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Developing a fast and effective network free-speed calibration procedure for agent-based transport simulations

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Abstract

Agent-based simulations play an essential role in transport planning. To ensure realistic and reliable outcomes, an accurate network model is essential. In this study, we propose a fast and effective network free-speed calibration procedure for agent-based transport simulation frameworks. To evaluate and quantify its performance, we implement the procedure in an agent-based transport simulation framework, MATSim. The results demonstrate that the proposed procedure effectively aligns the free-speed of the network with reference data. Moreover, it outperforms existing network calibration methods in output quality and computational efficiency. Specifically, the new approach further reduces the error statistics related to free-speed travel time by over 50% compared to existing methods. Additional experiments also reveal that the new network calibration procedure can still deliver good results even with limited reference data.

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1. Introduction

Nowadays, simulations play a pivotal role in forecasting traffic flow, evaluating the impacts of infrastructure changes, and optimizing traffic operations in transportation planning and traffic management. Among the various transport simulation models, agent-based simulation models are widely used in both industry and the academic world due to their ability to produce realistic and detailed results. For instance, the Swiss Federal Railway (SBB) and the Berlin Transit Authority (BVG) use agent-based transport models to assist the public transport planning process. Similarly, private companies, such as MOIA, a shared mobility provider, and ARUP, a consulting company, are also using the agent-based model to make projections in transport systems [10]. In academia, a vast number of studies

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and research have been carried out based on various agent-based models such as MATSim [4], TRANSIMS [12], and Polaris [2].

Together with the population models, the network plays a fundamental role in the agent-based transportation models. To generate realistic and reliable simulation results, the network needs to return reasonable travel time and distance between all the origin-destination (OD) pairs that resemble reality. Two key factors impact the network's accuracy in a traffic simulation model: the free-speed and the traffic dynamic. In this paper, we focus on the free-speed of the networks, as free-speed calibration is more broadly applicable to various transport modeling tools and involves less complexity than traffic dynamics. Furthermore, an accurate free-speed is also a prerequisite for a good traffic dynamic model. On top of that, a well-calibrated network free-speed model alone also enables the study of scenarios, where congestion does not play an important role or is modeled as an exogenous effect. Examples include studies on the demand-responsive transport (DRT) systems [1, 3, 8] and freight transport [9, 13].

Ideally, the network free-speed is the maximum speed at which a vehicle can travel without impediments, without the influence of other vehicles, traffic controls, or road signals. In reality, factors like traffic density, road type, and the presence of traffic controls, such as unmodeled traffic lights, complicate this calculation. Typically, traffic simulators adjust free flow speeds by reducing them on urban links where traffic lights are presumed to exist but are not explicitly modeled. This adjustment helps to simulate more realistic driving conditions in various traffic scenarios. However, this usually involves some amount of manual work and can become tedious when the network becomes larger. Furthermore, the procedure and the values used are likely to vary from network to network, limiting standardization.

Adapting machine learning techniques, including neural networks, has proven instrumental in refining calibration processes. These methods enable more accurate predictions of travel times and queue lengths, critical components in the realistic modeling of traffic scenarios [5]. For instance, a novel approach integrates microscopic simulation with machine learning to dynamically adjust free-flow speeds, using data from SUMO simulations and real-world travel times [11, 7]. This method enhances the realism of the simulated traffic conditions and significantly reduces the prediction errors in urban traffic modeling. These advancements in leveraging real-time data for simulation parameter calibration are pivotal. They enhance the accuracy of traffic management and urban planning models and suggest a future where simulations can more effectively mirror and adapt to real-world conditions, thus supporting informed decision-making in urban development and transportation planning.

A further review of the literature reveals that relatively few studies focus on developing systematic network calibration procedures, compared to other topics in agent-based transport planning and modeling. Moreover, the input data required by the calibration approaches proposed in some of the aforementioned studies may be challenging to obtain, or the approaches themselves may be limited to a specific simulation framework.

