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BI-LEVEL OPTIMIZATION MODEL FOR DTA FLOW AND SPEED CALIBRATION

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1 INTRODUCTION

Dynamic traffic assignment (DTA) models are capable of capturing traffic dynamics and are well-known as a critical tool in controlling and predicting the traffic situation Ameli (2019). DTA simulation allows us to measure the results of deploying different technologies and applying different policies along with real experiments Ameli *et al.* (2020); Chen *et al.* (2021); Balzer *et al.* (2023). One of the crucial steps to achieve realistic results from simulation tools is calibration. It aims to determine the DTA model's input such that the output represents traffic scenarios with a reliable level of accuracy (Antoniou, 2004; Zargayouna *et al.*, 2006). The inputs can be divided into two groups: demand and supply. The supply parameters define the environment of the simulation and the field constraints, e.g., traffic network topology and capacity, traffic signals, speed limitation, etc. In contrast, the demand inputs represent the travelers and their behavior in the system, e.g., time-dependent origin-destination matrix, routing, lane changing, etc. Besides, the simulation output is evaluated and validated based on the data collected from real operations of the transportation system. Many technologies, such as loop detectors, radars, and cameras, have been developed to measure and record traffic data Ksontini *et al.* (2016). The main key indicators to evaluate the simulation output are flow and speed of the road segment or the whole network, which are collected at certain locations and times (Hou *et al.*, 2013; Alisoltani *et al.*, 2019). The mentioned technologies usually provide us with spatiotemporal data. Indeed, the rich time-varying traffic data can reflect field conditions for online real-time applications Ameli *et al.* (2022); Alisoltani *et al.* (2022). However, the availability of such data for traffic modelers is restricted due to operational limitations and security reasons. This study aims to address the calibration problem for simulation-based DTA with multiple sources of aggregated data that are more likely to be available for road networks.

In this context, the calibration of agent-based DTA simulations is more complex than continuous (flow-based) models (Patwary *et al.*, 2021; Ameli *et al.*, 2021). Because the inputs of the model, in addition to the network supply, are the trip profile of each agent (particle), including the departure time, route, and driving model, which result in the agent's trajectory. In the state of the art of agent-based simulation, the calibration problem is defined mainly around flow or speed calibration. However, few studies address both problems. Motivated by a field experiment, called *MegaVanderTest* as a part of CIRCLES project ¹ (Bayen, 2020), this study is an effort to create a high-fidelity simulation scenario using aggregated available data of the road segment flow and speed. A new methodology is proposed for flow and speed calibration of agent-based DTA simulation, wherein the mathematical model does not depend on the type of simulator. The data needed to feed the model is time-dependent road segment flow and speed (i.e., aggregated data, which is not hard to achieve). The next section presents a literature review on calibration problems for agent-based dynamic traffic simulation to clarify the problem and highlight the research question.

¹<https://circles-consortium.github.io/>

Brief Literature review

For the literature review, we focus on the studies that have proposed a methodology to solve the DTA calibration problem for both flow and speed in an agent-based road simulation setting. Antoniou *et al.* (2011) has proposed a framework for offline and online flow and speed calibration. However, it has used a mono-objective function which may reduce the accuracy by adding scaling parameters for each data type. Djukic *et al.* (2017) has used a bi-level approach to solve the OD estimation problem, but it calibrates the network only according to the flow counts. (Hu *et al.*, 2017) consider a two-stage model to solve the calibration process according to the flow and speed data, while there is no iteration between the two stages to adjust the parameters accordingly.

The dynamic simulator determines the number of parameters to be calibrated, mainly for the supply side. Multiple dynamic simulators are developed for DTA models, e.g., SUMO, MATSIM, DYNASMART, and DYNAMIT. We use SUMO as an open-source simulator motivated by the project, and Langer *et al.* (2021). We deploy a simulation-based iterative approach to solve the DTA problem Idoudi *et al.* (2022). Note that exact solution methods are computationally expensive or even impossible to apply due to the non-linear (non-analytical) and stochastic nature of the DTA calibration problem for spatiotemporal data (Lu *et al.*, 2015). Using meta-models is also recommended in the literature but mostly for large-scale multimodal networks (Patwary *et al.*, 2021).

