CE 269
Traffic Engineering

Lecture 6

Calibration and Simulators

Previously on Traffic Engineering

The GM models track the accelerations (*response*) of the follower vehicle as a function of *sensitivity* and *stimuli* such as reaction time, velocity differential, and spacing.

$$\ddot{x}_i(t+\tau_i) = \alpha_{l,m} \frac{\Big(\dot{x}_i(t+\tau_i)\Big)^m}{\Big(x_{i-1}(t) - x_i(t)\Big)^l} \Big(\dot{x}_{i-1}(t) - \dot{x}_i(t)\Big)$$

where $\alpha_{l,m}$ is referred to as the sensitivity coefficient and l and m are the speed and spacing exponents.

Previously on Traffic Engineering

The intelligent driver model (IDM) by Treiber, Hennecke, and Helbing (2000) predicts the acceleration of a following vehicle using the velocity of the current vehicle and the desired spacing s^* that depends on the speed differential.

$$\ddot{x}_i(t+\tau_i) = \bar{a}_i \left[1 - \left(\frac{v_i}{v_i^{max}} \right)^\delta - \left(\frac{s_i^*(t)}{s_i(t)} \right)^2 \right]$$

$$s_i^*(t) = s_0 + \max\left(0, v_i(t) T_i + v_i(t) \frac{v_i(t) - v_{i-1}(t)}{2\sqrt{b_i \bar{a}_i}}\right)$$

Where
v_i^{max} is the desired speed
T is the time gap
s_0 is the minimum gap
δ is the acceleration exponent
b_i is a comfortable value of deceleration.

Lecture Outline

1. Calibration
2. Simulators

Lecture Outline

Calibration

Calibration

Introduction

Driving behaviours vary across geographies, traffic facilities, and time of day. Hence, it is necessary to adjust the parameters of the car following and lane changing models to better reflect local conditions.

This process is typically done by collecting data and calibrating and validating the models.

There is no universal approach to calibrating a model. In this lecture, we will explore a few methods that have been used in the literature

It is common to find inter-driver and intra-driver variations in driving behaviour.

With enough data, it is possible to find model parameters for each individual. Alternately, one can

- Estimate a set of global parameters from data pooled from multiple drivers.
- Assume that heterogeneity of parameters is captured using distributions and estimate their parameters.

Calibration of microscopic traffic flow models can be carried out using either microscopic or macroscopic data.

Microscopic data typically consists of spacing, velocity, and acceleration from a single vehicle or floating car data preferably from a leader-follower pair.

Popular methods for calibrating the models from microscopic data are:

- Least squares method
- Maximum likelihood
- Metaheuristics

Suppose $\boldsymbol{\beta}$ denotes the vector of parameters of the car following model. Let y_t denote a traffic variable of the follower at time t.

The following variants of the least squares objective are typically used.

$$
\begin{aligned}
S_y^{abs}(\boldsymbol{\beta}) &= \frac{\sum_t (y_t(\boldsymbol{\beta}) - y_t^{data})^2}{\sum_t (y_t^{data})^2} \\
S_y^{rel}(\boldsymbol{\beta}) &= \frac{1}{T} \sum_t \left(\frac{y_t(\boldsymbol{\beta}) - y_t^{data}}{y_t^{data}} \right)^2 \\
S_y^{mix}(\boldsymbol{\beta}) &= \frac{\sum_t (y_t(\boldsymbol{\beta}) - y_i^{data})^2 / |y_t^{data}|}{\sum_t |y_t^{data}|}
\end{aligned}
$$

Suppose y denotes the spacing, then the S_y^{abs} objective does well in fitting small gaps in slow moving traffic and S_y^{rel} performs better when gaps are larger (cruising).

If multiple types of measurements are available, a hybrid objective of the following form can also be used to calibrate parameters

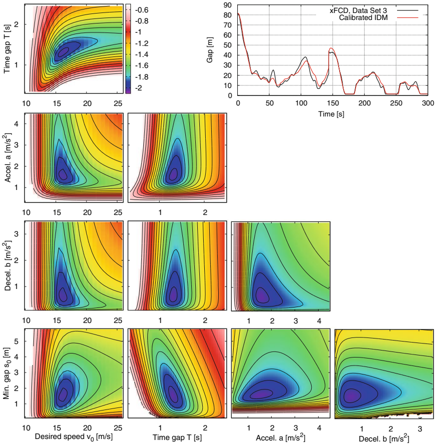
$$S^{hybr}(\beta) = \gamma_1 S_s^{mix} + \gamma_2 S_v^{mix} + \gamma_3 S_{\Delta v}^{mix}$$

Optimizing least square-type objectives are straightforward. In many cases, analytical expressions for the gradient of the objective with respect to the parameters are easy to obtain.