In this study, we address this gap by developing a fast and effective network free-speed calibration procedure based on available travel time data sources, such as actual measurements and online APIs. In addition to the original network, the only required data are the OD-pairs and the associated shortest route information during free-flow conditions, which are generic and easy to obtain. After the calibration procedure, the network should more closely resemble the reality. We compare the results of the new approach with those of an existing approach proposed in [11]. In principle, this procedure is compatible with different transport simulation frameworks. In this paper, we use MATSim, an agent-based transport simulation framework, as the carrier to implement this procedure.

2. Methodology

The workflow of the new network free-speed calibration approach is summarized in Figure 1. The input consists of three elements, all in generic formats. First, we need a list of OD-pairs that provide good network coverage. Then, we need reference data to acquire the shortest route information for each OD-pair under free-flow conditions, which can be derived from multiple data sources. Two of the most common data sources include online APIs and actual measurements. Most common online map platforms, such as Google Maps, HERE, and TomTom, provide APIs for route calculation, providing extensive and relatively accurate travel time data for a given OD-pair departing at a given time. On the other hand, actual measurements, such as GPS data collected from taxis, can also be used to create reference data. When multiple data sources are available, they can be integrated to achieve higher accuracy and broader coverage. Finally, we need the initial network. By comparing the routes calculated on the input network and acquired from the reference data, we can perform the calibration procedure.

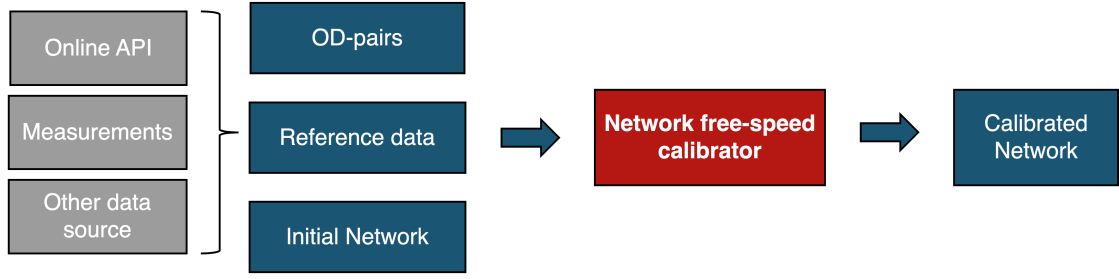


Fig. 1: Workflow of the new network free-speed calibration approach

In most cases, the lengths of road segments in a network model are accurate, thanks to advanced geographic tools such as satellite maps and data processing algorithms. Preliminary experiments also show that, for each OD-pair, the discrepancy in travel distance between the input network and the reference data is significantly smaller than the discrepancy in travel time. Therefore, the primary goal of the network calibrator is to reduce the travel time discrepancy under free-flow conditions by adjusting the free-flow speeds of road segments in the input network.

The network free-speed calibration algorithm adopts an iterative approach. In each iteration, the travel times of the OD-pairs are calculated on the network and compared against the reference data. A threshold for discrepancy $\epsilon \in (0, 1)$ is defined to determine the acceptable deviation between the simulated and actual travel times obtained from the reference data. If the simulated travel time on the network ($t_{p,network}$) is too fast compared to the travel time from the reference data (i.e., $t_{p,network} < t_{p,ref} \cdot (1 - \epsilon)$) or is too slow compared to the reference data (i.e., $t_{p,network} > t_{p,ref} \cdot (1 + \epsilon)$), it indicates that certain road segments in the network are likely too fast or too slow, respectively. Going through the OD-pairs, the algorithm identifies the links that are highly likely to be too fast and too slow, respectively. For instance, if most of the paths that pass through a specific road segment are too quick on the simulation network, then it is likely that the free flow speed of that road segment is too short, and vice versa. For those road segments, the free flow speed should be adjusted accordingly.

