied to a test case of the larger Munch metropolitan area.
- The approach allows link-by-link validation between real measurements, as well as the meso- and the micro-simulations; for the test case, both models showed a good fit between simulated and measured traffic flows, but the micro-model showed more realistic results with respect to the meso-model when average link speeds from floating car data were compared.

What is the implication of the main finding?

- With the presented hybrid approach, it will become feasible to efficiently model and simulate large-scale transport scenarios with individual users while enabling a consistent micro-simulation on dedicated areas, which are sensitive to the implementation of a wide range of complex transport services and policy measures.
- It is possible to quantify and directly compare the closeness to reality of the meso- and micro-model, which is useful to demonstrate whether a micro-simulation does offer added value and whether it is worth the additional efforts with respect to the meso-only approach.

Abstract: Mobility digital twins (MDTs), which utilize multi-modal microscopic (micro) traffic simulations and an activity-based demand generation, are envisioned as flexible and reliable planning tools for addressing today's increasingly complex and diverse transport scenarios. Hybrid models may become a resource-efficient solution for building MDTs by creating large-scale, mesoscopic (meso) traffic simulations, using simplified, queue-based network-link models, in combination with more detailed local micro-traffic simulations focused on areas of interest. The overall objective of this paper is to develop an efficient toolchain capable of automatically generating, calibrating, and validating hybrid scenarios, with the following specific goals: (i) an automated and seamless merge of the meso- and micro-networks and demand; (ii) a validation procedure that incorporates real-world data into the hybrid model, enabling the meso- and micro-sub-models to be validated separately and compared to determine which simulation, micro- or meso-, more accurately reflects reality. The developed toolchain is implemented and applied to a case study of Munich, Germany, with the micro-simulation focusing on the city quarter of Schwabing, using real-word traffic flow and floating car data for validation. When validating the simulated flows with the detected flows, the regression curve shows acceptable

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values. The speed validation with floating car data reveals significant differences; however, it demonstrates that the micro-simulation achieves considerably better agreement with real speeds compared to the meso-model, as expected.

Keywords: agent-based model; activity-based model; hybrid simulation; MATSim; SUMO; hybridPY

1. Introduction

In the quest for ever-more-realistic mobility models for planning, transport policy drafting, or transport technology development, there is a trend toward more fine-grained, individual methods, such as activity-based demand models (ABMs), as well as meso- and micro-traffic simulation models. ABMs are capable of replicating the daily or weekly activity–travel schedule of individuals by considering their socio-demographic status, residential location, mobility resources, the accessibility of transport infrastructures and amenities, household interactions, and so on [1]. This advanced approach can generate more temporally and spatially consistent mobility patterns compared to traditional four-step models (FTMs), which just model trips and allow trips made by the same individuals to overlap in time and space. The consistency of travel patterns in space and time can contribute to a more realistic traffic simulation with more granularity.

Using meso- or micro-simulators, the travel demand, calculated using ABMs, can be assigned to the street network to determine the routes taken by agents, for example in a user equilibrium condition [2]. Finally, during the micro-simulation, the agent's trip times and many other important key indicators can be quantified—which means, in general, that the mobility system's reaction to any changes on the demand or supply side can be determined.

Mesoscopic simulators use dynamic queues as a network edge model, with the edge capacity predefined according to network attributes [3]. Once the simulated flow rates into an edge exceed this capacity limits, queues form and may spill over into preceding edges. MATSim (Multi-Agent-Transport Simulation) [4], a popular, open-source meso-traffic simulation, is frequently used in optimization loops to determine user equilibrium, thanks to its efficiency in simulating large regions. In the optimization loop, agents egoistically optimize their daily activity schedules using a co-evolutionary algorithm, adjusting factors such as departure time, transport mode, or route. The optimization is run until an equilibrium state is reached. MATSim includes its demand sub-models and has been integrated with other ABMs to build large-scale scenarios, including TASHA [5], CEMDAP [6], mobiTopp [7], BEAM [8], and FEATHERS [9].

Microscopic simulators, in essence, solve vehicle-motion equations and generate vehicle trajectories and speed profiles. Through car-following models, vehicles interact based on speeds and distances between leader and follower, implicitly defining network edge capacities. Further details, such as lane-change models, lane-to-lane turning restrictions, and traffic light systems can also be simulated. Micro-simulators are much closer to what is understood as a *mobility digital twin (MDT)*. Practically, any policies or plans that aim to change the mobility system, physically or logistically, could be implemented and evaluated with such an MDT. *SUMO* (Simulation of Urban MObility), a widely used, open-source micro-simulation framework, developed and maintained by the German Aerospace Center in Berlin, Germany, employs car-following models to accurately replicate vehicle dynamics, including position, speed, and acceleration in both longitudinal and lateral directions.

However, it requires a precise description of the transport infrastructure such as lanes, lane properties, turning restrictions, and traffic signal programs [10].

While micro-traffic models are regarded as MDT platforms and are applicable to a wide range of problems, they do face two major limitations, which complicate the calibration and validation of the model, particularly in multi-modal, large-scale MDT scenarios, including the following:

- Micro-traffic models are sensitive to infrastructure details; inaccurately modeled details can result in unexpected behavior, such as artificial gridlocks. To prevent these issues, accurate network preparation and testing are essential, requiring significantly more modeling effort compared with meso-simulators.
- Micro-simulations face a high computational burden and excessively long simulation times compared to meso-simulations. The dynamic queue model in meso-simulations is much faster than the car-following models used for each vehicle on each edge [11]. Furthermore, meso-models can simulate scenarios with down-scaled demand by adjusting edge capacities accordingly [12].

However, meso- and micro-simulation models have complementary strengths in modeling effort, speed, and accuracy, making a hybrid approach advantageous. Hybrid models utilize a multi-level framework to comprehensively represent mobility dynamics by integrating large-scale meso-simulations with the detailed precision of micro-simulations in areas of particular interest. This combination enhances the understanding of traffic behavior by leveraging the unique strengths of each simulation environment [13].

Even if the advantages of hybrid traffic models, such as the shorter computation time [14] or reduced modeling complexity and effort while maintaining the ability to efficiently estimate the user equilibrium, are known and recognized, current approaches are often limited to small and often pure theoretical problems. However, no framework currently supports the development and execution of hybrid traffic models in practical applications. Additionally, no large-scale, multi-modal hybrid traffic model has been validated through hourly or daily link-to-link analysis.

This paper contributes to the state of the art by presenting a toolchain, named **hybridPY**, to efficiently generate hybrid traffic models by combining the open-source traffic simulation frameworks SUMO and MATSim. The method presented makes it possible to bridge the differences between MATSim and SUMO by synchronizing the networks and, based on this, to transfer the predicted user equilibrium from the meso-level to the micro-level. The proposed tool-chain is applied to a case study, in Munich, Schwabing. The results are validated using flow measurements and speed profiles obtained from floating car data. The remainder of this section describes the state of the art and defines the goals of this paper.

2. State of the Art

The development of hybrid models has led researchers to address several critical challenges: ensuring consistent traffic dynamics at model boundaries, maintaining uniform network and route choice representations, aligning traffic performance across different sub-models, and enabling effective data exchange between simulation modes [15]. State-of-the-art approaches to multi-level traffic models can be categorized in terms of applied models, the type of coupling, and the application area. In literature, macroscopic (macro)-micro and meso-micro hybrid traffic models can be found. The hybridization method itself can be categorized into sequential (or static) and parallel (or dynamic) approaches.Sequential coupling means the models are executed after another, what involves fixed interactions established at the initialization of each simulation, whereas parallel coupling allows for a real-time data exchange between both simulations executed in parallel during the run-time throughout the simulation, enabling more flexible and responsive model interactions [16].

Several studies have investigated the coupling of flow-based macro models with vehicle-based micro-models by proposing theoretical hybrid approaches to effectively manage transitions, particularly at the boundaries [17–20], routing integration [21] between scales. In the recent literature, different strategies have been proposed using multi-resolution agents combining the different resolutions in one entity [14,22], constructing a model-switching criterion designed to reduce the computational load while accurately capturing traffic jam dynamics, especially around highway merging sections [23,24], middleware-based solutions [25], and cluster principles [26] for managing data exchange, synchronization, and representation between simulations.

To achieve a higher resolution and accuracy in meso-simulations, several meso–micro-hybridization techniques have been proposed. Burghout et al. [13] introduced an integration architecture with a common module that manages the network by adjusting model detail levels and adding virtual edges to ensure consistent route choices and vehicle communication across boundaries. The framework was then utilized to develop a hybrid Mezzo–VisSim model, enabling an interface with an adaptive signal controller simulator at intersections [15]. A similar approach was proposed by Barceló et al. [27], a so-called dynamic traffic assignment server. Burghout et al. [28] further proposed a loading mechanism at the meso–micro-boundaries for a consistent representation of traffic dynamics. Claes et al. [29] proposed an adaptive strategy called the schedule–pull protocol, which enables switching between different simulation models at runtime to optimize performance. Joueiai et al. [30] focused on two main classes of consistency problems in hybrid modes, including local and global consistency, both aimed at ensuring the coherence of traffic features between model interfaces. Nevertheless, these hybrid model approaches have been applied to hypothetical testing scenarios only.