A simple gradient descent or Newton's method can help find the optimal parameters. Is the objective convex/concave?

Calibration

Example



Calibration

MLE Estimation

Recall that if $\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ is an n-dimensional random variable its joint PDF is given by

$$f_{\mathbf{X}}(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^n |\boldsymbol{\Sigma}|}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right)$$

In MLE estimation-based method, define a vector of multivariate Gaussian deviations as

$$\mathbf{e}_t(\boldsymbol{\beta}) = \mathbf{y}_t^{data} - \mathbf{y}_t^{sim}(\boldsymbol{\beta})$$

The log-likelihood function for a single trajectory can thus be written as

$$\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\Sigma}) = -\frac{n}{2} \ln(|\boldsymbol{\Sigma}|) - \frac{1}{2} \sum_t \mathbf{e}_t^T(\boldsymbol{\beta}) \boldsymbol{\Sigma}^{-1} \mathbf{e}_t(\boldsymbol{\beta})$$

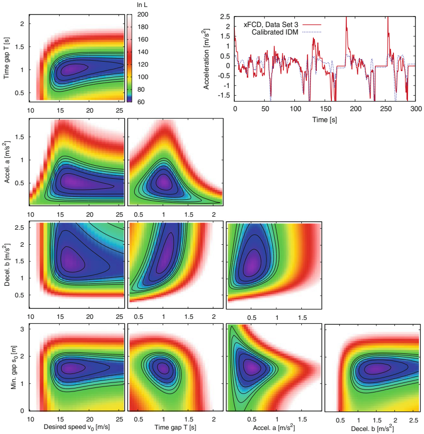
The covariance matrix is approximated using the $\boldsymbol{\beta}$s as

$$\hat{\boldsymbol{\Sigma}}(\boldsymbol{\beta}) = \frac{1}{n} \sum_t \mathbf{e}_t(\boldsymbol{\beta}) \mathbf{e}_t^T(\boldsymbol{\beta})$$

The log-likelihood function purely in terms of $\boldsymbol{\beta}$s is $\mathcal{L}(\boldsymbol{\beta}, \hat{\boldsymbol{\Sigma}})$

Calibration

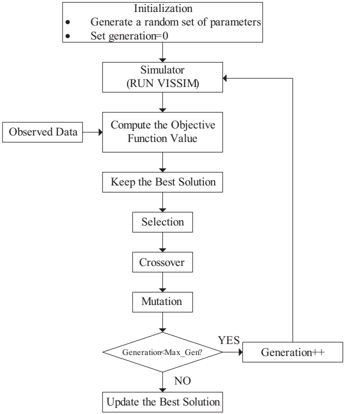
Example



Calibration

Metaheuristics

Metaheuristics such as genetic algorithms and Tabu search are also frequently used to calibrate parameters in commercial and non-commercial simulators.



Calibration

Metaheuristics

VISSIM code	Description	Feasible range (Min.∼Max.)	Unit
CC0	Standstill distance: Desired distance between lead and following vehicle at v = 0 mph	2∼10	ft
CC1	Headway Time: Desired time in seconds between lead and following vehicle	0.5∼1.5	sec
CC2	Following Variation: Additional distance over safety distance that a vehicle requires	5∼20	ft
CC3	Threshold for Entering 'Following' State: Time in seconds before a vehicle starts to decelerate to reach safety distance (negative)	−15∼−4	sec
CC4	Negative 'Following' Threshold: Specifies variation in speed between lead and following vehicle	−2∼−0.1	ft/s
CC5	Positive 'Following Threshold': Specifies variation in speed between lead and following vehicle	0.1∼2	ft/s
CC7	Oscillation Acceleration: Acceleration during the oscillation process	0.5∼1.5	ft/s^2

