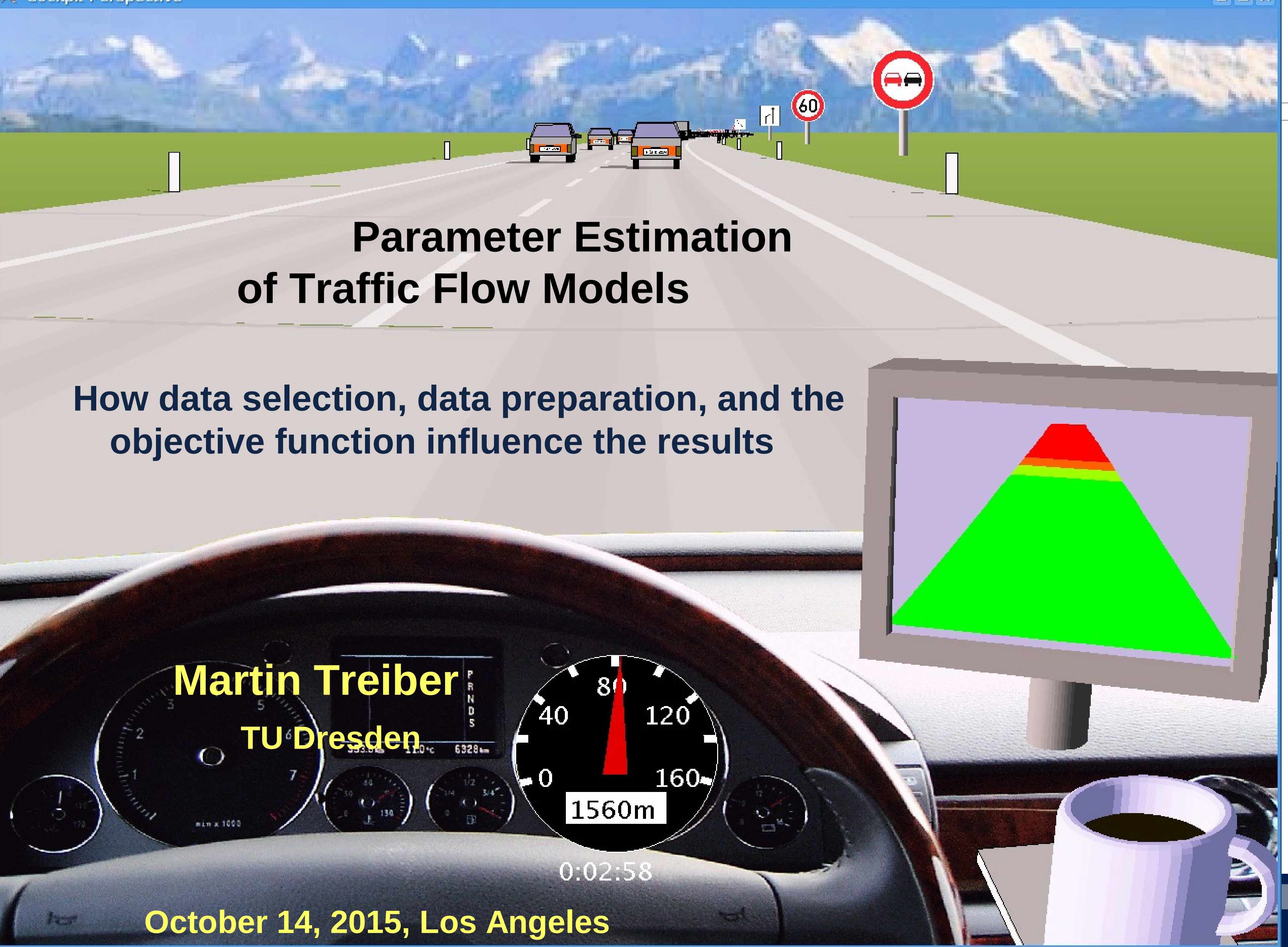
Parameter Estimation of Traffic Flow Models

How data selection, data preparation, and the objective function influence the results

Martin Treiber

TU Dresden

October 14, 2015, Los Angeles



Overview

- **General aspects**

- **Calibrating macroscopic features**
  - spatiotemporal speeds etc
  - extension of congested zones
  - propagation velocities
  - growth rates of instabilities

- **Calibrating car-following aspects**

- **What do we learn?**

General aspects: what is calibration?

"With four parameters I can fit an elephant, and with five I can make him wiggle his trunk"

Attributed to von Neumann

Definition in the traffic context:

"Calibration is the estimation of parameters to maximize the model's descripitive power to reproduce local driver behavior and/or collective traffic-flow characteristics. The descriptive power is specified by an objective function to be applied to representative traffic data"

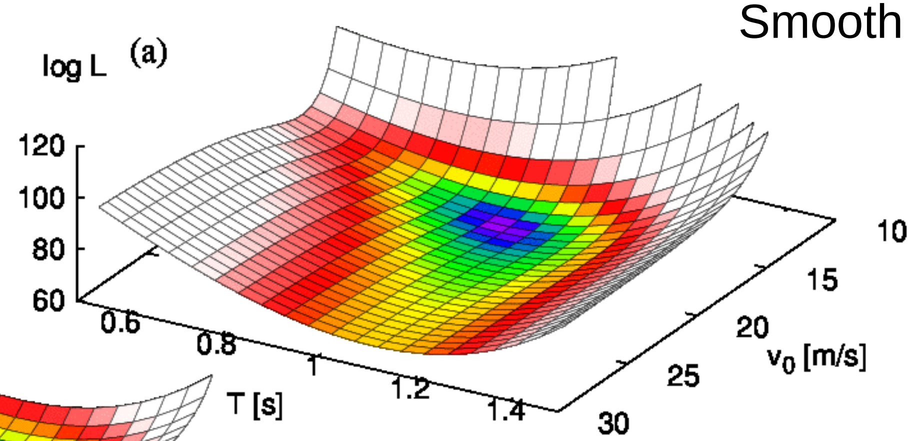
=> more like fitting a herd of running elephants!

