Improving simulation-based origin-destination demand calibration using sample segment counts data

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1 Introduction

High-resolution stochastic traffic simulators are vital tools for the planning and evaluation of urban mobility and transportation infrastructures and services. To fully leverage the benefits of these models, effective calibration is essential. One of the most critical calibration tasks involves identifying origin-destination (OD) demand patterns that accurately replicate observed traffic statistics from field measurements. Calibrating OD demand presents several challenges: the problem is high-dimensional, stochastic, non-linear, and underdetermined. A variety of optimization algorithms have been adapted for demand calibration, including simultaneous perturbation stochastic approximation (SPSA) Ben-Akiva *et al.* (2012), genetic algorithms Chiappone *et al.* (2016), and metamodel simulation-based optimization (SO) approaches Osorio (2019).

Traditionally, segment counts collected from loop detectors have been the primary data used for demand calibration. Advancements in traffic surveillance technologies have introduced new data sources that enhance the demand calibration process. These include mobile phone call data Iqbal *et al.* (2014), Bluetooth data Barcelo *et al.* (2012), and license plate recognition data Mo *et al.* (2020). Such data can yield various statistics about traffic flow — including counts, speeds, and travel times — on segment, path, or sub-path levels. The availability of these high-resolution datasets offers significant potential for improving the quality and scalability of OD demand calibration, providing extensive coverage without the need for often prohibitively expensive sensor infrastructure. Despite their advantages, these data sources have limitations. Although they can provide accurate speed and travel time statistics, the count data they provide can only be interpreted as samples rather than complete measurements of traffic flow, mainly due to limited penetration.

In this paper, we introduce a novel method for demand calibration that integrates path and segment-level traffic statistics from high-resolution, wide-coverage trajectory data. Our methodology builds upon the existing metamodel SO framework Osorio (2019) and recent advancements that utilize path travel times as ground truth data Zhang *et al.* (2024). The segment-level sample counts are integrated into the optimization problem as a regularization term despite unknown penetration rates, penalizing large deviations from the observed count distribution. This allows us to better capture network flow patterns and thus improve the accuracy of the calibrated demand. Importantly, our method preserves the scalability and sample efficiency of the original formulation. We evaluate the effectiveness of this approach on a large-scale use case of Seattle highway network across a range of traffic scenarios.

2 Methodology

2.1 Problem formulation

We focus on the *static* demand calibration problem, which aims to identify an OD demand matrix that reflects the observed traffic conditions aggregated over a time interval of interest. We utilize two types of field measurements: (1) the path-level travel time between OD pairs, and (2) a sample of the vehicular count on the segments. This unique combination of data is well-motivated in

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various contexts. For example, navigation-based field measurements provide accurate path-level travel time estimates and aggregated segment-level counts based on the fraction of commuters that use the navigation service. Both types of measurements have a wide spatial coverage.

To formulate the calibration problem, let $\mathcal{Z}$ denote the set of OD pairs and $d \in \mathbb{R}_{+}^{|\mathcal{Z}|}$ be the demand vector (flattened demand matrix). We denote by $\mathcal{P}$ and $\mathcal{I}$ the set of paths and segments in the network with field measurements, respectively. Let y_p^{GT} be the measured travel time on path $p \in \mathcal{P}$ and x_i^{GT} be the sample counts on segment $i \in \mathcal{I}$. We formulate the OD demand calibration problem as the following optimization problem:

$$\min_{0 \leq d \leq d_{max}} F(d) = \frac{w_1}{|\mathcal{P}|} \sum_{p \in \mathcal{P}} \left(y_p^{\text{GT}} - \mathbb{E}[Y_p(d;u)] \right)^2 + \frac{w_2}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \left(\frac{\mathbb{E}[X_i(d;u)]}{x_i^{\text{GT}}} - \frac{1}{|\mathcal{I}|} \sum_{j \in \mathcal{I}} \frac{\mathbb{E}[X_j(d;u)]}{x_j^{\text{GT}}} \right)^2, \tag{1}$$

where $\mathbb{E}[Y_p(d;u)]$ and $\mathbb{E}[X_i(d;u)]$ are the expected travel time on path p and expected flow of segment i, respectively, defined by the stochastic traffic simulator with exogenous parameter vector u. The first term in the objective function captures the distance between the travel times from the field measurements and those estimated by the simulator. The second term acts as a regularization term, penalizing large variances in the ratio between simulated and observed segment counts. This ensures the solution's physical plausibility and preserves the structure of the observed count data by matching their distributions. While this formulation is motivated by the assumption that the penetration rates of the sample segment counts are constant across the network, we use it as a regularization term rather than a hard constraint to tolerate the inherent variability in the penetration rates across different segments.