Authors	Journal	Algorithm[1]	Metric	Fitness function	Performance measurements[2]	No. of calibration parameters	Case study	Software
Ciuffo et al. (2008)	Transportation Research Record	OQMS	Traffic Counts, Speeds	$RMSPE(q,v)=\sqrt{\frac{1}{(42*2*2)}\sum_{t=1}^{42}\sum_{k=1}^{2}\sum_{d=1}^{2}\left(\frac{q_{tkd}^{obs}-q_{tkd}^{sim}}{q}{}_{tkd}^{obs}\right)^2+\frac{1}{(42*2*2)}\sum_{t=1}^{42}\sum_{k=1}^{2}\sum_{d=1}^{2}\left(\frac{v_{tkd}^{obs}-v_{tkd}^{sim}}{v_{tkd}^{obs}}\right)^2}$ $RMSE(v)=\sqrt{\frac{1}{T*2*2}\sum_{t=1}^{T}\sum_{k=1}^{2}\sum_{d=1}^{2}(v_{tkd}^{obs}-v_{tkd}^{sim})^2}$	RMSPE, RMSE, GEH	2 (driver's reaction time and speed acceptance)	E45 Naples–Pompei–Salerno freeway	AIMSUN 5.1.8
Ma et al. (2007)	Transportation Research Record	SPSA, GA, and IA	Capacity, Critical Occupancy	$\sum_{i=1}^{M}[GHE(cap_i)+A\times GHE(occ_i)]$	GEH	10 (MTH, MRT, and AGGR etc.)[3]	SR-99, Sacramento, California	PARAMICS
Cheu et al. (1998)	Journal of Transportation Engineering	GA	Average speed, Average volume	$\frac{\sum_{t-1}^{T}\lvert x^{field}(t)-x^{FRESIM}(t)\rvert}{T}$	Fitness Value and Average Absolute Errors	12 (free-flow speeds, Minimum car-following distances, lag to acc. etc.)	Ayer Rajar Expressway, in Singapore,	FRESIM
Paz et al. (2012)	IEEE Conference	SPSA	Speed	$\sum_{t=1}^{T}\sqrt{\sum_{i=1}^{I}(V_i-V_{simulated-i})^2}$	GEH	5 (driver behavior, vehicle performance etc.)	A network with 38 links, and a network with 20 links	CORSIM
Balakrishna et al. (2007)	Transportation Research Record	SPSA	O-D flows	Minimize the difference between observed and fitted measurements	RMSPE, GEH, RMSN[2]	2(Car-following and lane-changing coefficients)	Freeway network, Lower Westchester County, New York	MITSimLab
Toledo et al. (2004)	Transportation Research Record	Systemic search approach	O-D flows, travel times	Minimize the difference between observed and simulated O-D flows and travel times	Speeds on freeway sections and arterial sections	2 (Driving behavior, and Route choice parameters)	Three major freeways: I-5, I-405, and Route 133.	MITSimLab
Jha et al. (2004)	Transportation Research Record	Trial and error approach	O-D flows and traffic counts	Minimize the deviations between estimated and observed traffic counts and between the estimated O-D flows and field O-D flows	Traffic counts, travel times	2 (Route choice parameters and driving behavior)	Des Moines area network	MITSimLab
Kim et al. (2005)	Transportation Research Record	GA	Travel Time	$\frac{\sum_{i-1}^{n}\left\lvert\frac{S_i-O_i}{O_i}\right\rvert}{n}$	Moses', Wilcoxon, KS Test, and MAER	6 (look ahead distance, average standstill distance, and lane change distance etc.)	Arterial section of Bellaire Boulevard, Houston, Texas	VISSIM
Ma and Abdulhai (2002)	Transportation Research Record	GA	Flow	$\frac{\sum_{i-1}^{n}\lvert Q_{real}-Q_{sim}\rvert}{\sum_{i-1}^{n}Q_{real}}$	GRE	2 (mean headway and mean reaction time)	Port area network, Toronto, Canada	PARAMICS
Park and Qi (2005)	Transportation Research Record	GA	Average Travel Time	$\frac{\lvert TT_{field}-TT_{sim}\rvert}{TT_{field}}$	ANOVA test, Scatter plots	6 (look ahead distance, average standstill distance, and gap time etc.)	A intersection at the junction of Route 15 and Route 250, Virginia	VISSIM
Lee and Ozbay (2009)	Transportation Research Record	Enhanced SPSA	Flow, Speed	$\sum_{lane}\sum_{time}\left[\frac{\lvert Q_{real}-Q_{sim}\rvert}{Q_{real}}+\frac{\lvert S_{real}-S_{sim}\rvert}{S_{real}}\right]$	K-S test	2 (mean headway and mean reaction time)	I-880 in Hayward, California	PARAMICS
Hourdakis	Transportation	Non-linear	Speed	$\sum_{j=1}^{st}\sum_{i=1}^{m}\left(v_{si}^{j}-v_{ai}^{j}\right)^2$	RMSE, Theil's	12 (max. acc.	TH-160 from the	AIMSUN