For this, we define another threshold value for accumulated scores $c \in (0, 1)$, based on which we assign each road segment l into one of the three sets: F , likely to be too fast; S , likely to be too slow; U , undetermined. The logic is shown in Equation 1, where $n_{l,fast}$ and $n_{l,slow}$ are the number of paths that cover the road segment l and are too fast or too slow, respectively. $n_{l,total}$ is the number of paths covering the road segment l .

$$l \in \begin{cases} F, & \text{if } \frac{n_{l,fast} - n_{l,slow}}{n_{l,total}} > c \\ S, & \text{if } \frac{n_{l,fast} - n_{l,slow}}{n_{l,total}} < -c \\ U, & \text{otherwise} \end{cases} \quad (1)$$

We can adjust the speed after categorizing the road segments into three sets. For each road segment in set F (likely too fast), the free flow speed is reduced by ϵ ; for each road segment in set S (likely too slow), the free flow speed is increased by ϵ ; for each road segment in set U , the free flow speed is unchanged in this iteration. To avoid unrealistic values, upper bound and lower bound of free-speed are introduced to each road segment. By default, the walking speed (i.e., 5 km/h) is set as the lower bound for all the road segments, while the upper bound is determined based on the road type and the speed limit.

In order to calibrate networks with systematic bias more effectively, before the first iteration, the algorithm tackles the systematic bias by taking the average shortest travel time on the network for all the OD-pairs and comparing it to that acquired from the reference data. A correction factor k is acquired and used to modify the free-speed of all the road segments in the network so that the systematic bias is minimized. Algorithm 1 summarizes the newly developed network free-speed calibration procedure.

We implement the new network calibration approach to demonstrate its effectiveness in MATSim. MATSim (Multi-Agent Transportation Simulation) is a mesoscopic agent-based transport simulation framework capable of simulating large-scale scenarios with a good level of detail within a relatively short period of time [4]. As mentioned in the

introduction, MATSim only serves as a carrier for the new approach in this study, and we only use the MATSim network to perform network calibration.

Algorithm 1 Automated network free-speed calibration algorithm

Input: Uncalibrated Network, OD-pairs, reference travel time data (ref)

Output: Calibrated Network

```

1: Initialization:  $i \leftarrow 0$ 
2:  $k \leftarrow \sum_p t_{p,network} / \sum_p t_{p,ref}$  for  $p$  in  $OD - pairs$ 
3: for all  $l$  in  $network$  do
4:    $v_l \leftarrow \max\{\min\{k \cdot v_l, v_{l,max}\}, v_{l,min}\}$ 
5: end for
6: while  $i < \text{max\_iterations}$  do
7:    $F, S, U \leftarrow \emptyset$ 
8:   for all  $l$  in  $network$  do
9:      $n_{l,fast} \leftarrow 0, n_{l,slow} \leftarrow 0, n_{l,total} \leftarrow 0$ 
10:  end for
11:  for all  $p$  in  $OD-Pairs$  do
12:    for all  $l$  in  $p$  do
13:       $n_{l,total} \leftarrow n_{l,total} + 1$ 
14:      if  $t_{p,network} < t_{p,ref} \cdot (1 - \epsilon)$  then
15:         $n_{l,fast} \leftarrow n_{l,fast} + 1$ 
16:      else if  $t_{p,network} > t_{p,ref} \cdot (1 + \epsilon)$  then
17:         $n_{l,slow} \leftarrow n_{l,slow} + 1$ 
18:      end if
19:    end for
20:  end for
21:  for all  $l$  in  $network$  do
22:    if  $\frac{n_{l,fast} - n_{l,slow}}{n_{l,total}} > c$  then
23:       $F \leftarrow F \cup l$ 
24:    else if  $\frac{n_{l,fast} - n_{l,slow}}{n_{l,total}} < -c$  then
25:       $S \leftarrow S \cup l$ 
26:    else
27:       $U \leftarrow U \cup l$ 
28:    end if
29:  end for
30:  for all  $l$  in  $F$  do
31:     $v_l \leftarrow \max\{v_l \cdot (1 - \epsilon), v_{l,min}\}$ 
32:  end for
33:  for all  $l$  in  $S$  do
34:     $v_l \leftarrow \min\{v_l \cdot (1 + \epsilon), v_{l,max}\}$ 
35:  end for
36:   $i \leftarrow i + 1$ 
37: end while
  
```

3. Network free-speed calibration in a real-world scenario

3.1. The Melbourne scenario

This study uses the network extracted from an existing agent-based MATSim model of the Greater Melbourne area [6]. In the original model, the network is generated using the available OSM data (as of 3 April 2024)¹. Some recent investigations on the network reveal that the free-speed of the network is different from the values provided by some of the commonly used online map platforms (e.g., Google Maps). Therefore, this network is a suitable use case for the newly developed calibration procedure. Since the original network is very large, we extract the network and focus on the inner Melbourne area based on the Statistical Areas Level 4 (SA4)². Figure 2a shows the extracted network on the map.