In recent years, hybrid traffic models have been developed and applied to real-world problems. Casas et al. [31] enhanced Aimsun's meso–micro-capabilities to model a coarse freeway network of 1160 km in Madrid, Spain, focusing on network consistency, route choice, communication, and data exchange. The model employed a trip-based approach to simulate morning car travel demand and compared the results with real data. The hybrid model of Aimsun was also coupled with an FTM named CUBE to model 24-h multi-modal travel demand for Minneapolis–Saint Paul, Minnesota, USA in 2015 [32]. The study used loop detector flow and turning movement data for model calibration at mayor roads at peak hour. However, different validation methods and validated data (e.g., hourly and daily link-by-link volumes and speed data) have not been comprehensively considered. Nevertheless, Aimsun is commercial software, and it is not available as an open source.

Efforts to couple the open-source frameworks MATSim and SUMO into a hybrid, small-scale network traffic model are detailed in the study by Gütlein et al. [33,34]. The authors proposed a co-simulation framework running MATSim and SUMO in parallel. Nevertheless, their model focuses on operational efficiency and technical synchronization between sub-modules instead of validating with real-world data. To tackle the overestimation of junction capacities in meso-models, Rakow et al. [35] combined SUMO and MATSim to simulate autonomous vehicles (AVs) by first using first using SUMO micro-simulation environment to assess traffic-flow capacities at signalized intersections and then feeding the results into MATSim to explore system-wide and long-term impacts. Therefore, the traffic dynamics in micro-simulation (e.g., vehicle interactions beyond the junction area) have not been comprehensively accounted for in the hybrid model. Moreover, the model was validated solely based on the car-model share and total trip numbers. Triebke et al. [36,37] sequentially coupled MATSim and SUMO to model fleet strategies for shared autonomous vehicles (SAVs), initially employing MATSim for preliminary modeling and subsequently refining the results with SUMO, utilizing uncleaned micro-networks from OpenStreetMap (OSM). These efforts focus purely on simulating SAV performance, rather than modeling mobility aspects.

Furthermore, a very recent daily, large-scale, mono-modal, co-simulation approach has been developed for the City of Berlin, Germany [38]. Car-based traffic demand was extracted from a calibrated MATSim scenario and transferred to a manually cleaned SUMO network in a scaled and randomized manner for micro-simulation. This study demonstrated the feasibility of the method by comparing link-by-link hourly simulation results to actual traffic counts, proving its applicability to analyzing new mobility solutions. However, the model considers exclusively car traffic, neglecting other modes such as buses, trams, commercial vehicles, bicycles, and pedestrians. Notably, the approach relies on re-estimating user equilibrium through iterative SUMO simulations and route-choice adjustments, which may significantly extend simulation times.

Table 1 summarizes the published hybrid models applied to large-scale scenarios from the literature. The state of the art shows that recent advancements in hybrid, multi-level macro–micro- and meso–micro-modeling techniques are increasingly being explored to construct more comprehensive and realistic MDT scenarios.

But despite recent advancements, significant research gaps remain in developing hybrid models: (i) Current approaches *lack a framework for creating hybrid traffic simulations using open-source simulators*. These models lack a seamless workflow that allows for the insertion and connection of a smaller micro-network into a larger meso-network while the routes are reconfigured, in particular the network boundaries between the meso-model and the micro-model. This leads to difficulties in maintaining scenario consistency across all phases, from network and travel demand generation to meso- and micro-simulations, and in enabling seamless comparisons with real-world traffic volumes, as well as GPS-based speed data. The manual approach using the micro-network for the entire city reported in [32] is very time-consuming. This is a major limitation, and it impedes the widespread adoption of the hybrid approach for large-scale scenarios. (ii) Multi-modal, large-scale hybrid models have not been thoroughly validated with daily and hourly link-by-link comparisons. While some efforts have been made to address certain aspects, they are not comprehensive.

To fill these research gaps, an effective toolchain for generating a consistent, large-scale, multi-modal hybrid scenario is developed with the following aims: (i) achieving seamless integration between meso- and micro-networks and demand models; (ii) validating both meso- and micro-sub-models with real data, such as daily and hourly counts from traffic detectors and floating car data, while also enabling a comparison of the closeness to reality between meso- and micro-models. The latter is not only important for qualifying the models as MDTs but also quantifying the usefulness of the hybrid approach as such, e.g., whether it is worth the effort to create an additional micro-layer in a meso-model.

The remaining parts of this paper are structured as follows: Section 3 describes the methodology behind the hybrid traffic simulation approach, detailing the overall framework and developed methods for hybrid network synchronization and demand transfer. Section 4 explains the process of building the hybrid scenario for the case study, focusing on the methods and data used for model validation. Section 5 describes, and Section 6 discusses, the hybrid traffic simulation results, comparing them to real-world traffic counts and observed speeds. Section 7 concludes the current HybridPY development and outlines potential future advancements.

Table 1. Comparison of published hybrid models in large-scale scenarios.

Publication	Simulator	Demand Model	Network Coverage	Approach/ Information Exchange	Validation
Casas et al., 2011 [31]	AIMSUN	Trip-based model, morning car demand	1160 km road network in Madrid, Spain	Parallel/Network consistency, route choice	GEH index of hourly observed versus simulated volumes
Zitzow et al., 2015 [32]	AIMSUM	Trip-based model, daily multi-modal demand	26,196 km road network in Minnesota, USA	Parallel/meso-to-micro-travel time transfer for mode choice and route assignment	Using hourly loop detector flows for model calibration, not validated purely
Rakow et al., 2021 [35]	MATSim and SUMO	Activity-based model, 14% multi-modal demand	739,098 road links in the Greater Düsseldorf area, Germany	Sequential/micro-to-meso-intersection capacity transfer for meso-simulation	Car model share, absolute trip numbers
Triebke et al., 2023 [36]	MATSim and SUMO	Simulating fleet strategies of SAVs with 80% citywide activity-based demand	Berlin, Germany	Sequential/meso-to-micro-travel demand transfer	Not yet validated
Schrab et al., 2023 [38]	MATSim and SUMO	Scaled-up daily activity-based model, mono-modal car demand	Road network covering 800 km^2 in Berlin, Germany	Sequential/O-D location matching, meso-to-micro-routing transfer	Distribution of hourly simulated versus observed volumes
This paper	MATSim and SUMO	Daily activity-based model, multi-modal demand	88,133 km of road length in the Munich, Germany	Sequential/ Synchronization of network, travel demand, and routing	Time and spatial distribution of traffic volumes, linear regression, and scalable quality value (SQV) for daily and hourly link-by-link comparisons of simulated versus observed volumes and speeds

3. Hybrid Modeling Framework

The mesoscopic simulation MATSim models the traffic dynamics in a simplified way using a queueing model [4]. In contrast, the microscopic traffic simulation models the underlying traffic dynamics based on vehicle-following models for longitudinal dynamics, such as Krauss [39] or IDM [40], and lane-changing models for lateral dynamics, such as LC2013 [41]. A comparison of both simulations reveals the different levels of complexity. Using simplified, queue-based models and combining them with microscopic models in the area of interest allows us to save computing resources. Although theoretical advances, e.g., for combining MATsim and SUMO by [36], have been studied, building hybrid traffic models for real-world problems is still challenging.

A first concept of developing a tool-based, sequential coupling of meso- and micro-traffic simulations is presented in a previous publication [11], where meso-trips, overlapping with the smaller micro-area, were regenerated and rerouted on the micro-network, which clearly leads to alternations in link flows. To fully leverage the potential of the hybrid traffic simulation, the current work presents two methods for solving both problems, laying the foundation for an efficient modeling process for real-world transport scenarios. The overall procedure is shown in Figure 1, which comprises six steps, as follows:

Step 1—microscopic network import and cleaning: The micro-network needs to be imported into the hybridPY framework (e.g., from Openstreetmap—OSM [42]) and afterwards manually checked and cleaned. The micro-network defines the reference coordinate system.

Step 2—mesoscopic network import and projection: The meso-network is imported and projected onto the micro-network. Now, both networks are in the same coordinate system.

Step 3—hybrid network integration: The networks are aligned using the proposed novel hybrid network integration method (detailed in Section 3.1), ensuring equivalence between the two simulation levels in terms of properties and identifiers.

Step 4—mesoscopic simulation and user equilibrium estimation: The meso-simulation is executed to perform the meso-traffic assignment and achieve user equilibrium.

Step 5—meso–micro-demand transfer: The user equilibrium is transferred to the micro-level in the fifth step, which is further presented in Section 3.2

Step 6—microscopic simulation: The micro-model in areas of particular interest is executed; additional traffic demand (e.g., commercial vehicles) can also be added to achieve a more realistic micro-traffic simulation.

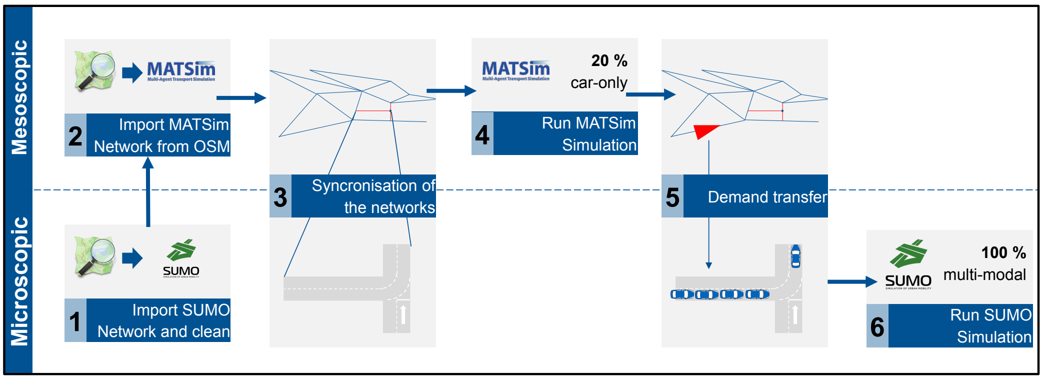


Figure 1. Proposed hybridPY simulation pipeline: sequential order of models.