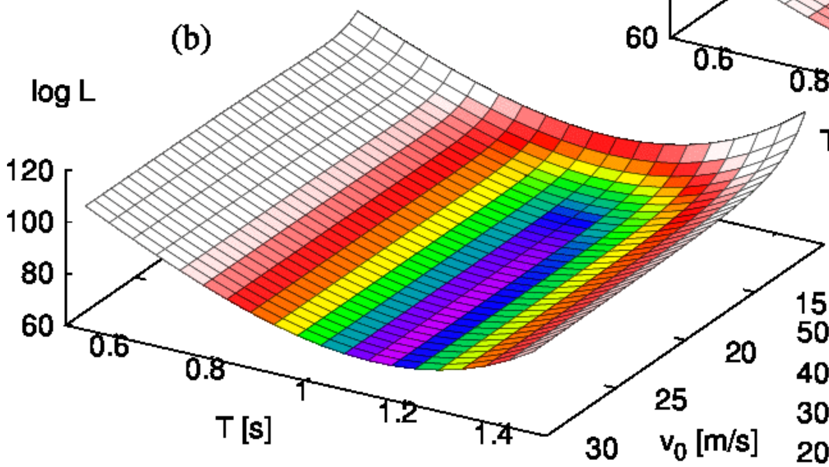
Aspects of calibration methods

- **Methodology**
  - Least squared errors (LSE)
  - Maximum Likelihood (ML)
  - Combined with uncertain data and in real time: Kalman filter
- **Objective**
  - variable/variables to be calibrated (speed, gap, acceleration,...)
  - functional form of objective function (LSE) or statistical assumptions (ML)
- **Underlying model**
  - deterministic/stochastic
  - microscopic/macroscopic
- **Degree of coherence**
  - local (point by point)
  - global in time (whole trajectory)
  - global in spacetime (many trajectories)

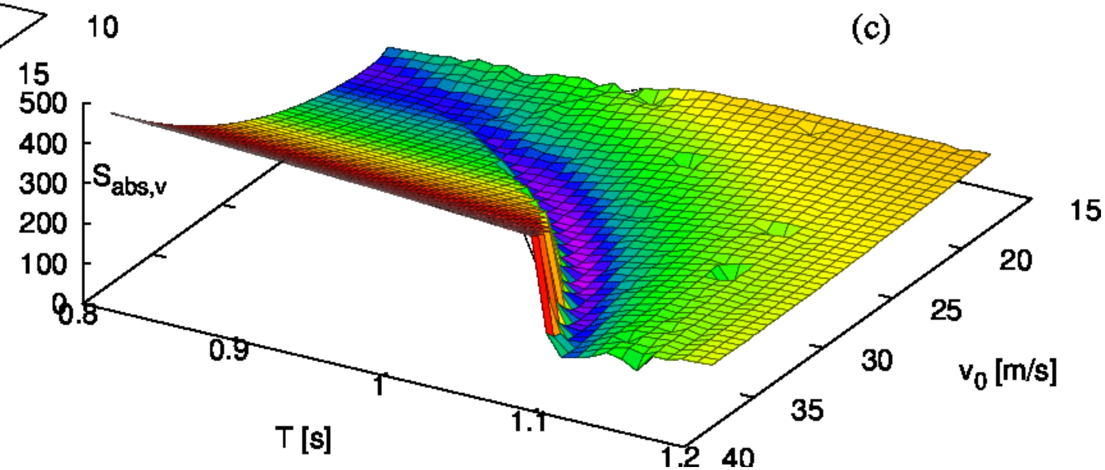
Qualitative types of objective functions: the “objective landscape”

