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Optimal road traffic operations for an increasingly autonomous and connected vehicle fleet

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1 Project Goals

The goal of this project is to develop decision-making tools that enhance our understanding of the intricate relationship between vehicle autonomy, traffic operations and congestion externalities. A detailed traffic simulation tool was used to investigate the relationship between vehicle autonomy, travel demand attributes (e.g., driver behavior), and network supply (e.g., prevailing traffic management strategies). The project carried out the following tasks. We have formulated, designed and prototyped, offline and online, calibration algorithms, such as to fit the input parameters of the new generation simulators that simulate both autonomous and/or connected vehicles. We then also formulated and implemented simulation-based optimization algorithms to address traffic management problems with mixed (i.e., autonomous and manually driven) traffic.

2 Introduction

Stochastic traffic simulators are comprised of supply and demand models that inform driver and network behavior and the interactions between the two within the simulator. These models contain parameters that must be tuned to ensure realistic and reliable simulator output, and accurate calibration of model parameters is a fundamental step in using traffic simulators to reproduce the behavior of real-world traffic systems. This becomes even more important for the online calibration problem, which aims to account for real-time fluctuations in traffic measurements within the simulator. Online applications of stochastic traffic simulators, such as real-time congestion routing and traffic control for incident management, rely on accurate and time-sensitive calibration to be more reflective of current conditions and to model time-dependent phenomena like rush hour demand and weather-related network constraints. Accurate online calibration of traffic simulators is also necessary for effective prediction of future traffic conditions.

Transportation demand and supply are increasingly intricate and real-time responsive. In particular, demand is increasingly connected (e.g., vehicle-to-vehicle communications, vehicle-to-infrastructure communications) and autonomous. Hence, there is a need to both develop novel disaggregate traffic models (e.g., car-following, lane-changing) suitable to represent this new generation of vehicle technology, as well as to enable, through online calibration, the use of standard (i.e., traditional) traffic models to accurately fit or represent traffic conditions observed once this new vehicle technology is deployed. This project has developed computationally efficient online calibration techniques that enable traditional and novel traffic models to be used to inform traffic operations accounting for the presence of innovative vehicle and communication technology.

Our research focuses on simulation-based, rather than analytical, traffic simulators. Calibration of these simulators is a difficult problem due to the complexity of the supply and demand interactions modeled. The relationship between model input parameters and output of the simulator (e.g., link count estimates) is stochastic and does not have a closed-form expression. In addition, the relationship is often nonlinear, non-convex, and non-differentiable. For large traffic networks, calibration becomes a high-dimensional optimization problem, as the number of parameters to be calibrated scales with network size. Finally, large-scale traffic simulators are computationally expensive to evaluate, which poses an issue for online calibration problems with a limited computational budget each calibration interval. These characteristics make online calibration a complicated optimization problem to solve, for which an accurate but efficient approach is needed.

The online parameter calibration problem can be formulated as such:

$$\min_{x^h \in \Omega} \sum_{j \in \mathcal{J}} (y_j^h - \hat{y}_j(x^h))^2 \qquad \text{for } h = 1, 2, 3, \ldots \tag{1}$$

The notation is defined as follows:

Ω	set of constraints on the calibration parameters;
$\mathcal{J}$	set of links on which measurements are observed;
x^h	vector of calibration parameters for time period h;
y_j^h	observed measurement for time period h on link j;
$\hat{y}_j(x^h)$	simulated estimate of expected measurement given parameters x^h for time period h on link j.

The above formulation is a flexible framework for general online calibration problems. It aims to determine the parameter values x^h that minimize the squared difference between observed and simulated measurements on a subset of links in the network at each time interval h. The vector of calibration parameters x^h can represent any combination of simulator parameters, from demand parameters like OD flows and route choice model parameters to supply parameters like speed-density function parameters. The observed measurements y_j^h can represent link flows, speeds, and densities, among other observable data.

Because of the complexity of stochastic traffic simulators, most existing online calibration approaches use data-driven methods that treat the simulator as a black box. While a few online calibration methods focus on specific subproblems constrained to speed-density parameters (Tavana and Mahmassani, 2000) or freeway settings (Wang and Papageorgiou, 2005) in order to exploit the problem structure, the majority of general methods utilize the simulator only for simulator evaluations. Many of these approaches require gradient information, and since the simulator has no closed-form expression, numerical gradient approximations are used. Numerical methods like finite differences and simultaneous perturbation, as used in methods like stochastic gradient descent (Huang et al., 2010), require multiple evaluations of the simulator to approximate the gradient and are computationally expensive.

One established online calibration method found in the literature is to formulate the problem as a state-space model with the calibration parameters defined as the state (Ashok and Ben-Akiva, 2000, Zhou and Mahmassani, 2007). Antoniou et al. (2007) develop a nonlinear state-space model and solve the model using an Extended Kalman filter to determine the optimal parameter values at each time interval. The measurement equation of the state-space model is given by the simulator, which is nonlinear and has no closed-form expression, so numerical gradient approximation is employed in the linearization step of the Extended Kalman filter algorithm.