Regarding the data for calibrating flow and speed, we consider two data sources: loop detectors and Probe vehicles. The loop detectors count the number of agents in road segments, and Probe vehicles measure the average speed of the road segment for each time interval. The characteristics of the two data sets are not synced, meaning that the time interval, the data collectors' positions, and the devices' accuracy are not the same for the two data sets. This leads us to formulate a new bi-level optimization framework to iterate between two levels to calibrate the simulation scenario with respect to both data sets while considering the correlation between speed and flow results from the agents' route and departure time.

2 METHODOLOGY

Figure 1 presents the bi-level calibration framework proposed by this study. The process is started by importing the data of link flow and building the network graph. The initial link flow distribution is denoted by \hat{X} , and it is the set of time-dependent link flows collected by the loop detectors. \hat{x}_i^k represents the reference flow of link i ($i \in E$, set of all links) at time interval k , $\hat{x}_i^k \in \hat{X}$. K is the set of time intervals for the flow data, $k \in K$. Note that for the speed data, we consider the same time horizon. However, the set of time intervals is different and denoted by R and indexed by $r \in R$. The reason is that the duration of time intervals in R and K is given by the data set and is not necessarily equal for both sets. In this study, the flow data is collected every hour, and speed data is collected every minute. Thus the duration of r is less than k . In the first (upper) level, the flow calibration problem is formulated as a mixed integer linear model and solved to determine the path flow distribution, Π . The flow of link i at time k resulting from Π is denoted by x_i^k . The objective function of the upper level is to minimize the Squared Error (SE) between x_i^k and \hat{x}_i^k . The output of this step is the Origin-Destination (OD) matrix and the number of agents traveling on paths between each OD pair, $\pi_{OD}, \forall \pi_{OD} \in \Pi$. We fixed the path flow distribution for the second (lower) level, wherein we determined the departure time distribution of agents.

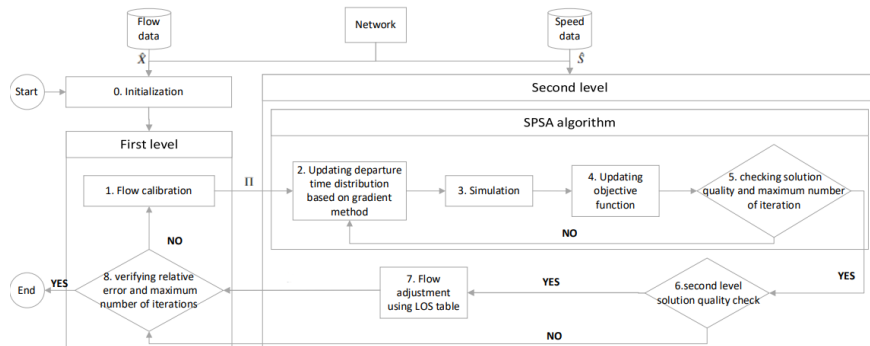


Figure 1: Methodology process

To find the optimal departure time, we propose a modified version of the simultaneous perturbation stochastic approximation (SPSA) algorithm inspired from Lu *et al.* (2015). For the initial solution in Step 2, we consider the uniform distribution for the departure times. In every iteration of the SPSA algorithm, we run a simulation (Step 3) with the demand profile from the previous step. In this study, we run SUMO simulation with speed variable sign (Lopez *et al.*, 2018) come from the data set. We consider a variance around the speed sign for the speed choice of the agents. In Step 3, We also measure s_l^r , the average speed of road segment l at time intervals r and compare it to the corresponding value \hat{s}_l^r from data set \hat{S} collected by the Probe vehicles. Then in step 4, the objective function of the lower level is updated based on the simulation results.

The next step is checking the convergence conditions of the SPSA algorithm based on the maximum number of iterations and comparing the solution quality (SE of the speed values) with a threshold. If the convergence is not achieved, we go to Step 2. Otherwise, we perform the second level solution quality check in Step 6 by considering the speed absolute error: $|x_i^k - \hat{x}_i^k|$. If there is any link with more than 10% absolute error, we go to the next step; otherwise, we go to Step 8. In Step 7, we aim to address the temporal correlations between two data sets. We modify the values in \hat{X} w.r.t the level of service (LOS) of the targeted network. LOS gives us a level of flow for the targeted speed considering the characteristic of the road, e.g., number of lanes and road type (Prassas *et al.*, 2020). For example, if the speed measured by simulation is higher than the data, we increase the value of the target flow. As a result, the density will increase at k then we can expect that the speed will reduce at r . This modification results in additional errors for the upper level. Therefore, in Step 8, we check the relative error of flow and speed in addition to the convergence of the model by the maximum number of upper-level iterations. In other words, if the modification of the flow is minor and the speed error is acceptable, we converge; otherwise, we go to Step 1 to update the path flow distribution. We deploy the Intelligent driver model (IDM) in this study. The calibration of IDM parameters is carried out based on the characteristics of the test case, e.g., driving laws and culture in the location of the test case. In our study, we address this issue by conducting multiple sensitivity analyses on the parameter of the simulator driving model. Then we set the parameters based on the available data and expert comments. The detailed mathematical model of the proposed framework (Figure 1) and further information about the sensitivity analysis will be presented at the conference.