For the calibration of our network model, 20,000 OD-pairs have been generated from previous studies [15, 16]. The coverage of the shortest path route of the selected 20,000 OD-pairs is shown in Figure 2b. As shown in the figure, the OD-pairs provide comprehensive network coverage. This is also indicated by the statistics: more than 82% of all road segments are covered at least once. Furthermore, 64% of the road segments are covered at least 3 times, and 54% of the road segments are covered at least 5 times.

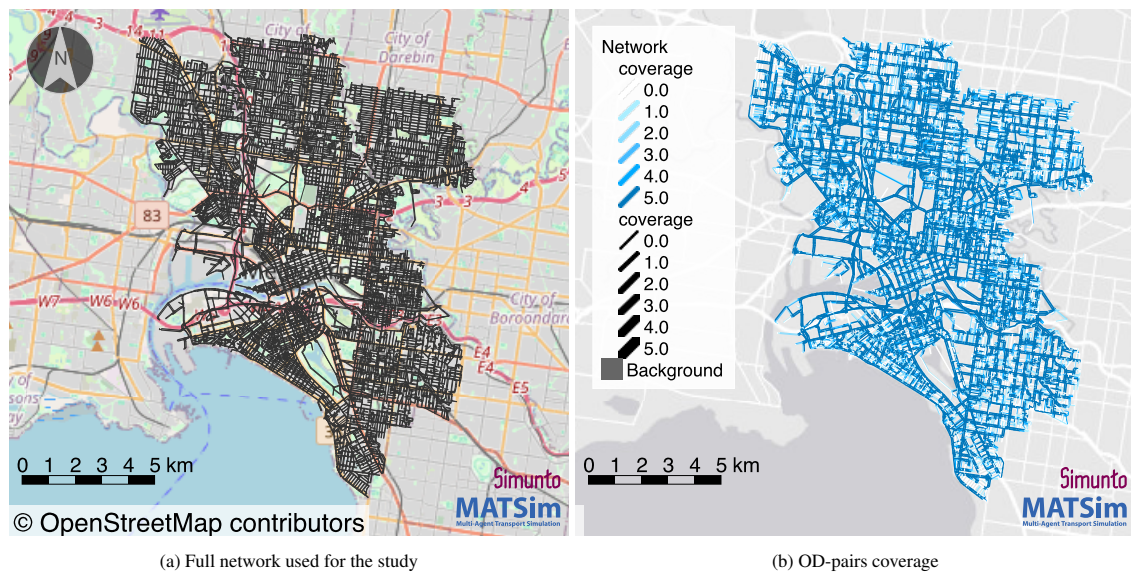


Fig. 2: Illustration of the Network

3.2. Travel time data source: Google Map API

In this study, we use the Route API from the Google Maps platform to generate reference data³. Google Maps is widely recognized for its extensive use in daily life and various commercial applications. The Route API accepts queries of OD-pairs in the generic format of {from coordinate, to coordinate, departure time} and returns travel time and distance at the given departure time, along with the base travel time and distance. To estimate the free-speed travel time of the network, we use 1:00 am as the departure time, as the congestion is usually minimal at that time (more details can be found in Section 4 and Figure 5b). Using this approach, we construct the reference data for the 20,000 OD-pairs, serving as the basis for the calibration of the network.

¹ <https://download.geofabrik.de/>

² The largest sub-state regions in the Main Structure of the Australian Statistical Geography Standard: <https://www.abs.gov.au>

³ <https://mapsplatform.google.com/>

3.3. Experiments with the new approach

We divide the 20,000 OD-pairs into two groups: the first 19,000 OD-pairs perform network calibration (i.e., training), while the last 1,000 OD-pairs are used as validation data. Since each OD-pair is unique and different data sets are used for network calibration and validation, the risk of overfitting is reduced.