Having a look at the sequential process in Figure 1 reveals that the hybrid network integration (Step 3) and the meso-micro-demand transfer (Step 5) are the two main innovations needed to efficiently couple MATSim and SUMO. These innovations will be discussed in more detail in Sections 3.1 and 3.2, respectively. The procedure presented here is exemplary for MATSim but can be transferred to BEAM [43] and other meso-simulations as well.

3.1. Hybrid Network Integration

The core idea of merging the smaller micro-network with the global meso-network is as follows: (i) to convert the more detailed, manually reviewed micro-network into a meso-network patch; (ii) to cut a hole into the global meso-network where the micro-network is located; and (iii) to patch the meso-network patch into the hole of the global meso-network by connecting all fringe nodes.

The conversion and the associated merging of the simulation networks enable data and information to be exchanged easily between the two simulation environments. Changes, such as road closures or structural changes, can be applied to the micro-network and projected onto the meso-network. Additionally, the traffic demand can be transferred to the micro simulation.

A SUMO network with lane accuracy as the standard enables precise intersection models to be stored. In contrast, MATSim generally relies on a simple and quickly calculable node and edge model, where nodes allow all possible turns and edges to have a predefined capacity function. As the MATSim network is mono-modal in our setup and contains only the car mode of transport, only the car-accessible SUMO network is considered for conversion. The integration procedure is visualized in Figure 2:

Step 3.1—network conversion: The underlying SUMO network is converted into a MATSim network based on the nodes and edges. Herein, the concept of *expanded nodes*, which is known in the MATSim community, is used to integrate the turning relationships from the SUMO network into the MATSim network for nodes that do not allow certain turns inside the micro-area. The concept of *expanded nodes* expands an intersection node into multiple sub-nodes and afterward explicitly connects all incoming and outgoing lanes via small edges to reflect turning restrictions. The characteristics of the inserted edges (e.g., capacity and free-flow speed), are derived from SUMO's internal edges. These edges are additionally flagged to ensure traceability throughout the simulation process. For all other edges, capacities are estimated based on the MATSim community standard [4]; for example, motorways and trunk roads have a capacity of 2000 vehicles per lane.

Step 3.2—connection analysis: The connections between the MATSim and SUMO networks are analyzed. First, the fringe nodes of the micro-area need to be identified. Fringe nodes in SUMO are defined as nodes where the number of incoming or outgoing edges is equal to zero. Edges connecting the same two nodes to reflect both directions are ignored within the number of incoming and outgoing edges. Once the fringe nodes of the SUMO network are identified, the corresponding MATSim nodes are located. The algorithm first searches for corresponding nodes within a radius of 3 m, $(|node, node_{MATSim}| < 3m)$. If a MATSim node is found, it is designated as a corresponding node. Otherwise, a suitable edge with an orthogonal distance lower than 10 m and within the same direction is chosen as the corresponding edge, $(|node, edge_{MATSim}| < 10m) AND (|\angle edge_{sumo} - \angle edge_{MATSim}| < 20^{\circ}$.

Step 3.3—cutting the MATSim network: Afterwards, the original MATSim edges within the SUMO area are deleted. The algorithm checks, for each MATSim edge, whether a corresponding SUMO edge exists, and if so, the MATSim edge is removed. The detection is based on geometric constraints, namely the orthogonal distance and the direction $(|edge_{sumo}, edge_{MATSim}| < 10m) AND (|\angle edge_{sumo} - \angle edge_{MATSim}| < 20^{\circ}$.

Step 3.4—patching the networks: The newly created meso-network patch is integrated into the existing MATSim network. The nodes identified as corresponding within the MATSim network are renamed to align with the SUMO node IDs.

Step 3.5—ensuring the reachability of the MATSim network: MATSim requires a fully reachable network for a simulation to work. For this purpose, the algorithm guarantees reachability by selecting the biggest fully connected network within the resulting network. This algorithm is in accordance with the MATSim community standard.

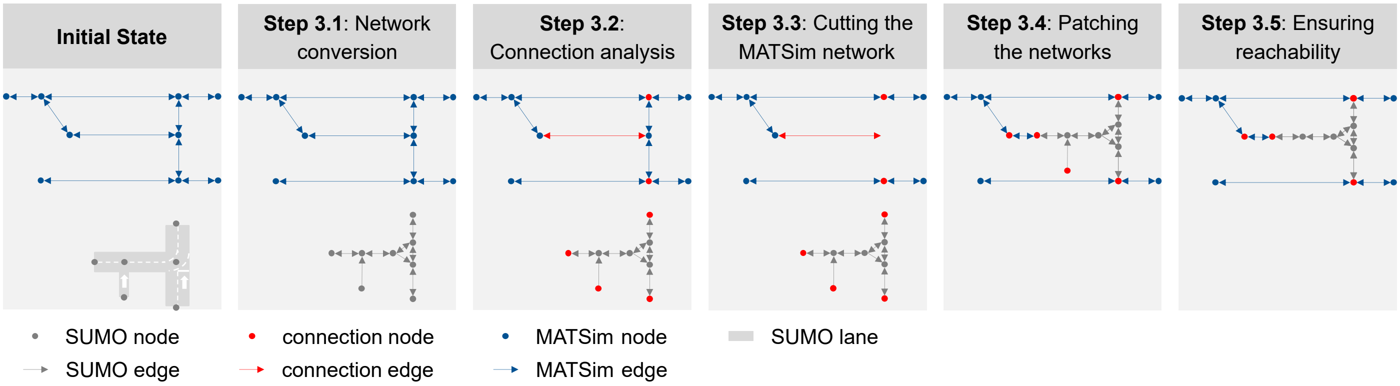


Figure 2. Workflow for the hybrid network integration.

3.2. Meso–Micro-Demand Transfer

The MATSim demand is a collection of daily mobility plans for each synthetic individual in the study area generated via an ABM developed by [1]. The plan file contains the route information and trip times of all vehicle types and persons, and it constitutes the demand input for the present hybrid framework. As the patched MATSim network, as described in Section 3.1 and visualized in Figure 2, Step 3.5, is used to generate the plans, all routes in the plan file will be valid on the meso- and the micro-network alike. Also, after the user-equilibrium assignment with the meso-simulator MATSim, the resulting routes from the plan file and the timing from the events file are valid for the micro-network.

The MATSim demand is only a sample (e.g., 20%) of the total travel demand. The demand is, therefore, scaled up with a distribution within a defined temporal period (e.g., plus and minus 20 min) relative to the trip start time within the micro-simulation area, as indicated in the meso-events file. In a post-processing step, it is necessary to cut of unnecessary U-turns at the end of the trips, which, in some cases, creates circulation problems. Furthermore, routes that consist of only a single edge due to truncation are excluded.

In the current setup, MATSim utilizes a car-only network, meaning that modes like biking and walking are teleported within the meso-simulation. Nevertheless, these modes need to be integrated into the micro-simulation as well. To transfer the trips of teleported modes, the process begins by checking whether the airline between the trip's start and end points intersects the SUMO area. If it does, the next step is to identify the first edge where the trip enters the SUMO area and route it through all edges that allow the corresponding mode until it reaches the destination.

4. Hybrid Traffic Simulation Case Study: Munich–Schwabing

This section presents a large-scale hybrid traffic simulation case study for the metropolitan area of Munich, Germany, focusing on the micro-area of Schwabing. The first sub-section outlines the experimental set-up, followed by an introduction to the data sources and how to integrate these data into the hybrid model for validation.

For this case study SUMO [10] in version 1.20.0 and MATSim [4] in version 15.0 are used.

4.1. Munich–Schwabing Road Network Model

The large-scale hybrid model was deployed in a case study of Munich, a major city in southern Germany. The meso-simulation encompasses the cities of Munich, Ingolstadt, Augsburg, Regensburg, and Rosenheim, while the micro-simulation focuses on the city quarter of Schwabing. Figure 3 displays the hybrid road networks, with the meso-MATSim network represented in black and the micro-SUMO network depicted in blue.

Both networks were exported from OSM using SUMO's OSM Web Wizard [44]. To create the MATSim network, the OSM data was initially saved as car-only scenario in SUMO format. The node-edge structure of the SUMO network was then reduced to its largest fully connected network, ensuring that every node is reachable from every other node and vice versa. This process generated the meso-MATSim network with 559,796 edges and 232,632 nodes, covering a total length of 88,133 km. The network is mono-modal, containing only edges accessible by car.

The SUMO network was initially designed to accommodate only cars as well. Subsequently, sidewalks and cycle lanes were incorporated using the netconvert tool [45]. The resulting network was manually verified and adjusted based on aerial images and on-site inspections. All traffic light controls were configured to "actuated". As a result, the micro-SUMO network consists of 3248 edges and 1505 nodes, covering 316 km of streets.