Smooth and unimodal



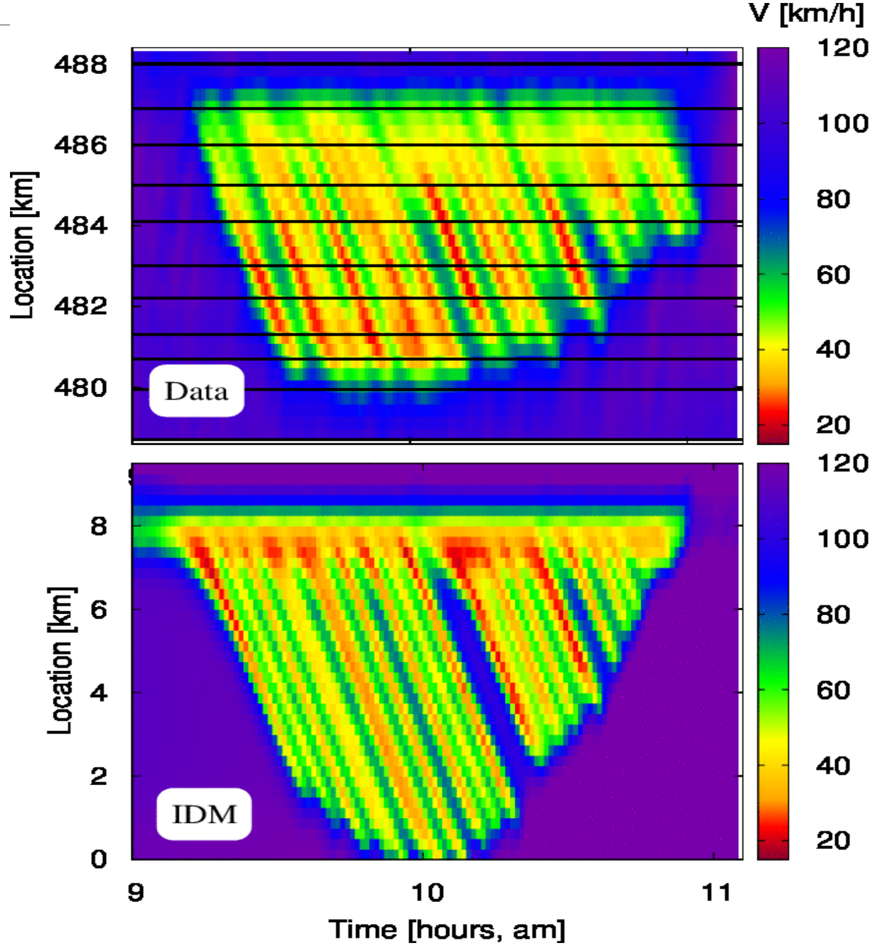


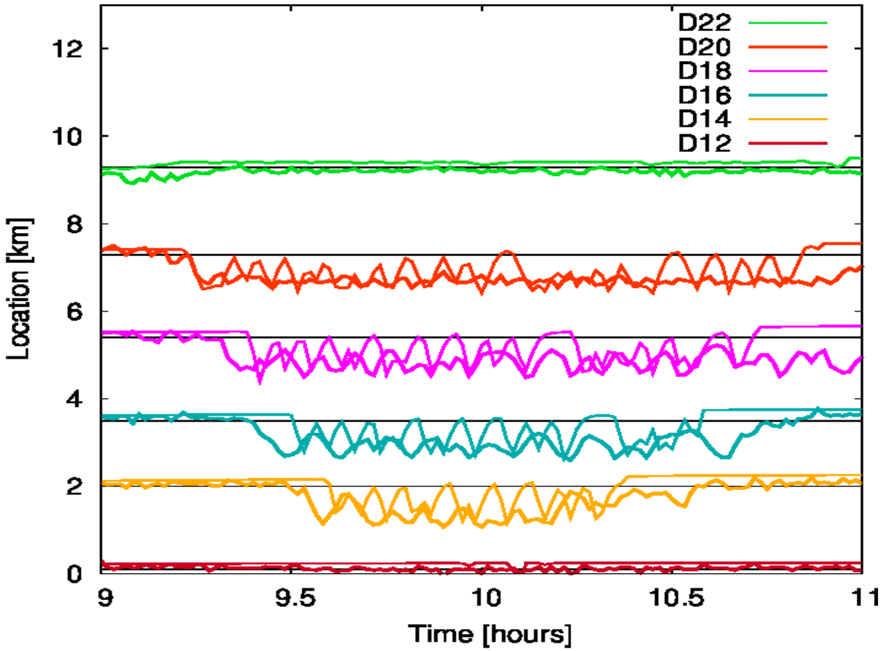
Smooth, no unique minimum



Multimodal, “rugged” objective landscape

Calibrating macroscopic features: how NOT to do it

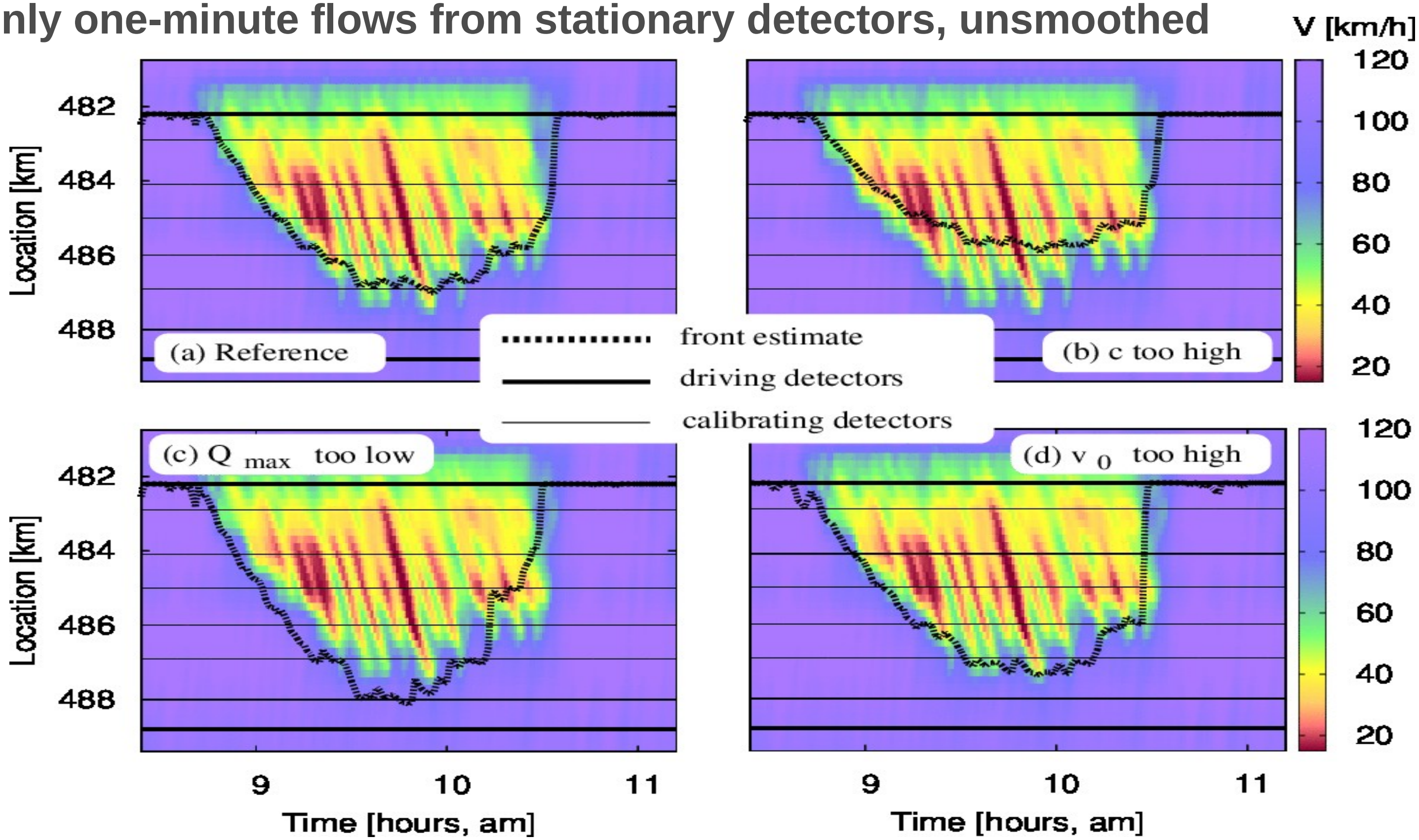




No chance to predict any single stop-and-go wave
=> some 1-norm or 2-norm of spatio-temporal speed/gap/density differences is unsuitable

Calibrating macroscopic features I: Spatiotemporal extension of congested regions