When validating the network, we use mean absolute percentage error (MAPE, see Equation 2) and root-mean-square error (RMSE, see Equation 3) to evaluate the quality of the network. n is the number of OD-pairs used for validation, y_i is the free-speed travel time of OD-pair i obtained from the reference data (e.g., online API), and \hat{y}_i is the free-speed travel time on the network for the same OD-pair. The former criterion provides information on the average percentage error to be expected, and the latter provides the predicted error in terms of absolute value (i.e., seconds in this case). In addition, we also make scattered plots to provide additional illustrations.

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

The validation results for the calibrated network are summarized in Table 1. For comparison, we also include the original network directly generated based on the OpenStreetMap data (i.e., uncalibrated network), the calibrated networks from the manual calibration procedure mentioned in [14, 8] and from the automated calibration approach proposed in [11]. For all the networks, the same 1000 OD-pairs are used for validation. For the new approach and the existing approach from [11], the same 19,000 OD-pairs are used for calibration. For the new approach, we set $\epsilon = 0.05$, $c = 0.1$, and the number of iterations to 50. These values were chosen based on preliminary experiments, which showed that good performance can be achieved. The scattered plots of the networks are shown in Figure 3.

Table 1: Summary of the results

Evaluation criteria	Original Network	Manual Calibration	Previous Approach [11]	New Approach
MAPE	52.73	13.00	11.26	4.83
RMSE	653.60	186.52	164.87	66.71

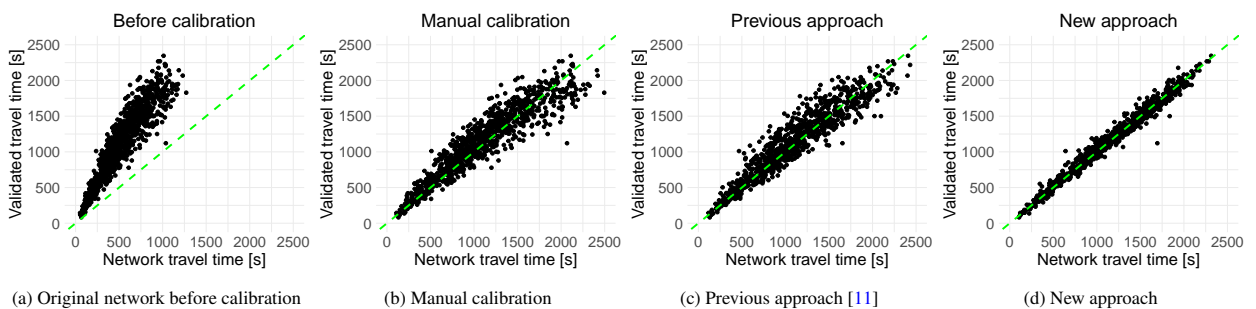


Fig. 3: Scattered plot of the validation data

The results show that the new approach performs significantly better than manual calibration and the previous approach. In the scatter plot 3d, the dots are distributed much more closely around the $y = x$ line (i.e., the green dashed line in the plot) compared to other calibration approaches. This indicates that the network calibrated with the

new approach is more realistic, as the free-speed travel time of OD-pairs calculated on the network closely aligns with the reference data.

3.4. The relationship between output network quality and the number of OD-pairs used

As both the new approach and previous approach rely on a relatively large number of input OD-pairs, we have also conducted an experiment to observe the relation between the output network quality and the number of OD-pairs used for validation. In this experiment, we use the same 1,000 OD-pair to perform the validation, while the number of OD-pairs for calibration varies. The OD-pairs used for network calibration are always chosen from the rest 19,000 OD-pairs. We use the same criteria to evaluate the performance of the calibrated network. The results of the experiments on the number of OD-pairs used are summarized in Figure 4.