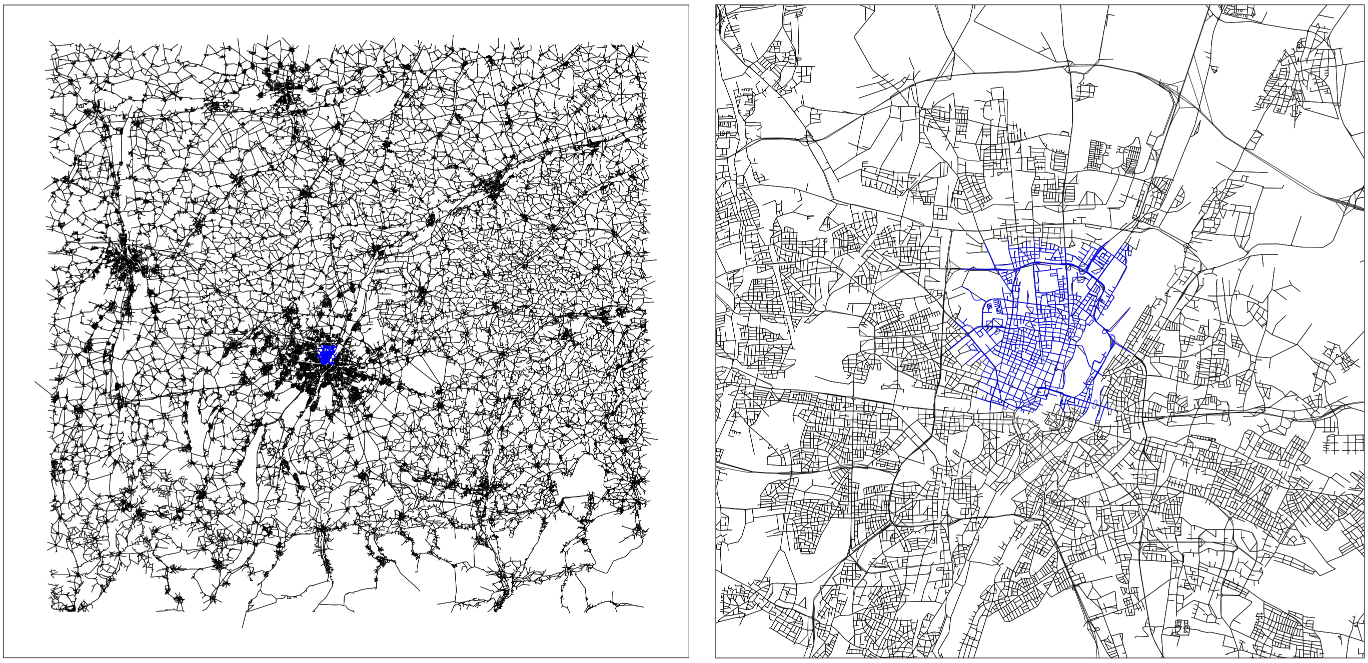


Figure 3. Road network of the case study: micro-area (blue) and meso-area (black).

4.2. Munich Activity-Based Travel Demand Model

In this paper, travel plans were generated via the activity-based incremental travel demand model (ABIT) [46]. The ABIT model generates a week-long activity–travel schedule for the set of a synthetic population that statistically represents the population in the Munich Metropolitan Area by Moreno et al. [47]. They used the micro-census data of Germany in the year of 2011 and applied the Iterative Proportional Updating (IPU) approach to generate the synthetic population for the same year. The synthetic population contains social-economic and demographic information at the personal, household, and dwelling levels, such as age, gender, household composition, car ownership, and so on, which play roles in people's traveling demand and behavior. For this paper, we further expanded the synthetic population generated for the year of 2011 to 2022 to achieve the number of population and households in the registry in order to meet the increased traveling demand in recent years.

After the synthetic population is updated, it is used in the ABIT model to generate travel plans. The plan generation combines rule-based and random utility-maximization models. The rule-based approach structures the decision-making hierarchy in activity generation, scheduling, and travel-related behavior in ABIT. For example, ABIT assumes that individuals prioritize their mandatory activities (e.g., work and education) before their discretionary activities (e.g., shopping and socializing). Although such a rule-based assumption might not be valid for every agent, it is a reasonable compromise based on the complexity of human behavior and data availability. Random utility maximization models (RUMs) are applied in multiple decision models, such as the mode choice model, where the utility function of transport modes between origin and destination is calculated, and individuals choose based on probability. All of these RUM models were estimated using a household travel survey available in Germany, as [46] described in their paper.

The travel plan, also called travel demand, generated via ABIT is calibrated using the most recent German National Household Travel Survey collected in 2017, with all errors controlled within a reasonable range. The final product of ABIT is a list of legs and activities files that can be further used and converted to corresponding formats for different traffic assignment models. The activities file describes the activity participation of each individual across a week, including the starting time, ending time, activity type/purpose, spatial location, and so on. The legs file describes the previous activity and its location, the next activity and its location, the travel mode connecting the two locations, the departure time of the trip, and so on. A random 20% of the total travel demand from Monday, the first day of the weekly demand, was selected for the meso-simulation. The meso-simulation was then executed for 50 iterations to achieve user equilibrium. All parameters, apart from the stuck-time parameter, were chosen to meet the community standard. The stuck-time parameter was chosen to be 60 s.

After the user equilibrium was determined, the demand was transferred to the micro-environment, following the method proposed in Section 3.2. Nevertheless, the generated travel plans only describe the individual's travel demand. To more accurately reflect real-world conditions, commercial traffic and heavy goods trips (>3.5 tons) were incorporated using a count-based sampling method. Random routes for this additional demand were generated in the micro-area using SUMO's routeSampler [48]. These routes were selected to ensure that the generated traffic volumes for heavy-goods vehicles aligned with actual traffic flows. The absolute traffic volume was based on the 2022 heavy-goods traffic-volume map [49]. In order to incorporate commercial traffic below 3.5 tons, the same amount of traffic as above, 3.5 tons, was added to the simulation using a car-based vehicle class.

The micro-simulation was executed, allowing 30% of all traffic participants to change their route during micro-simulation. Stuck vehicles were removed from the simulation after 60 s.

4.3. Validation with Speed Data

To derive the floating car data, we used the data collected with the smartphone application called "Mobilität.Leben". The smartphone app automatically collects users' GPS coordinates in a frequency of 1 to 5 s and reports them to a backend server. The user's mode of transport is detected automatically [50].

This study used the raw data from the smartphone-based survey to validate the observed travel speeds inside the simulation environments SUMO and MATSim. The raw points contain the following information: location, time, speed, and accuracy in meters. The trips from the travel survey were filtered based on the following criteria: (i) occurring on weekdays from Monday to Thursday; (ii) GPS accuracy of less than 15 m; (iii) speed reaching over 40 km/h at least once during the trip; (iv) the automatically detected mode is "car"; and (v) the trajectory length is greater than 3 km.

The filtered raw data is first map-matched to the corresponding edges. The SUMO network serves as the underlying network, especially the geometry of the edges and the geometry of the intersections. For map-matching, first, the most probable trajectory is created based on the underlying SUMO network using the pgMapMatch approach [51]. All turn relationships are ignored herein. Route generation ensures that all individual segments represent a valid route according to network properties. The GPS point is, afterwards, geometrically assigned to the respective road vector. All points that do not fall within the start or end area of the trajectory (20 m) are used to calculate the average speed. We consider only edges with more than 30 different trips delivering measurement points. These data is then aggregated to calculate the average speed of each edge.

The edge-based space-center velocity from the edge-based SUMO standard output serves as the reference velocity within SUMO. For MATSim, the speed calculated from the average link travel time and edge length serves as the reference speed. The average link travel time is derived from the events file.

4.4. Validation with Flow Detectors

In the city district of Munich, many traffic light-controlled intersections, as well as primary roads, are equipped with traffic detectors. The values are reported automatically via a web interface [52] on a 15 min basis. The detectors are lane-based, and they measure the absolute vehicle traffic volume per lane. To compare the edge flows of the meso- and micro-environments to reality, the detectors are matched to the road network and aggregated to an edge-based count. The advantage of the hybrid model is that we can again use the more detailed, micro-model to match the detectors and then transfer the information directly to the meso-network. For most detectors, we know the coordinates, the type of detector (traffic light or primary road), the name, and the group of the detectors (which reflects the direction), as well as, for detectors on primary roads, the direction.

To assign the traffic light detectors, first, the traffic light position is calculated as the center of gravity of the positions of all detectors of a traffic light. In the second step, all groups of detectors are then assigned to the respective best-rated edge of the individual group. The rating is based on the distance of the group center to the edge and the edge direction relative to the traffic light. In addition, the evaluation considers whether the edge leads to a traffic light and cars are permitted on the edge. For detectors on primary roads, the given direction is used instead of the relative position towards the traffic light.

As a stringent safety criterion, we ensure that the number of assigned detectors precisely matches the number of lanes of the respective edge. This check guarantees that the sum of all detectors assigned to an edge accurately reflects the absolute flow of that edge.

For validation in Section 5, this study used the averaged traffic counts of Mondays in April, May, and June 2022.