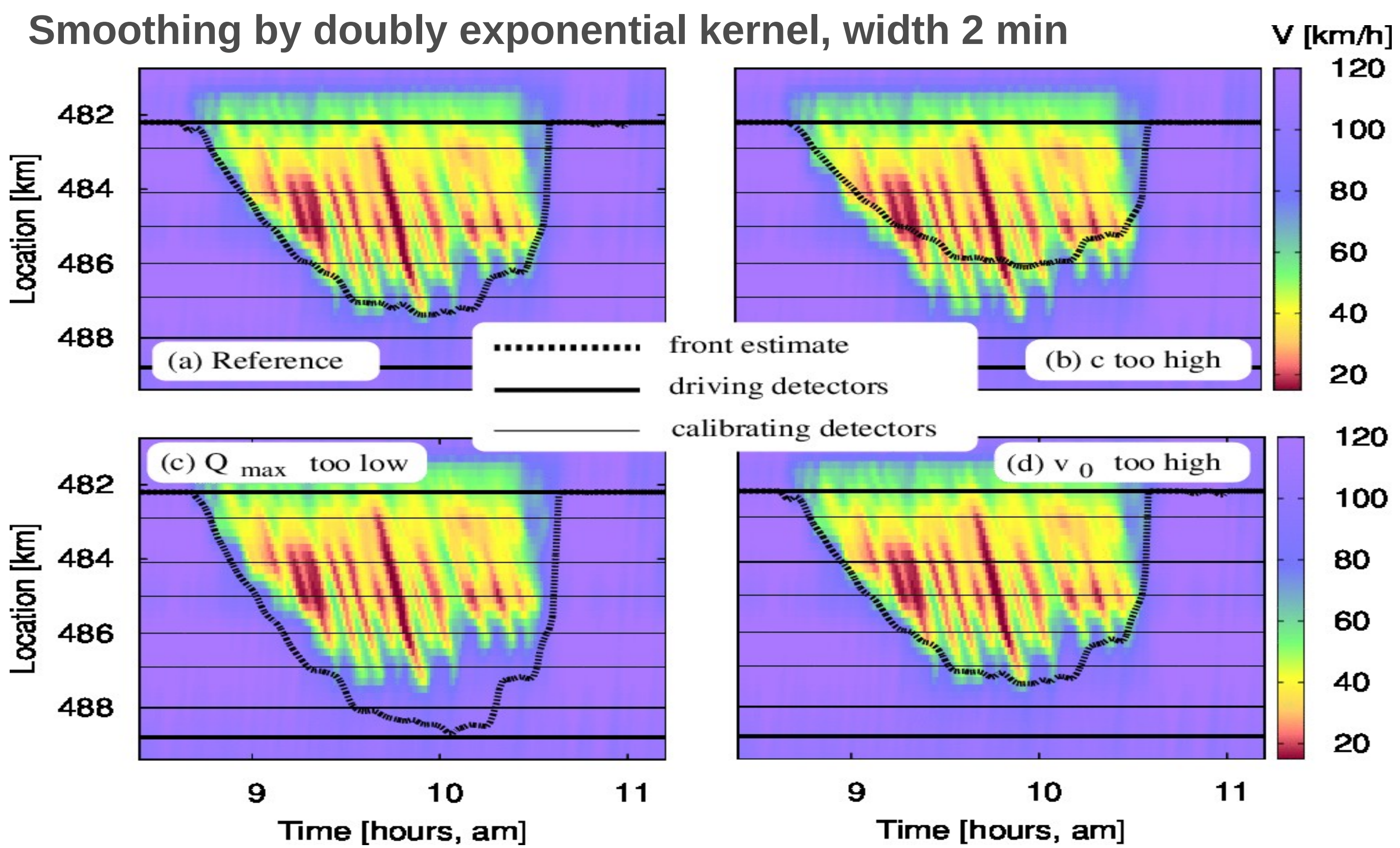
Data: only one-minute flows from stationary detectors, unsmoothed



- Example: LWR with triangular FD
- parameters: Qmax, V0, and c
- system dynamics: shockwave formula