Authors	Journal	Algorithm[1]	Metric	Fitness function	Performance measurements[2]	No. of calibration parameters	Case study	Software
et al. (2003)	Research Record	Programming Techniques			Inequality Coefficient	rate, max. speed diff, and avg. speed etc.)	interchange with I-494 and ending with I-94	
Chiappone et al. (2016)	Expert system with application	GA	Speed, Density	$\frac{1}{N}\sum_{k=1}^{N}\left[\frac{1}{2}(D_k - D_k(\beta))^2 + \frac{1}{2}(S_k - S_k(\beta))^2\right]$	Speed-Density graph	3 (reaction time, min. distance between vehicle, and max. desired speed)	A22, freeway, Italy	AIMSUN
Menneni et al. (2008)	Transportation Research Record	GA	Maximum 5-min flows	Sum of all the speed-flow area in the field data that is not covered by simulated data	Flow-Speed graph	5 (CC1, CC2, CC3, CC4, and CC5)	US-101, San Mateo, California	VISSIM
Abdalhaq and Baker (2014)	Journal of Algorithm and Optimization	GA, TS, PS, and SPSA	Travel Time	$\frac{\sum_{i=1}^{n}\frac{\lvert sim_i - observed_i \rvert}{observed_i}}{n}$	Average Fitness	4 (deceleration, acceleration, and driver imperfection etc.)	A signalized segment in a vital city center	SUMO
Paz et al. (2015)	Transportation Research Part C	Memetic Algorithm, and SPSA	Vehicle Counts and Speeds	$\frac{1}{\sqrt{N}}\sum_{t=1}^{T}\left(W * \sqrt{\sum_{i=1}^{N}\left(\frac{V_{i,t}-V(\theta)_{i,t}}{V_{i,t}}\right)^2} + (1-W) * \sqrt{\sum_{i=1}^{N}\left(\frac{S_{i,t}-S(\theta)_{i,t}}{S_{i,t}}\right)^2}\right)$	GEH	11 for freeway and 15 for surface streets (pedestrian delays, and max. deceleration etc.)	A portion of the Pyramid Highway in Reno, NV and a hypothetical network provided by McTrans	CORSIM
Hale et al. (2015)	Transportation Research Part C	SPSA and "Directed Brute Force" (DBF)	Speed and Density	Minimize the Difference between Simulated and Field-measured outputs	Objective Function Value	5 (entry headway, and off-ramp reaction distance etc.)	I-95 near Jacksonville, FL	FRESIM

[1] OQMS, OptQuest/Multistart Algorithm; GA, Genetic Algorithm; IA, Trial-and-Error Method; SPSA, Simultaneous Perturbation Stochastic Approximation; PS, Particle Swarm Optimization; TS, TS.

[2] RMSPE, root mean square percent error; RMSE, root-mean-square error; GEH, Geoffrey E. Havers statistics; MAER, mean absolute error ratio; GRE, global relative error; RMSN, Normalized root-mean-square error.

[3] MTH, mean target headway; MRT, mean reaction time; AGGR, driver aggressiveness.

Alternately, one can use point-sensor data at multiple locations to calibrate car following models. The data from the most upstream sensor can be used as initial conditions along with a approx. trajectory constructed from the lead vehicle data at all other locations.

The follower vehicles can then be simulated using car following models and the velocities at the sensor locations can be used to match the measured values using least squares type objectives as shown below

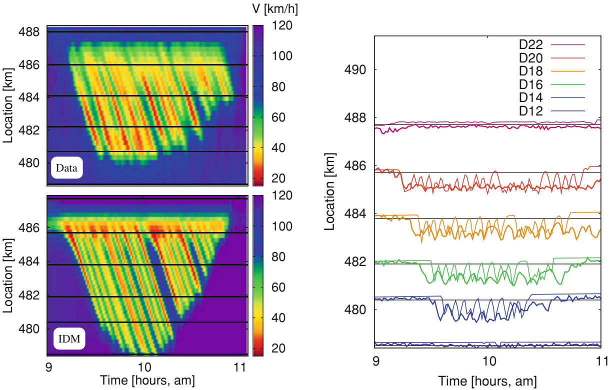
$$S_v^{abs}(\beta) = \frac{1}{tK}\sum_{k=1}^{K}\sum_{t}\left(v_{tk}(\beta) - v_{tk}^{data}\right)^2$$

$$S_v^{rel}(\beta) = \frac{1}{tK}\sum_{k=1}^{K}\sum_{t}\left(\frac{v_{tk}(\beta) - v_{tk}^{data}}{v_{tk}^{data}}\right)^2$$

or a convex combination of such objectives for other measurements such as flow.

Calibration

Example



Lecture Outline

Simulators

Simulators

Several commercial and non-commercial tools are available for microscopic simulation of traffic.

- SUMO
- VISSIM
- AIMSUN
- CORSIM
- PARAMICS
- TRANSYT
- TransModeler
- CityFlow

Simulators

Demo

Install SUMO from https://www.eclipse.org/sumo/ and perform the following tasks

- Create a small network of links in netedit
- Adjust the number of lanes, speeds, and update the connectors
- Generate flows from one edge to another
- Add a detector to measure point-sensor data
- Save the network, routes, and additional elements, and the configuration files
- Run your model using sumo-gui and notice the sensor outputs

Your Moment of Zen