5. Results

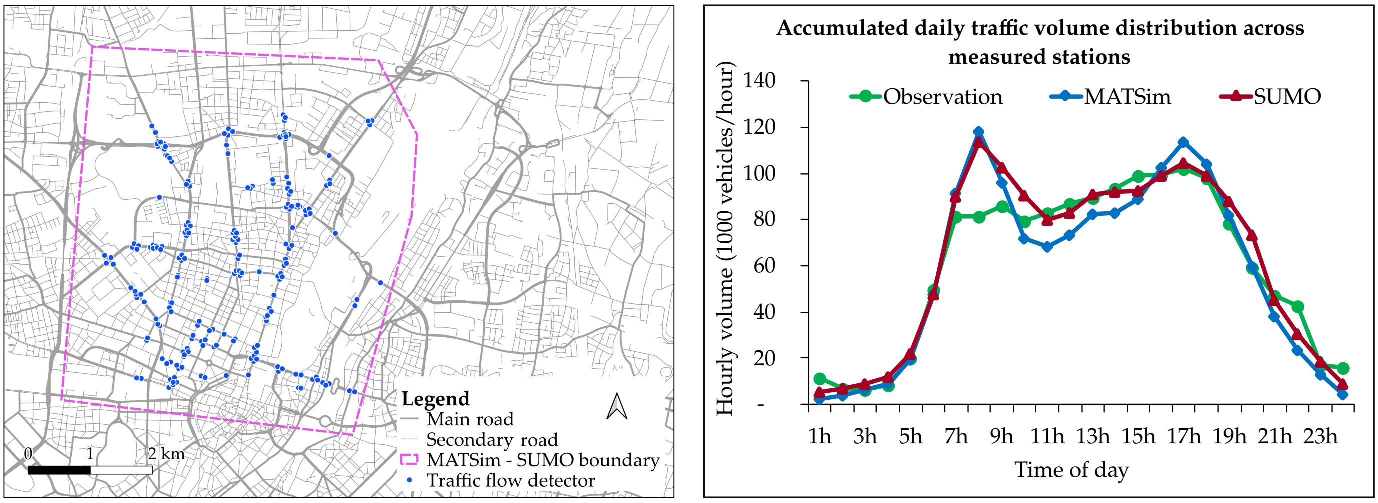
This section presents the results of the hybrid traffic simulation with a primary focus on traffic volumes and edge speeds. Firstly, the distributions of accumulated daily traffic volumes by hour, as well as traffic volumes by station of observed data, are compared with simulated flows from MATSim and SUMO. This comparison is followed by a descriptive analysis of a Kolmogorov–Smirnov test (K-S), Pearson's correlation coefficients (r), and the mean absolute errors (MAE). Subsequently, further validation methodologies, consisting of a linear regression analysis and a scalable quality value (SQV) indicator, are used to compare the simulated and observed traffic volumes. Lastly, the simulated edge-based travel speeds from the meso- and micro-simulation are analyzed compared to actual data.

5.1. Distribution of Daily Traffic Volumes

Two hundred detectors distributed across the micro-simulation area were used to compare the results and validate the hybrid model. The locations of these observed stations are illustrated in Figure 4a. These detectors measured traffic volumes for motorized vehicles, with an absolute daily total of 1.44 million vehicles/day. The MATSim simulation results predicted a volume of 1.40 million vehicles/day, while SUMO simulated 1.50 million vehicles/day.

Figure 4b presents the hourly distributions of accumulated daily traffic volumes by hour across observed stations. Overall, the accumulated traffic volumes in the hybrid simulations closely align with the actual daily traffic volume profiles with most traffic concentrated during the peak hour in the morning (6:00 a.m. to 9:00 a.m.) and afternoon (3:00 p.m. to 6:00 p.m.), followed by lower volumes during midday and nighttime.

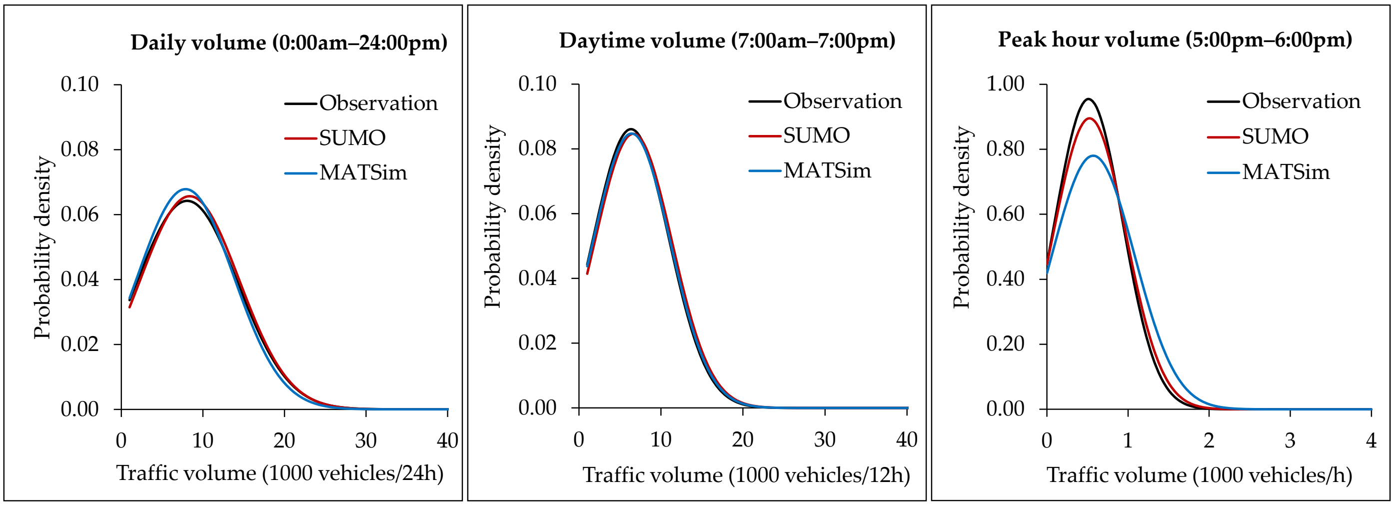
The results also demonstrated that both MATSim and SUMO modeled significantly higher-than-observed traffic volumes during the morning peak, between 7:00 a.m. and 8:00 a.m., with deviations of 45.2% and 39.7%, respectively. Furthermore, during peak hour, especially in the afternoon peak, the MATSim traffic volumes were approximately 8% higher than SUMO volumes. In contrast, during off-peak hour, the MATSim throughput was compared to that of SUMO, with discrepancies ranging from 10% to 17%.



(a) **(b)**

Figure 4. Location of 200 flow measurement detectors (blue dots) in the micro simulation area (**a**), and distribution of MATSim and SUMO daily simulated volumes compared to observed data (**b**).

Figure 5 presents the probability density function, illustrating and comparing the distribution of traffic volumes at all monitoring stations. The differences in distribution densities are assessed using the Kolmogorov–Smirnov test, as detailed in Table 2. The analysis reveals that, overall, traffic volumes are similarly distributed when the observed data are compared with simulations. However, during peak hour, there are differences in the probability density distribution, with the actual data showing more locations having traffic volumes below 1000 vehicles/hour, followed by SUMO and MATSim. Despite these variations, the differences in distribution are not statistically significant (p-value > 0.05).



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

Figure 5. The probability density function depicts the distribution of traffic volumes at monitoring stations, comparing actual measured volumes with those simulated via MATSim and SUMO over different time periods: the entire day (**a**), daytime (**b**), and peak hour (**c**).

Table 2. The Kolmogorov–Smirnov test (K-S) to compare the distribution of traffic volumes at monitoring stations over different time periods between observations, MATSim simulation, and SUMO simulation.

Time	Observed vs. MATSim		Observed vs. SUMO		MATSim vs. SUMO	
	K-S Test Statistic	*p*-Value	K-S Test Statistic	*p*-Value	K-S Test Statistic	*p*-Value
Daily	1.34	0.06 *	1.04	0.23 *	0.79	0.56 *
Daytime	1.34	0.05 *	0.95	0.33 *	0.70	0.72 *
Peak hour	1.10	0.18 *	0.95	0.32 *	0.75	0.62 *

Note: * No significant difference between the distribution of two samples (*p*-value > 0.05).

Complexity analysis outputs are depicted in Table 3 , which illustrates the variations in Pearson's correlation coefficients (r) and mean absolute errors (MAEs) among the observed, MATSim, and SUMO volumes at measured stations over a one-hour interval within the 24-h simulation. The results demonstrated significant correlations ($p < 0.05$) among hourly observed, MATSim, and SUMO volumes across all stations, with the exception of simulated MATSim and SUMO volumes during the periods of 1:00 a.m.–2:00 a.m. and 9:00 p.m.–10:00 p.m.

Furthermore, the correlation coefficients (r) indicated positive correlations (0 < r < 1) and strong correlations (r > 0.8) [53] between the observed, MATSim, and SUMO volumes from 6:00 a.m. to 9:00 p.m. with higher correlation values between MATSim and SUMO compared to the other comparisons. Notably, the higher correlation coefficients between the MATSim and SUMO results are supported by lower mean absolute error (MAE) values for the traffic volumes per hour.

Table 3. Pearson' s correlation coefficients (r) and MAEs between observation, MATSim, and SUMO simulation in hourly volumes at measured stations by time.