- objective function: 1-norm of positional errors of front

Smoothing the data

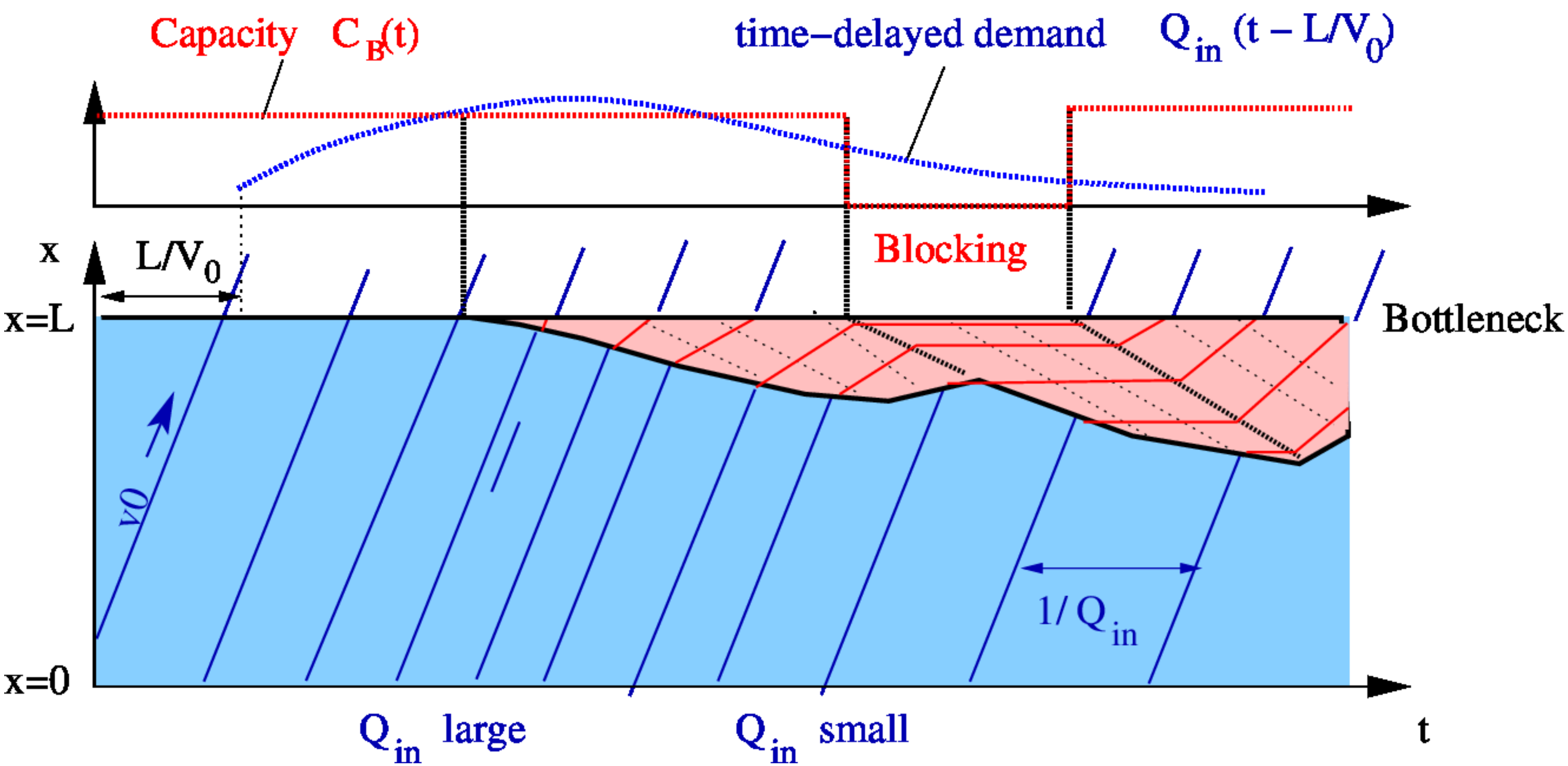


- LWR with triangular FD
- parameters: Qmax, V0, and c
- system dynamics: Shockwave formula

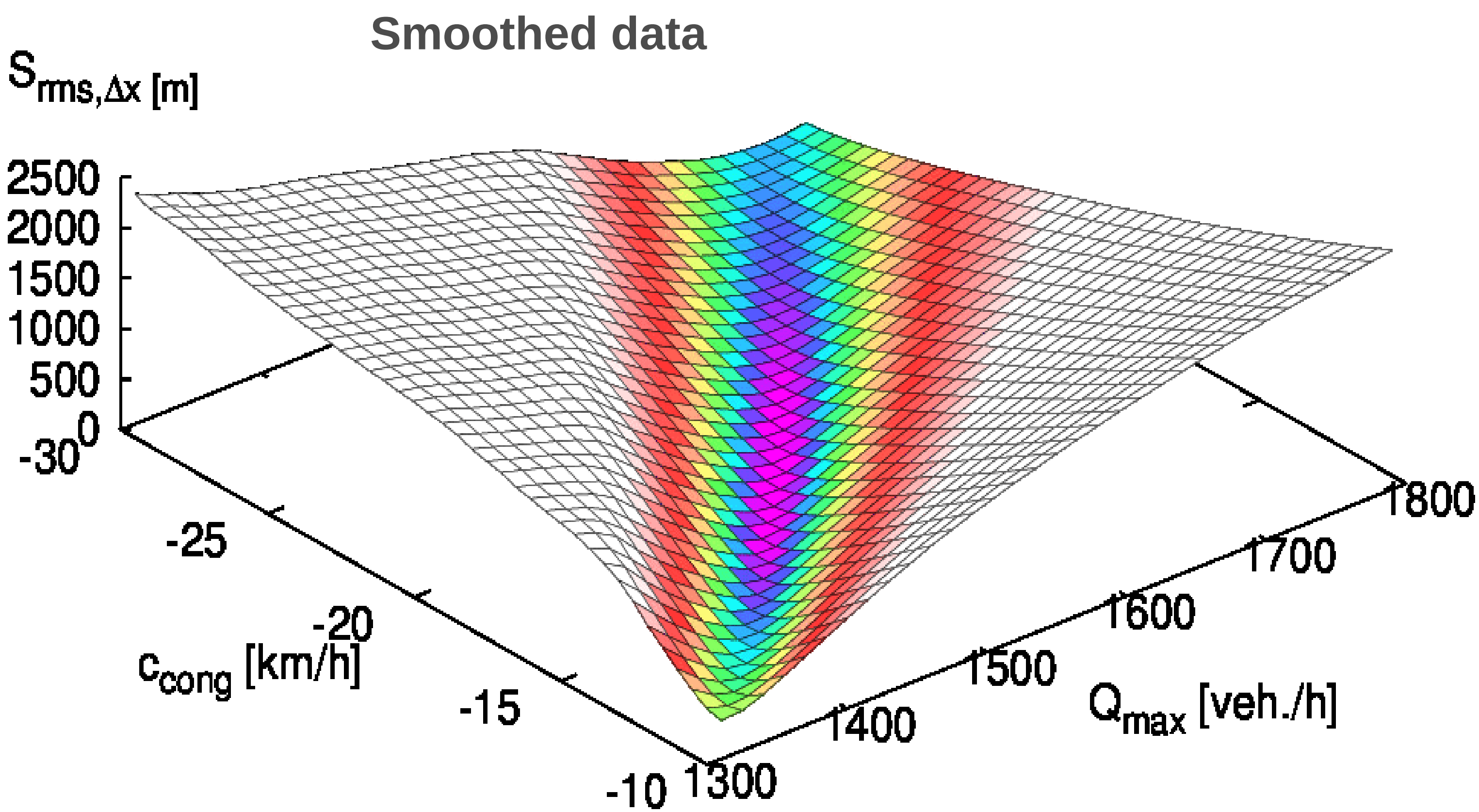
- objective function: 1-norm of positional errors of front