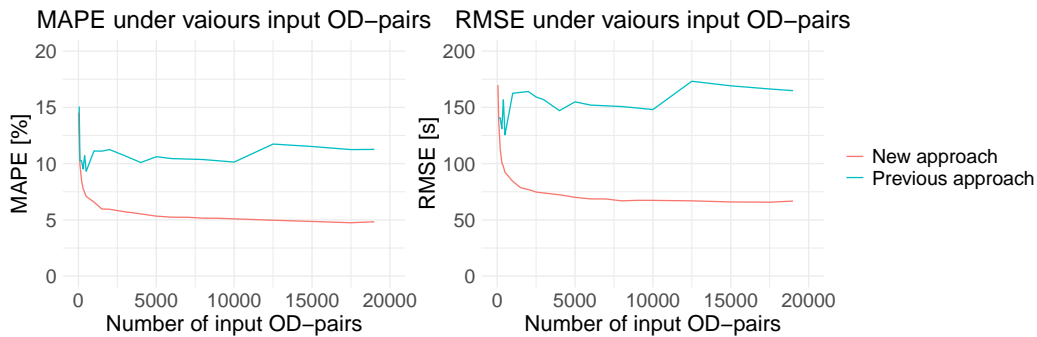


Fig. 4: Performance of the network calibration approaches under different number of input OD-pairs

From the plots, it can be observed that the quality of the calibrated network based on the new approach improves significantly when we increase the number of OD-pairs from 100 to 2,000. With 5,000 OD-pairs, a good result can already be achieved. As the number of OD-pairs further increases, the quality of the network continues to improve, but only marginally. This suggests that the new approach can still effectively calibrate the free-speed of the network even with limited reference data. Compared to the previous method, the accuracy of the network calibrated by the new approach is consistently better for the same number of OD-pairs. Furthermore, the performance of the new approach improves much more steadily than the previous approach as the number of input OD-pairs increases.

4. Discussion

The experimental results suggest that the new network free-speed calibration procedure is highly effective and outperforms the existing approach. In addition to that, there are also some interesting findings that are worth pointing out.

The original network, adapted from the OSM with default convention parameters, such as default free-speed for each road type, overestimates the free-speeds compared to the reference data from the Google Maps API. As shown in Figure 3a, the free-speed in the original network is significantly faster than the reference data, highlighting a systematic bias in the default network conversion procedure.

After the manual calibration (i.e., see Figure 3b), the systematic bias is significantly reduced, and the free-speed travel times of the OD-pairs are distributed around the $y = x$ line in the scattered plot. Nevertheless, the points are more widely spread than in the scattered plot for the network calibrated with the new calibration procedure (i.e., Figure 3d). By comparing the manually calibrated network with the network calibrated using the new approach, we can identify which parts of the network have free-speeds that are overestimated or underestimated in the manually calibrated network.

In Figure 5a, we plot the relative change in free-speed of each road segment from the manually calibrated network to the network calibrated by the new approach (i.e., normalized delta value with respect to the free-speed in the manually calibrated network). In the figure, a positive delta value means that the network free-speed calibrated by the new

calibration procedure increases, and vice versa. From the figure, we can see that, in the manually calibrated network, overestimation of the free-speed mainly happens in the city center and other busy areas, while underestimation of the free-speed usually occurs on the highway and in the less busy areas. The new calibration procedure is effective in eliminating those individual biases.

Another point worth mentioning is that we use 1:00 am as the departure time when querying the travel time from Google Map API. This is because the congestion is minimal, and the average travel times of the OD-pairs are the shortest. Figure 5b illustrates the trajectory of travel time progression throughout the day for 20 randomly chosen OD-pairs. The travel times for each OD-pair at different times of the day are normalized to their respective travel times at 1:00 am, which enables them to be displayed in a single plot. The red line in the figure represents the average trajectory of the normalized travel times. As can be seen from the plot, the average travel time curve reaches the lowest value from 1:00 am to 4:00 am. This suggests that 1:00 am is suitable for querying free-speed travel time.