We build upon the state-space model and Extended Kalman filter framework established by Antoniou et al. (2007) but propose an algorithm that reduces online computational cost by eliminating the need for numerical gradient approximations. More specifically, we develop an algorithm that can provide accurate calibration within a limited computational budget. Our approach utilizes problem-specific network information to give the calibration problem more structure, unlike purely data-driven algorithms that treat the simulator as a black box. By exploiting network structure, our algorithm is able to search the parameter space in a more intelligent way, with the overarching goal of improving the computational efficiency of the online calibration approach.

Algorithm 1 Metamodel EKF for Online Calibration

Offline Phase

Point Generation: generate calibration parameter candidates $\mathbf{x}_1, \mathbf{x}_2, \ldots$, and evaluate with simulator and macroscopic traffic model

Online Phase

Initialization:

$$\mathbf{x}^{0|0} = \mathbf{x}^0 \qquad \mathbf{P}^{0|0} = \mathbf{P}^0 \tag{2}$$

for $h = 1$ **to** N **do**

Time Update:

$$\mathbf{x}^{h|h-1} = \mathbf{x}^{h-1|h-1} \qquad \mathbf{P}^{h|h-1} = \mathbf{P}^{h-1|h-1} + \mathbf{Q} \tag{3}$$

Evaluation: compute $\hat{\mathbf{y}}(\mathbf{x}^{h|h-1})$, $\mathbf{q}(\mathbf{x}^{h|h-1})$, and $\frac{\partial \mathbf{q}(\mathbf{x})}{\partial \mathbf{x}}\Big|_{\mathbf{x}=\mathbf{x}^{h|h-1}}$

Metamodel Update: fit α_j^h, $\boldsymbol{\beta}_j^h$ for $j \in \mathcal{J}$

Linearization:

$$\mathbf{H}^h = \frac{\partial \mathbf{m}(\mathbf{x})}{\partial \mathbf{x}}\Big|_{\mathbf{x}=\mathbf{x}^{h|h-1}} \tag{4}$$

Measurement Update:

$$\mathbf{G}^h = \mathbf{P}^{h|h-1}(\mathbf{H}^h)^\intercal \left(\mathbf{H}^h \mathbf{P}^{h|h-1}(\mathbf{H}^h)^\intercal + \mathbf{R}\right)^{-1} \tag{5}$$

$$\mathbf{x}^{h|h} = \mathbf{x}^{h|h-1} + \mathbf{G}^h \left[\mathbf{y}^h - \mathbf{m}(\mathbf{x}^{h|h-1})\right] \tag{6}$$

$$\mathbf{P}^{h|h} = \mathbf{P}^{h|h-1} - \mathbf{G}^h \mathbf{H}^h \mathbf{P}^{h|h-1} \tag{7}$$

end for

3 Proposed approach

We propose to solve Problem (1) using a hybrid approach that embeds an analytical approximation of the traffic simulator within an Extended Kalman filter (EKF) in place of the simulator. The analytical approximation, which we call the metamodel, provides a relationship between calibration parameters and observed measurements similar to the simulator; the difference is the metamodel is analytical, computationally tractable, and differentiable. In particular, our proposed metamodel contains network-specific structural information from an analytical traffic model that relates the calibration parameters to the observed measurements. The analytical approximation of the simulator is used to improve the computational efficiency of the black-box Extended Kalman filter approach by eliminating the need for numerical gradient approximations involving many simulator evaluations, while continuing to provide an accurate fit to real-time data. The full algorithm is given in Algorithm 1.

In replacing the simulator with an analytical metamodel approximation, we essentially solve the following optimization problem related to the online calibration problem:

$$\min_{x_h \in \Omega} \sum_{j \in \mathcal{J}} (y_h^j - m^j(x_h))^2 \qquad \text{for } h = 1, 2, 3, \ldots \tag{8}$$

where $m^j(x_h)$ is the measurement estimated by the metamodel on link j for time interval h and is constructed to be an approximation of the simulator. Our proposed algorithm solves this optimization problem at each time interval using an Extended Kalman filter. Note that since the metamodel has an analytical gradient, the linearization step of the EKF is more straightforward than with the simulator measurement equation, which requires computationally expensive numerical differentiation methods.

More specifically, we construct a metamodel approximation $m^j(x_h, \alpha_h^j, \beta_h^j) = \alpha_h^j q^j(x_h) + \phi(x_h, \beta_h^j)$ for each simulator output $\hat{y}^j(x_h)$, where α_h^j and β_h^j are the metamodel parameters for time period h and link j. The coefficients α_h^j and β_h^j of each metamodel $m^j(x_h, \alpha_h^j, \beta_h^j)$ are fitted at each time interval h by running weighted least-squares on the set of previously-evaluated simulator points $\{(z_1, \hat{y}^j(z_1)), (z_2, \hat{y}^j(z_2)), \ldots, (z_N, \hat{y}^j(z_N))\}$.