System dynamics

Shockwave formula: c12=(Q1-Q2)/(ρ1-ρ2)
plus propagation velocities V0 and c



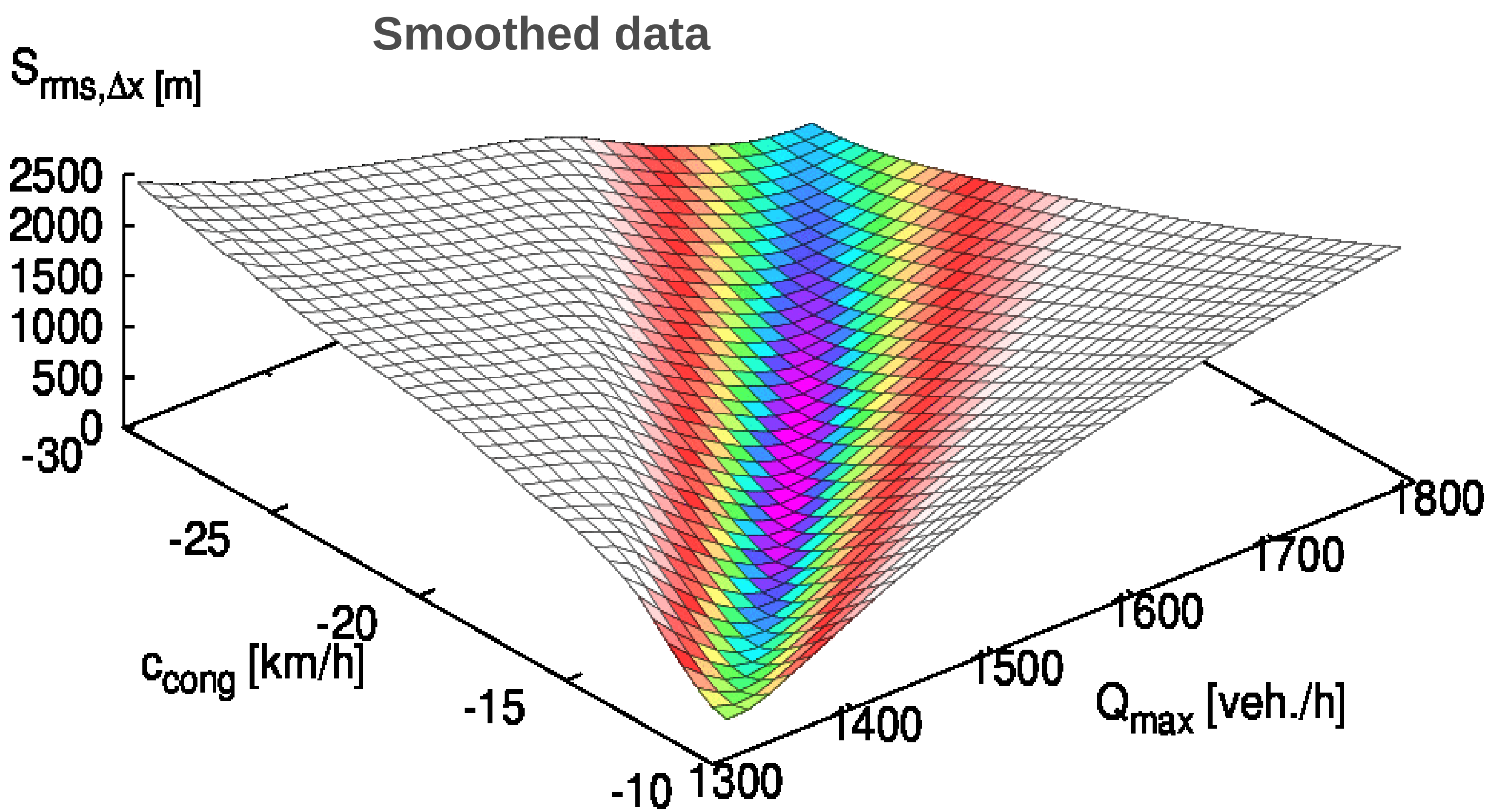
Objective landscape for V0=80 km/h



- LWR with triangular FD
- parameters: Qmax, V0, and c
- system dynamics: Shockwave formula