Time	Observed vs. MATSim		Observed vs. SUMO		MATSim vs. SUMO	
	r	MAE	r	MAE	r	MAE
0:00–1:00	0.55 ***	56.12	0.23 *	42.28	0.52 ***	17.32
1:00–2:00	0.62 ***	26.70	0.42 ***	21.86	−0.06 ns	20.10
2:00–3:00	0.60 ***	23.59	0.39 ***	25.43	0.79 ***	17.78
3:00–4:00	0.65 ***	29.34	0.48 ***	32.15	0.87 ***	18.92
4:00–5:00	0.64 ***	65.05	0.54 ***	60.80	0.95 ***	19.90
5:00–6:00	0.71 ***	123.11	0.70 ***	119.81	0.27 ***	21.93
6:00–7:00	0.84 ***	166.08	0.82 ***	155.45	0.99 ***	41.21
7:00–8:00	0.88 ***	230.56	0.89 ***	202.65	0.98 ***	77.19
8:00–9:00	0.86 ***	151.48	0.88 ***	163.48	0.98 ***	67.17
9:00–10:00	0.85 ***	137.16	0.82 ***	153.16	0.97 ***	101.47
10:00–11:00	0.85 ***	151.76	0.81 ***	138.01	0.97 ***	66.20
11:00–12:00	0.87 ***	146.26	0.85 ***	134.15	0.98 ***	60.23
12:00–13:00	0.87 ***	152.30	0.84 ***	141.05	0.98 ***	60.18
13:00–14:00	0.87 ***	165.67	0.84 ***	147.98	0.98 ***	62.02
14:00–15:00	0.87 ***	165.50	0.84 ***	151.96	0.99 ***	50.15
15:00–16:00	0.88 ***	164.42	0.88 ***	153.99	0.99 ***	53.97
16:00–17:00	0.89 ***	171.38	0.89 ***	152.58	0.97 ***	82.08
17:00–18:00	0.89 ***	165.41	0.89 ***	148.75	0.98 ***	72.32
18:00–19:00	0.84 ***	132.49	0.86 ***	147.92	0.97 ***	63.30
19:00–20:00	0.83 ***	111.79	0.82 ***	130.54	0.96 ***	75.96
20:00–21:00	0.83 ***	95.74	0.80 ***	87.53	0.97 ***	42.64
21:00–22:00	0.75 ***	118.05	0.71 ***	98.95	0.14 ns	42.09
22:00–23:00	0.71 ***	41.28	0.68 ***	43.39	0.91 ***	32.99
23:00–24:00	0.72 ***	67.37	0.43 ***	48.72	0.79 ***	25.66

Note: Statistically significant levels in hourly traffic volumes at measured stations between observation, MATSim, and SUMO simulation: ns = not significant ($p > 0.05$), * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.2. Validation with Traffic Volumes

The accuracy of the hybrid model is further analyzed using linear regression analysis and the SQV indicators to compare simulated versus observed traffic volumes.

Figure 6 presents the regression analysis between simulated and observed traffic flows with the slopes and R^2 values indicating the performance of the hybrid model. It is evident that the hybrid model's performance during the daytime (7:00 a.m.–7:00 p.m.) and the peak hour (5:00 p.m.–6:00 p.m.) closely matched the actual traffic volumes, demonstrating slightly better accuracy compared to daily results due to the exclusion of nighttime simulations. Specifically, the regression slopes during daytime (SUMO: 0.92; MATSim: 0.90) and peak hour (SUMO: 0.95; MATSim: 1.10) predominantly matched the acceptable threshold of $0.9 < m < 1.1$, and their R^2 for daytime (SUMO: 0.82; MATSim: 0.80) and peak hour (SUMO: 0.81; MATSim: 0.82) at the acceptable criterion of $R^2 > 0.8$, according to [54].

In addition, the SQV, an enhanced quality measure based on the GEH statistic method was further employed to validate the hybrid model. This method is a variant of the Chi-squared statistic that accounts for both relative and absolute errors [55]. The SQV is defined in Equation (1):

$$SQV = \frac{1}{1 + \sqrt{\frac{(m-c)^2}{f \cdot c}}} \tag{1}$$

wherein m represents the simulated values, c represents the observed values, and f is a scaling factor that depends on the type of compared traffic volumes, with a value of 1000 for hourly traffic volume and 10,000 for daily traffic volume.

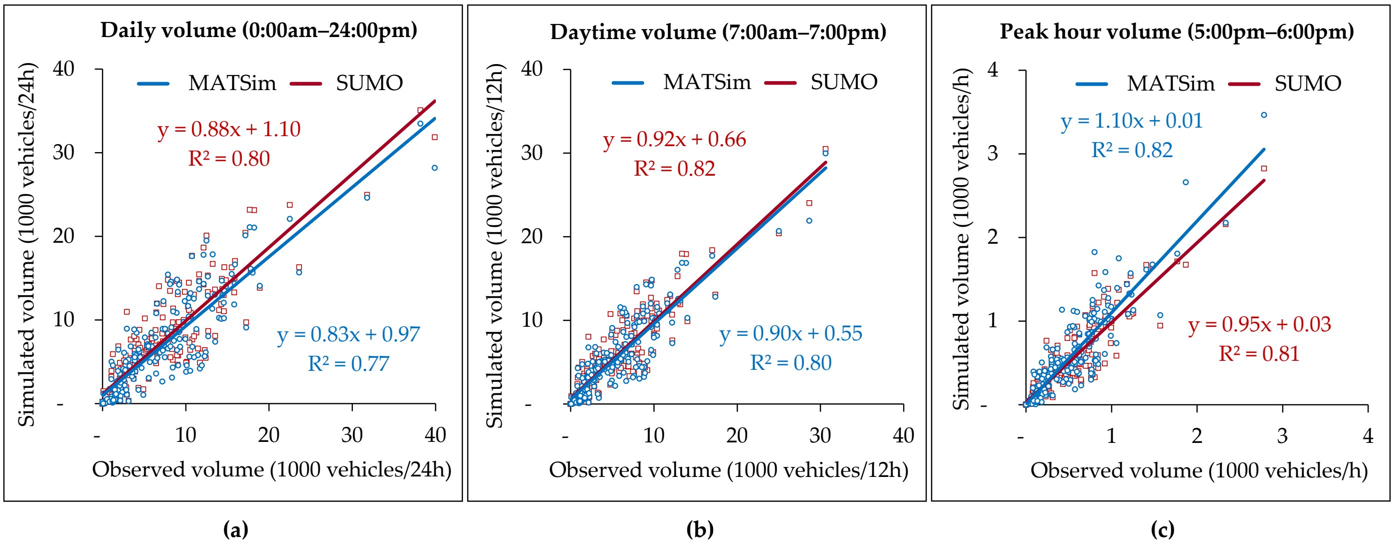


Figure 6. The regression diagrams display the comparison between simulated and observed traffic volumes over different time periods: the entire day (**a**), daytime (**b**), and peak hour (**c**).

Figure 7 illustrates the interquartile ranges (IQRs) of SQV values, comparing the hourly simulated values of SUMO and MATSim to the actual hourly traffic volumes. The analysis indicated that the hybrid model generally performed at an acceptable level, with mean SQVs > 0.8 [56] for most of the day, except during the morning peak (7:00 a.m.–8:00 a.m.), when the meso-SQVs showed a slightly lower value of 0.77.

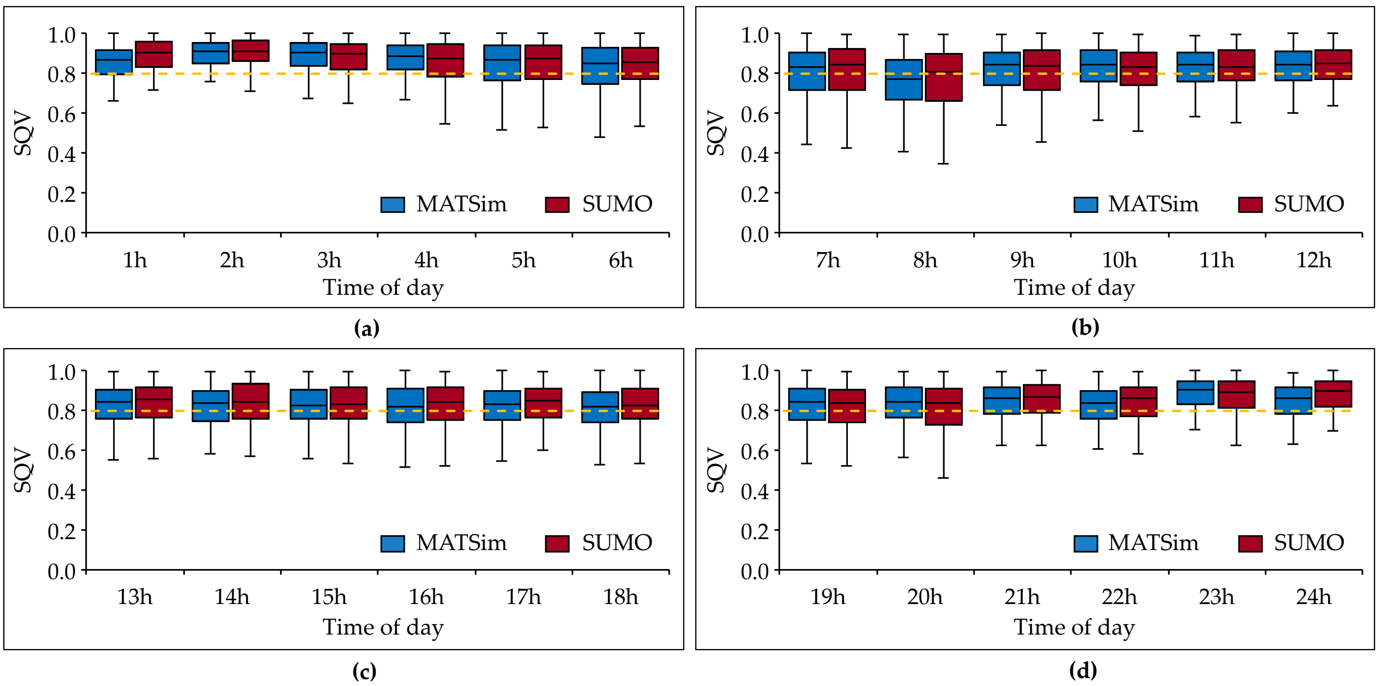


Figure 7. The SQVs indicate deviations between observed and simulated traffic volumes across different times of day: early morning (**a**), morning (**b**), afternoon (**c**), and evening (**d**).