The metamodel formulation comprises two components. The first component $\alpha_h^j q^j(x_h)$ is a physical term derived from an analytical traffic model denoted by q. The macroscopic analytical traffic model offers a series of equations, using network- and simulator-specific information, that relate the parameters to estimates of the measurements. The expression $q^j(x_h)$ represents the estimated measurement on link j found using the analytical model with parameters x_h. The second component $\phi(x_h, \beta_h^j)$ is a functional (polynomial) term used as a local error correction around the current estimated state x_h.

Within the Extended Kalman filter framework, replacing the simulator with the metamodel leads to the following changes:

- The simulator mostly runs offline. The simulator is used to generate evaluated points with which to fit the metamodel online.

- At each time interval h in the EKF, the metamodels m^j are fit before the linearization and measurement update steps. These metamodels are fit by weighted least-squares to the set of evaluated simulator points.

- Linearization is done analytically for the fitted metamodels m^j instead of numerically for the simulator. Similarly, the measurement update is completed using the fitted metamodels instead of the simulator.

4 Main results

We have developed and refined the proposed algorithm through a lower-dimensional case study on the Florian toy road network shown in Figure 1 (Astarita et al., 2001). The network contains three origin nodes and three destination nodes, and the parameters we aim to calibrate are demand flows for the nine different origin-destination (OD) pairs for every 15-minute time interval. To calibrate these flows, we have observed counts from 12 link sensors spread throughout the network for every 15-minute period. The simulator used in the case study is DynaMIT, a mesoscopic real-time stochastic traffic

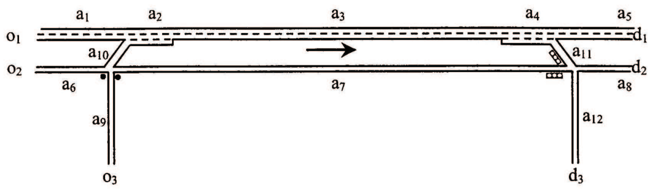

Figure 1: Florian toy network.

simulator used for traffic estimation and prediction, developed at the MIT Intelligent Transportation Systems Laboratory (Ben-Akiva et al., 2010).

In our initial experiments, we considered scenarios with fixed OD demand parameters across the entire simulation period. The demand scenarios used were chosen to have varying levels of congestion and to represent different traffic conditions on the network. We benchmark our proposed approach against the Extended Kalman filter approach developed by Antoniou et al. (2007), using central finite differences to calculate the gradient of the simulator in the linearization step. We started runs of our proposed algorithm by evaluating the simulator at 20 parameter settings chosen uniformly random over the sample space; these were used at each iteration to fit the analytical metamodel as an approximation for the simulator.

The lower-dimensional experiments with time-invariant OD demand were used to compare the performance of our proposed approach against the benchmark algorithm, both in terms of accuracy of parameter estimates and computational performance as measured by number of simulator evaluations required. These experiments were also used to determine the sensitivity of our algorithm to choice of initial parameter estimates. So far, we have seen performance comparable to the widely accepted benchmark algorithm, with a reduction in computational cost due to the use of an analytical gradient approximation instead of numerical gradient approximation. Performance has been robust to choice of initial parameter estimates.

We then considered scenarios with time-varying OD demand parameters. In these experiments, we focused on a simplified one-dimensional case where we constrained all OD demand parameters to be equal. Again, we compared the performance of our algorithm against the Extended Kalman filter approach developed by Antoniou et al. (2007). We have continued to see comparable performance with the benchmark algorithm in these experiments. In addition, we have used the performance of our algorithm in these time-varying OD demand scenarios to tune the Extended Kalman filter parameters for sensitivity to changes in OD demand, specifically the covariance matrices Q_h and R_h of the underlying state-space model.

Finally, we have been validating a couple of analytical traffic models for use in the case study, with the goal of finding a reliable but also scalable analytical approximation of the simulator to use as a component of the metamodel. The first analytical model we used was a macroscopic traffic model formulation developed by Osorio (2010) and expanded upon by Osorio et al. (2015) to include endogenous route choice assignment. In the model, each link is modeled as a finite-space capacity queue. The model was successful in reproducing the trends in link counts seen in the simulator, but its scalability to problems of larger size was unclear. We have since started using a new analytical traffic model which leverages simulator- and network-specific information to approximate the simulator, and is based off a multinomial logit route choice model and the fundamental diagram. In our experiments with this analytical model so far, it has proven to be both an accurate and scalable approximation of the simulator.

Through our experiments so far, our proposed online calibration algorithm has found parameter values capable of recreating observed measurements in the majority of demand scenarios tested. Its performance is comparable to the benchmark, while requiring fewer simulation evaluations, reducing the computational cost.

This project has also enabled us to launch a collaboration with faculty in the University of Coimbra to extend our work in the area of autonomous mobility. As part of ongoing collaboration, we are combining the calibration ideas with novel SO for autonomous mobility ideas to perform large-scale traffic management for connected and autonomous networks.

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