- objective function: 1-norm of positional errors of front

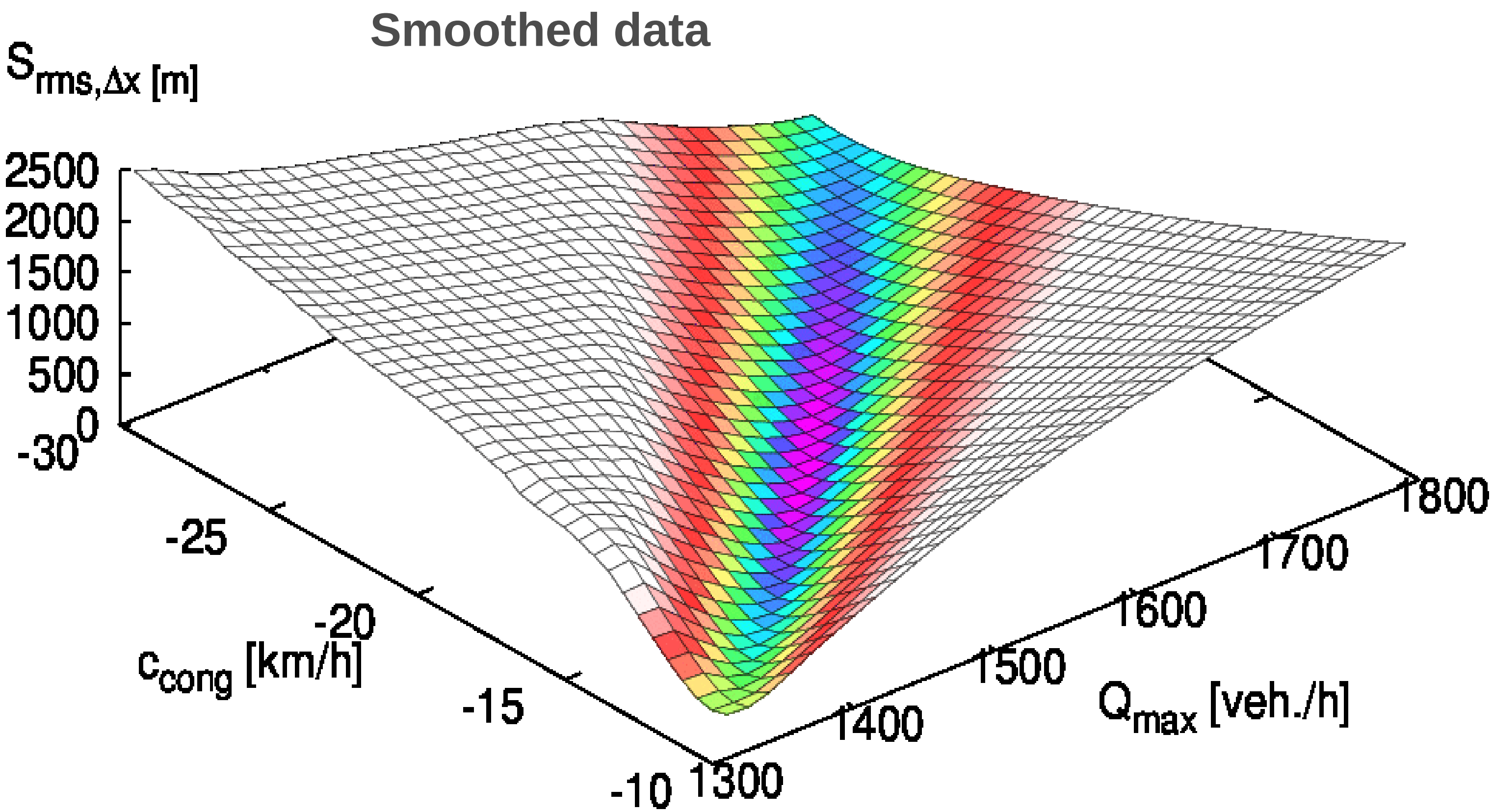
Objective landscape for V0=100 km/h



- LWR with triangular FD
- parameters: Qmax, V0, and c
- system dynamics: Shockwave formula

- objective function: 1-norm of positional errors of front

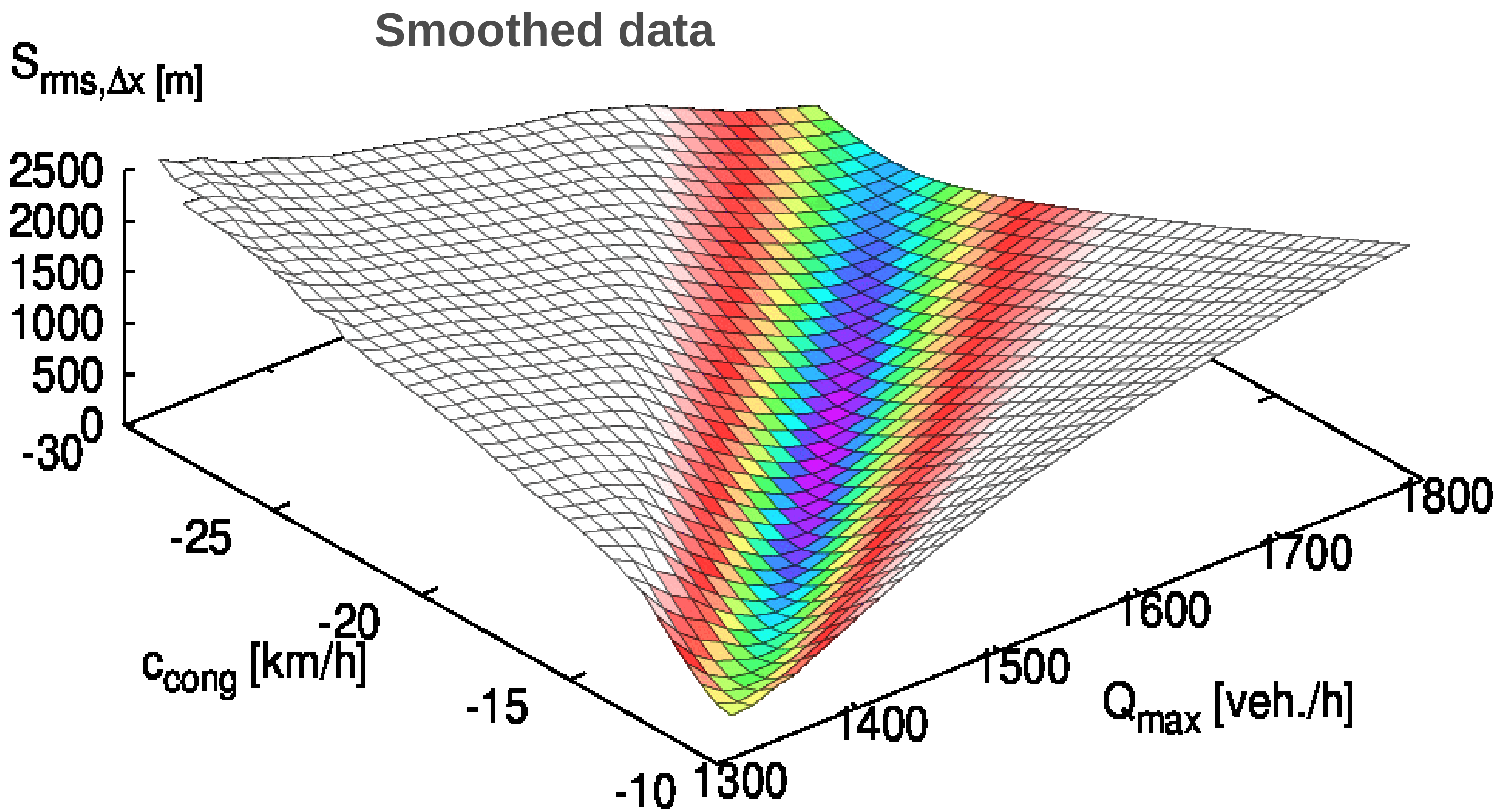
Objective landscape for V0=130 km/h



- LWR with triangular FD
- parameters: Qmax, V0, and c
- system dynamics: Shockwave formula