5.3. Travel-Speed Comparison

The travel speeds obtained from the smartphone-based survey for cars were analyzed and compared with the average edge travel speeds within the MATSim and SUMO simulation environments, as described in Section 4.3. The results indicate that the simulated travel speeds in the hybrid model are consistently higher than the observed speeds. MATSim modeled higher travel speeds than both SUMO and observed data across all periods of the day. Specifically, MATSim recorded average simulated speeds of 45.49 km/h at night, decreasing to 41.58 km/h in non-peak hour and 39.82 km/h during peak hour. These speeds surpassed those of SUMO and the observed data by 17.45% and 36.65% at night, 24.12% and 40.00% in non-peak hour, 25.54% and 47.37% during peak hour, respectively.

These findings further reveal consistent variations in travel speeds with similar patterns between different times of the day, regardless of the observed and simulated speeds. The nighttime average travel speeds of MATSim are significantly higher, depicted in Figure 8, followed by off-peak and peak hour speeds. During nighttime hours, MATSim vehicles mostly operate at a narrower speed range (mean: 45.49 km/h; IQR: 44.73–48.60 km/h) compared to SUMO speeds (mean: 38.73 km/h; IQR: 28.34–47.24 km/h).

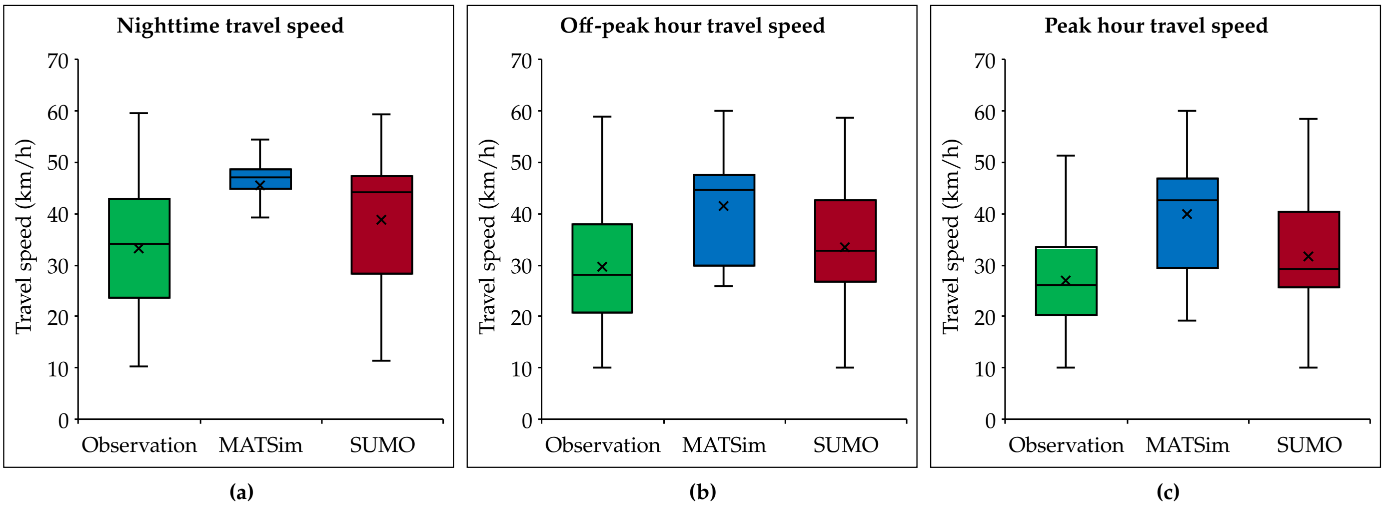


Figure 8. The distribution of the observed vehicle travel speeds (green) compared to the average edge speeds from MATSim (blue) and SUMO (red): nighttime (**a**), off-peak hour (**b**), and peak hour (**c**).

Figure 9 presents the linear regression analysis of observed and hybrid simulated speeds. The indicators in the regression function show that simulated travel speeds during peak hour most closely aligned with observed real-world speeds, followed by those simulated during off-peak hour and nighttime, as evidenced by higher slope values (m) and a higher coefficient of determination (R^2). The SUMO regression models demonstrated generally higher m and R^2 values ($m = 0.62$ to 0.68 and $R^2 = 0.36$ to 0.44) compared to the MATSim models ($m = 0.35$ to 0.52 and $R^2 = 0.28$ to 0.41), indicating a closer alignment with real-world data. Simulated speeds in MATSim were excessively compliant with the free-flow speed limits set for different road hierarchies within the network model (i.e., 30 km/h, 50 km/h, and 60 km/h). In contrast, SUMO simulated speeds exhibited a wider range of values, reflecting greater sensibility to the actual traffic flow speeds.

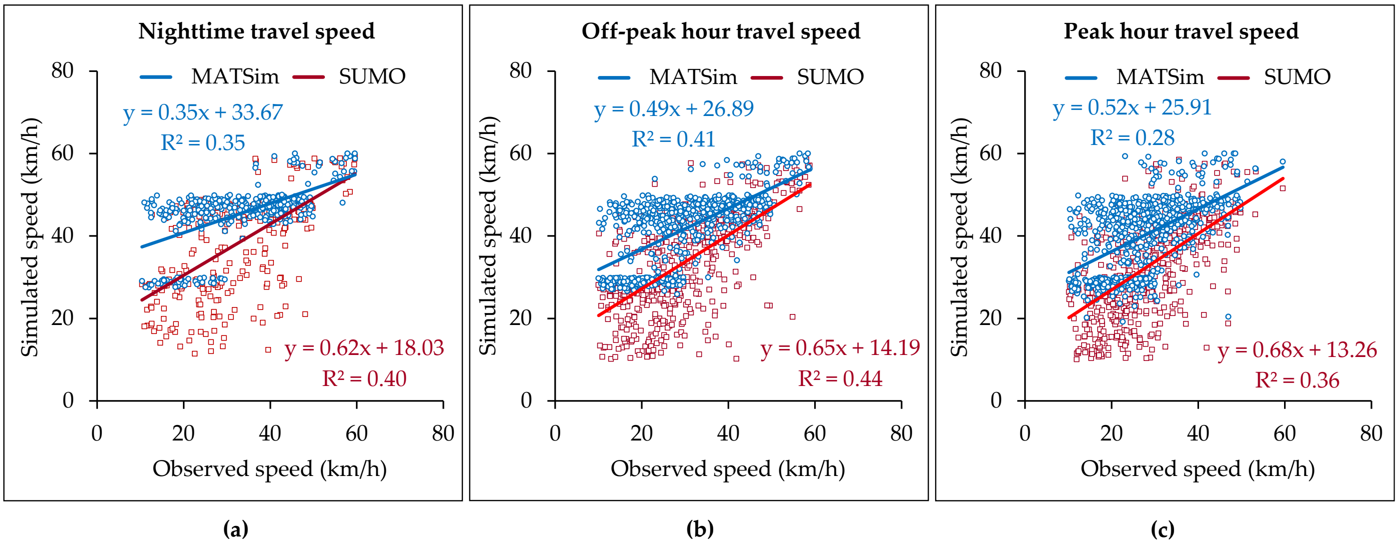


Figure 9. The regression diagrams illustrate the comparison between simulated and observed speeds across different time periods: nighttime (**a**), off-peak hour (**b**), and peak hour (**c**).

6. Discussion

This section discusses the proposed method for creating the hybrid traffic simulation, supported by the findings from the simulation results of the case study in Munich, Germany.

The established toolchain, the highlight of the study, was able to successfully transfer the road network information, travel demand, and route choice between meso- and micro-models with a high degree of consistency. These results also demonstrate the success of the map-matching algorithm developed to integrate traffic volumes from actual detectors to the corresponding edges in the hybrid model. This facilitates a reduction in complexity in developing large-scale, multi-modal transport scenarios.

Various validation methods were employed to evaluate model accuracy, which mutually reinforce one another. The K-S test evaluates the statistical similarity of temporal and spatial distributions between observed and simulated data. Pearson's correlation analysis examines the linear association of link-by-link traffic volumes. Regression models validate results across multiple time scales, providing detailed parameters (e.g., slopes and R^2) for the model evaluation of both volume and speed data. Meanwhile, the SQV method is scalable and interpretable for daily volumes, overcoming the limitations of the traditional GEH statistic method, which only allows for comparisons of hourly indicators.