2.2 Metamodel algorithm

The problem formulated in eq. (1) is a high-dimensional SO problem (with OD variables in the order of hundreds to thousands). It also involves expensive evaluation of a black-box stochastic traffic simulator that is generally non-convex and non-differentiable. To address these challenges, we need sample-efficient algorithms that can reduce the needed number of function evaluations. For this we utilize the metamodel algorithm proposed in Osorio (2019). The core idea is to approximate the simulation-based objective function $F(d)$ with a convex and differentiable analytical function $M(d)$ known as the metamodel. The algorithm solves the metamodel optimization problem iteratively to produce candidate solutions that are then evaluated in simulation. In every iteration, the quality of the metamodel is improved by fitting a correction term based on the accumulated simulation evaluations. At the beginning of each iteration, the best OD vector encountered thus far is used as an initial guess for the metamodel optimization sub-problem. We give details of the metamodel problem below and refer the reader to Osorio (2019) for details of the full iterative approach for solving the SO problem.

Let $\mathcal{I}_{all}$ denote the set of all segments in the traffic network and $\mathcal{I}_p$ the set of segments comprising path p. For segment $i \in \mathcal{I}_{all}$, we define its length l_i, number of lanes n_i, and speed limit $v_i^{\max}$. Additionally, λ_i, k_i, and v_i represent analytical demand, density, and space-mean velocity, respectively. For simplicity, we assume all segments share common parameters: minimum velocity $v^{\min}$, jam density k^{jam}, critical density k^{crit}, density scaling factor κ, and fundamental diagram parameters, γ_1 and γ_2. y_p^A denotes the analytical travel time of path $p \in \mathcal{P}$. At each iteration k, we approximate each term of the simulation-based objective function by an analytical component $f^A(d)$ and a functional component $\phi(d)$, which acts as a correction term for enhanced accuracy. For each functional component, we fit a parameter set: α^k for the travel time term and β^k for the regularization term. We can now define the metamodel optimization problem for iteration k as the following convex problem which can be solved efficiently using standard optimization solvers.

$$\min_{0\le d\le d_{max}} \quad M_k(d;\beta^k,\alpha^k) = w_1\left(\beta_0^k f_1^A(d) + \phi_1(d;\beta^k)\right) + w_2\left(\alpha_0^k f_2^A(d) + \phi_2(d;\alpha^k)\right)$$

$$\text{s.t.} \quad f_1^A(d) = \frac{1}{|\mathcal{P}|}\sum_{p\in\mathcal{P}}\left(y_p^{\text{GT}} - y_p^A\right)^2, \qquad f_2^A(d) = \frac{1}{|\mathcal{I}|}\sum_{i\in\mathcal{I}}\left(\frac{\lambda_i}{x_i^{\text{GT}}} - \frac{1}{|\mathcal{I}|}\sum_{j\in\mathcal{I}}\frac{\lambda_j}{x_j^{\text{GT}}}\right)^2,$$

$$\lambda = Ad, \qquad k_i = \frac{\kappa k^{\text{jam}}}{n_i}\lambda_i, \quad \forall i\in\mathcal{I}_{all}$$

$$v_i = v^{\min} + (v_i^{\max} - v^{\min})\left(1 - \left(\frac{\max(k_i, k^{\text{crit}}) - k^{\text{crit}}}{k^{\text{jam}}}\right)^{\gamma_1}\right)^{\gamma_2}, \quad \forall i\in\mathcal{I}_{all}$$

$$y_p^A = \sum_{i\in\mathcal{I}_p}\frac{l_i}{v_i}, \quad \forall p\in\mathcal{P}$$

$$\phi_1(d;\beta^k) = \beta_1^k + \sum_{z\in\mathcal{Z}}\beta_{z+1}^k d_z, \qquad \phi_2(d;\alpha^k) = \alpha_1^k + \sum_{z\in\mathcal{Z}}\alpha_{z+1}^k d_z.$$

3 Seattle case study

We use the highway network of the Seattle metropolitan area as a case study. The network has 1,820 highway segments and 305 ramp-to-ramp OD pairs. We synthesize three scenarios resembling different congestion levels: low, medium, and high with total demand of $20,000$, $35,000$, and $50,000$, respectively. We generate and simulate the ground truth demand matrices for each scenario. Ground truth travel time and count measurements are obtained by sampling 15% of simulated trips and aggregating travel times at the path level and counts at the segment level. We note that this sampling method results in some variability in the penetration rate across ODs (and across segments).