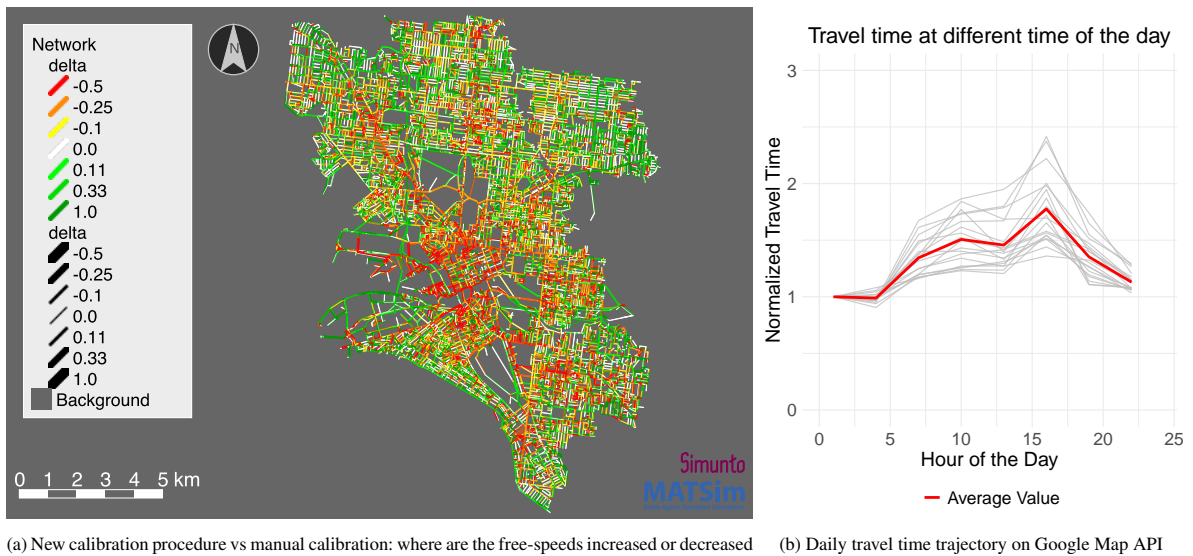


Fig. 5: Some remarks on the results

Finally, the new calibration procedure is more effective and consistent than the previous approach presented in [11]. The computational speed of the new approach is also significantly faster: with the same 19,000 input OD-pairs, the new approach calibrates the network in minutes, whereas the previous approach requires hours. The previous approach builds an underlying free-speed model that utilizes link attributes and optimizes it using stochastic gradient descent. However, it lacks spatial features, which prevents it from distinguishing between links in different areas that have distinct free speed characteristics. Furthermore, due to the stochastic optimization, it is more sensitive to hyperparameters and initial conditions, as evidenced by the fluctuations seen in 4. Nevertheless, it is worth noting that the previous approach's underlying model enables its use in policy studies where the road network is modified or extended, which is not possible with the approach presented in this paper.

5. Conclusion and Outlook

In this study, we have developed a fast and effective network free-speed calibration procedure for agent-based transport simulation frameworks. We have implemented the procedure in MATSim and tested the performance of the new calibration procedure. The new approach demonstrates a promising performance, paired with reference data based on the Google Map API. The errors, including RMSE and MAPE, are significantly reduced after the calibration procedure. Furthermore, the new approach also outperforms the existing network calibration approach in terms of both the quality of the output network and the computational speed. Additional experiments indicate that the new calibration procedure can also provide good results even when only a limited amount of reference data is available.

As the network plays an essential role in agent-based transport modeling, further studies can be built based on this newly developed calibration procedure. One use case is to create multiple reference data, each representing a different time of the day. Then the procedure can be repeated for each reference data set, and a time-varying network can be created. The time-varying network developed this way is helpful for simulations where congestion is treated as an exogenous effect. On the other hand, when the congestion needs to be modeled as an endogenous effect, more efforts must be invested into the traffic dynamic calibration. And a network with well-calibrated free-speed by this new approach can serve as a good starting point.

Since the procedure calibrates the network based on the reference data, the quality of the reference data determines the quality of the calibrated network. There are various ways to improve the reference data quality, such as integrating multiple data sources. With these, a more accurate network can be acquired. On top of that, a more systematic parametrization of the algorithm and the ability to enable additional configurations, such as accepting various objective functions, could make this calibration procedure even more powerful.

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