The proposed validation methods facilitated the evaluation of model outcomes by assessing the consistency of traffic distribution at monitoring stations, as demonstrated by the K-S test with a p-value > 0.05 and strong correlations between the detected, MATSim, and SUMO traffic volumes with Pearson' s correlation coefficients (r), which lies predominantly over 0.8 at all observation locations throughout the day. This consistency underscores the robustness of the approach across different simulation scales.

Although the validation results generally indicate a notable overestimation of MATSim and SUMO volumes compared to the observed volumes during the morning peak, this discrepancy could be attributed to deficiencies in the demand-generation models, for example, a behavioral change in society after the COVID-19 pandemic, such as the possibility of remote working. Recent changes in travel patterns are not captured in the traveled survey collected in 2017. This means the comparison against the traffic count data from the year 2022 might explain a certain level of discrepancy. Furthermore, it is important to acknowledge that the lower off-peak volumes in the MATSim model compared to SUMO are likely due to the exclusion of commercial vehicle demand in the meso-simulation, which predominantly occurs during off-peak hour in Munich, as reflected in the SUMO results.

The link-by-link traffic-volume validation results from the linear regression models, as well as being supported by the SQV indicators, investigated that the simulated volumes closely reflect the actual volumes during daytime and afternoon peak hour periods. However, the performance slightly fell below acceptable thresholds when nighttime results were incorporated, due to lower travel demand and fewer observation samples. The update of the ABIT demand model to reflect the up-to-date travel demand in the study area, while ensuring compatibility with the traffic supply capacity, could further potentially improve the accuracy of the flow calibration results.

The regression values between the observed speeds and those simulated via the hybrid model fall below the threshold for accuracy commonly used for traffic volume validation. However, this discrepancy is justifiable due to the inherent sensitivity of velocity data to specific time points and factors such as the length of the observed data, as well as instantaneous acceleration and deceleration patterns due to local traffic situations. Both MATSim and SUMO assume perfect conditions at all times and simulated travel speeds via MATSim, followed by SUMO, consistently exceeded observed speeds. The majority of simulated traffic speeds in the MATSim model exhibited asymptotic behavior relative to the free-flow speed limits established homogeneously within the road network model (i.e., 30 km/h, 50 km/h, and 60 km/h).

The observed speed results can be explained by the fact that MATSim does not simulate speeds explicitly but estimates speeds indirectly by means of the traffic flow and a heuristically determined flow-speed function, which reflects the road properties on a specific link. Lane-change behavior, vehicle following, spontaneous traffic breakdowns, or the presence of bicycles in the same lane are not part of this meso-model. This is why speeds tend to stay at free-flow velocity. By contrast, SUMO does model car-following, lane-change, and even sub-lane behavior, and it overestimates speeds to a lesser extent. For the differences between SUMO and measured speeds, many factors can be responsible: imprecise instantaneous traffic densities, an inexact modeling of vehicle following behavior, or imperfect traffic conditions (e.g., spontaneous breaking or lane-change maneuvers to avoid obstacles like cars entering parking, etc.). These results were confirmed by the findings from Triebke et al., 2022 [37], through an investigation of an in-depth analysis of traffic speeds throughout the day, instead of one-hour tracking.

One primary limitation of the current approach is that the improved link-speed estimated via the micro-model only has an effect on the routes of the simulated vehicles in the micro-area. The changes in link travel times do not affect the overall user-equilibrium assignment on the meso-level, where the routes are determined globally. This means that particularly congested links in the micro-area will not be avoided by rerouting vehicles also outside the micro-area. In the future, this shortcoming can be avoided by feeding the updated link travel times back to the meso-model in order to repeat the user-equilibrium assignment and, successively, the micro-simulation with the new routes. Such an iterative process has been applied in previous works [32].

However, this approach involves a drawback, as only the link travel times in the micro-area are updated, which means they are generally increased, as demonstrated above. The consequence may be that, with a global assignment, the vehicles will generally avoid the micro-area as speed times are, on average, lower than those outside the micro-area. This effect could be mitigated by also increasing the link travel times on the meso-network outside the micro-network, based on similarities in road type and volumes from links within the micro-area. But the risk of such adaptation is that unrealistic adaptation can distort the overall results.

Another shortcoming is that public transport was not explicitly modeled. Instead, buses were simulated as part of commercial traffic demand without actually transporting passengers. Nevertheless, there is the potential to model public transport explicitly in SUMO, as well as MATSim, by creating bus and tram lines using the open access General Transit Feed Specification (GTFS) available for Munich. HybridPy provides algorithms to match the GTFS data onto the SUMO network create the required bus stops and generate bus/tram/train routes with the specified runs of a particular day. This information can be manually refined and, afterward, projected into the public transport model of MATSim.

7. Conclusions

This paper has contributed to the state of the art by proposing a novel hybrid approach with an effective toolchain. With this approach, it has been possible to couple MATSim, a meso-traffic simulator able to simulate large-scale networks, with SUMO, a micro-traffic simulator able to simulate a detailed network on a smaller scale.

We have proposed a novel solution to merging both modeling environments by blending the typically smaller yet more refined micro-network into the meso-network, which ensures that the network edges of both models are identical within the micro-area. This integration has enabled a seamless travel demand and route exchange between the meso- and micro-models. But the true advantage of the present approach is the possibility for validation, link by link, compared to real data for both the meso-model and the micro-model. This means that, for the first time, it is possible to compare the closeness to reality of the meso- and micro-models and, hence, to justify the additional efforts for creating a hybrid model with respect to a pure meso-model. In particular, the developed map-matching algorithms allow the integration of real-world data obtained from traffic detectors and floating car data into the hybrid model, facilitating seamless comparison and validation. The large-scale hybrid model was successfully deployed in a case study of Munich, Germany, with the micro-simulation concentrating on the city quarter of Schwabing.

Various validation techniques were applied, and they mutually reinforced one another to ensure the model's accuracy, including the K-S test, Pearson's correlation analysis, regression models, and SQVs. The proposed validation methods enabled the assessment of the successful synchronization between the road network, travel demand, and route choice between meso- and micro-simulations, showing a high degree of consistency. This is indicated by strong Pearson's correlation coefficients ($r > 0.8$) and close K-S statistic distributions (p-value > 0.05) when comparing the observed, MATSim, and SUMO traffic volumes at the monitored stations. The linear regression model and SQV analysis demonstrated a strong representation of simulated traffic volumes compared to real-world data. Key validation indicators were at acceptable values ($0.9 < m < 1.1$, $R^2 > 0.8$, and $SQV > 0.8$), particularly during daytime and afternoon peak hour. Maintaining temporal consistency between observed traffic volumes and mobility data used in developing ABM may improve model accuracy, especially during morning peak hour.

In addition, the model enabled a link-by-link comparison of simulated average edge speeds with real-world data for both the meso- and the micro-models. While the speed regression values fell below commonly accepted thresholds, this may be justified by the inherent sensitivity of speed data to many internal simulation parameters, such as vehicle following models. An important finding has been that the micro-SUMO model outperforms MATSim in terms of the simulation speed relative to real-world data. The model's speed results have allowed proof that the limited vehicle interaction representation in the meso-model enables vehicles to travel at higher speeds than in the micro-simulation model. This difference explained the higher peak hour traffic volumes in MATSim compared to SUMO.

Additionally, the increase in off-peak simulated volumes in SUMO may be attributed to the contribution of commercial vehicle demand in this micro-simulation. Furthermore, the results also allowed for a demonstration that simulated speeds in the MATSim model tend to asymptotically approach free-flow limits, whereas the SUMO model shows a wider speed distribution, reflecting actual traffic dynamics in the micro-simulation.

These analyses clearly indicated that, in the present case study, the hybrid approach offers advantages over a pure meso-approach, as observed speed from floating car data is better reproduced.

The proposed hybrid approach offers transport researchers and practitioners realistic and flexible methods for the planning process that can be validated and that require fewer resources compared to pure micro-approaches. It is further possible to quantify how much closer the hybrid approach is to real data with respect to a pure meso-model, based on the same network. However, the proposed model involved limitations, and it calls for future works to automatically feed simulation results back from the micro-level to the meso-level, ensuring that the micro-area is not artificially compromised by overestimating travel demand in the meso-model. Additionally, integrating public transport services and coupling synthetic populations between the meso- and micro-levels, rather than on a trip basis, could further strengthen the proposed framework.

Author Contributions: The authors contributed to this work in the following ways: conceptualization, F.S.; methodology, F.S.; software, F.S.; validation, F.S. and N.A.N.; formal analysis, F.S. and N.A.N.; investigation, F.S.; resources, F.S.; data curation, F.S., W.-C.H., and N.A.N.; writing—original draft preparation, F.S., N.A.N., W.-C.H., and J.S.; writing—review and editing, F.S., J.S., and M.L.; visualization, F.S. and N.A.N.; supervision, M.L. and J.S.; project administration, F.S.; and funding acquisition, M.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The underlying SUMO networks originate from freely accessible and usable OpenStreetMap data extracts. The historical traffic flow data used in this study were obtained from the City of Munich and are currently accessible via [52].

Conflicts of Interest: The authors declare no conflicts of interest.

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