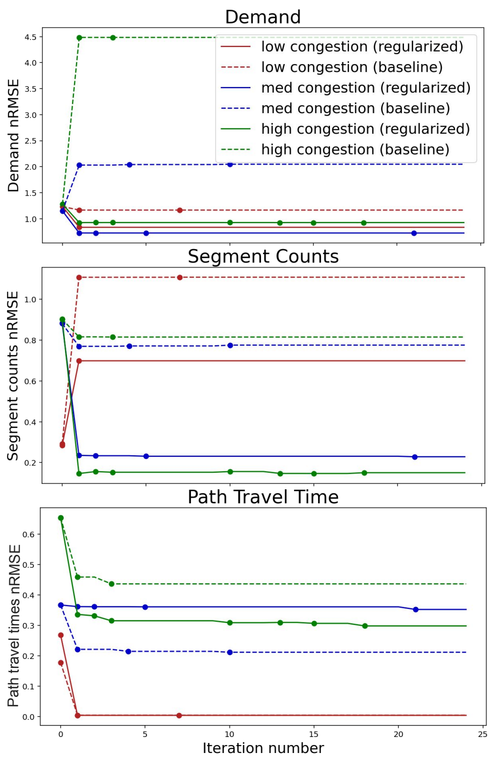
We compare the proposed formulation to the baseline metamodel approach without regularization in Zhang *et al.* (2024). For every iteration, we evaluate the solution by calculating the normalized root mean squared error (nRMSE) of (1) the demand vector, (2) the path travel times, and (3) the segment counts, averaged over five simulation rollouts, respectively. We use SUMO software Lopez *et al.* (2018) to model the network and perform all simulations. Each scenario is initialized with a randomized OD vector and the two weights parameters w_1 and w_2 are selected for each scenario to ensure the objective function terms are of similar magnitude.

3.1 Results

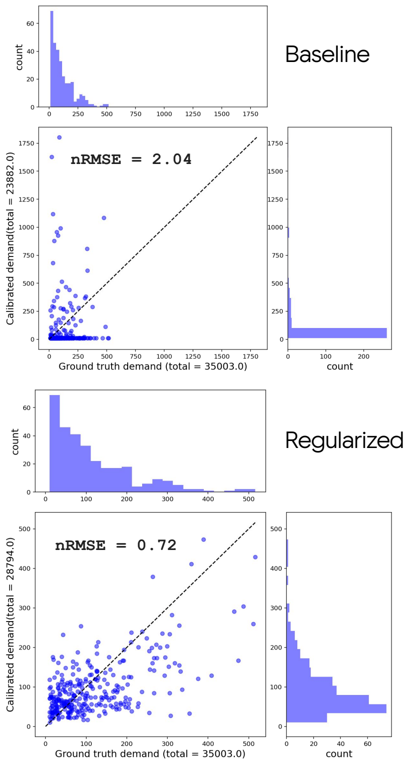
In fig. 1a, we report the three metrics for the baseline and the regularized metamodel solvers at each iteration. While the baseline solver shows better performance in terms of path travel time for the medium and low congestion scenarios, regularization significantly improves the segment counts and demand fit for these scenarios. In the high congestion scenario, the regularized solution outperforms the baseline in all metrics. Notably, the baseline solver may even worsen the estimation of demand, to achieve lower path travel time error. This reveals a critical limitation of such calibration methods: different demand vectors can yield similar path travel time measurements, obscuring the true underlying demand patterns. The proposed regularization effectively addresses this issue. Through this use case, we illustrate its ability to better reproduce the spatial distribution of the true demand by leveraging the sample counts across segments. This is further illustrated for the medium demand scenario in fig. 1b.

4 Discussion

This work presents a novel formulation for demand calibration, introducing a new segment count regularization method to tackle the underdetermination challenge. Our approach offers significant improvements in recovering the true demand vector, achieving up to a 65% decrease in terms of nRMSE compared to the unregularized solution, with only a slight degradation in the travel time performance. The proposed formulation exhibits generalizability, enabling its application to a wide range of calibration objectives, leveraging diverse field measurement data.



(a) *The performance of the calibrated demand across the three metrics at each iteration of the algorithm*



(b) *Scatter plot of the ground truth vs. calibrated demand vector (medium congestion).*

Figure 1 – *Comparison of the baseline and proposed regularized solver performance across different metrics and scenarios*

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