3 NUMERICAL EXPERIMENT

The proposed methodology is applied to a road network of a portion of I24 highway in Nashville, Tennessee, the U.S., presented in Figure 2. The road network consists of 154 nodes, 452 links, and 16 traffic signals. The flow data set, LOS data and the cycle time of signals are provided by the Tennessee Department of Transportation (TDOT), and the speed data is provided by INRIX company. TDOT flow data corresponds to the network links, while the INRIX data provide the speed for every road segment. One link can consist of more than one road segment, and there is no overlap between road segments and links. The data sets represent the morning peak hour (6:30 am - 8:30 am). 20 min simulation warm-up is considered to insert the agents with their optimal departure times.



Figure 2: I24 road network.

4 PRIMARY RESULTS AND DISCUSSION

We first execute the bi-level process sequentially to evaluate the performance of each level. Figure 3 presents the primary results of flow and speed calibration. For the first level, we calculate the solution of the MILP model with the Scipy optimization solver. Next, we use calibrated demand profile with uniform departure time distribution to run the simulation-based speed calibration.

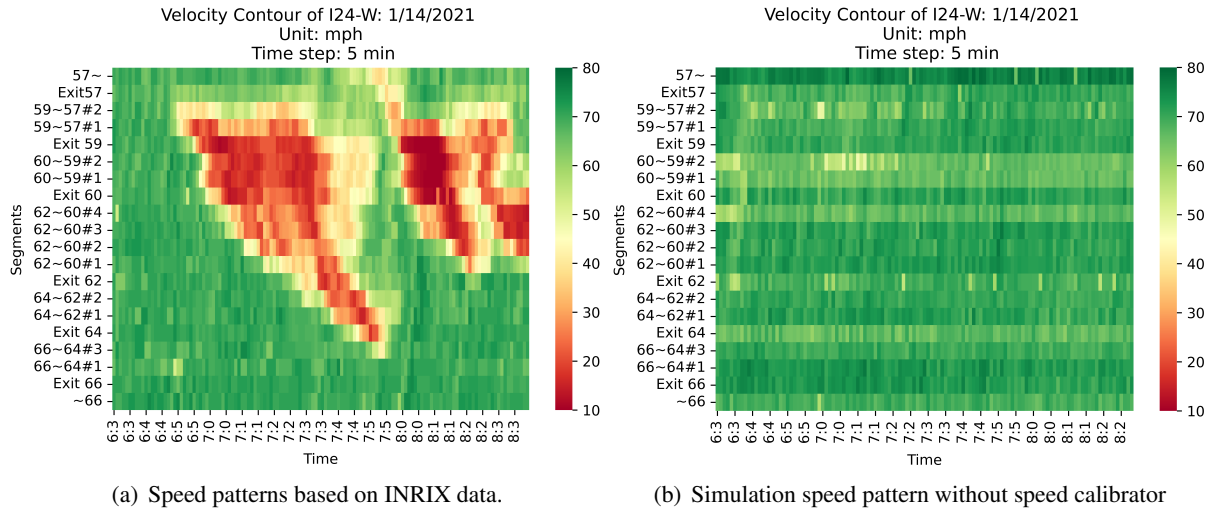


Figure 3: Primary results

Figures 3(a) and 3(b) illustrate the spatiotemporal speed pattern of the road network. Figure 3(a) corresponds to the INRIX data for a real scenario, which shows a traffic jam starting from Exit 59 at 7:00 am. Recall that the two optimization levels are conducted sequentially for these results. We are currently coupling the two levels in order to execute the iterative bi-level framework, which seems promising according to the primary results.

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