- objective function: 1-norm of positional errors of front

Objective landscape for V0=180 km/h

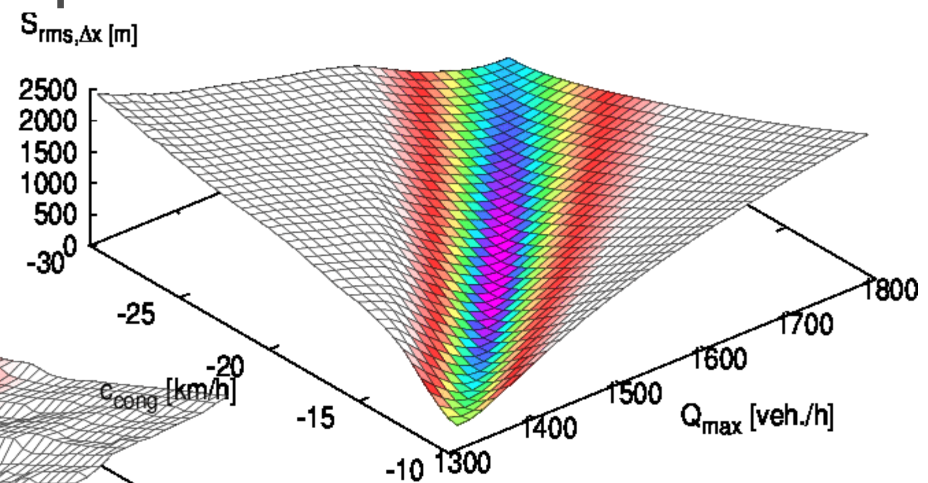


- LWR with triangular FD
- parameters: Qmax, V0, and c
- system dynamics: Shockwave formula

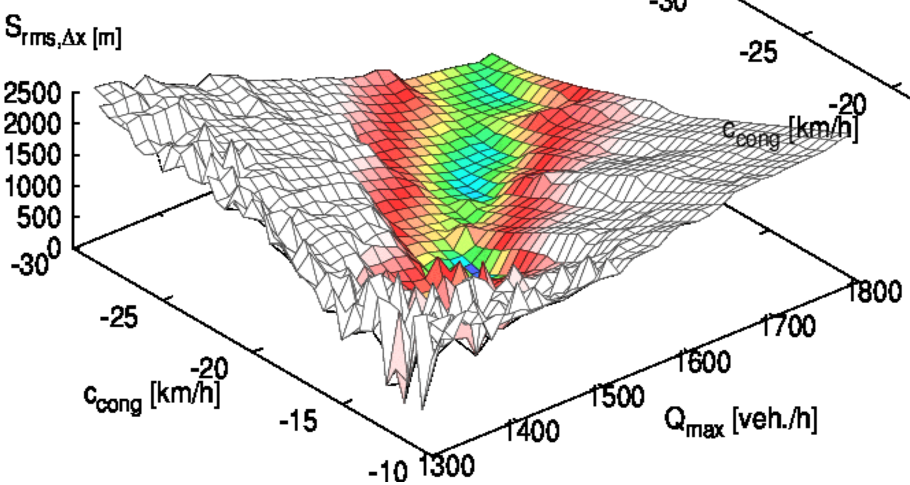
- objective function: 1-norm of positional errors of front

Objective landscape: Effect of smoothing the data

Maximum speed V0=100 km/h



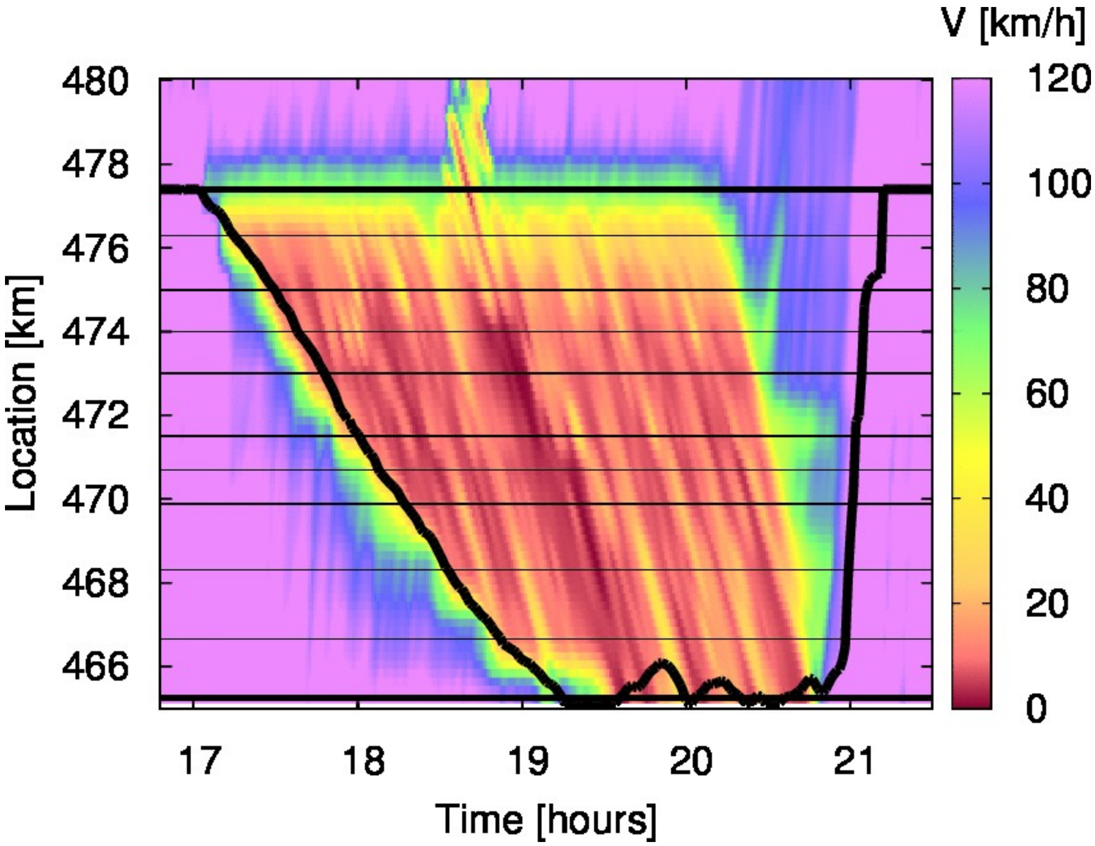
Smoothed data (double-exponential kernel, 2 minutes)



unsmoothed detector flow data

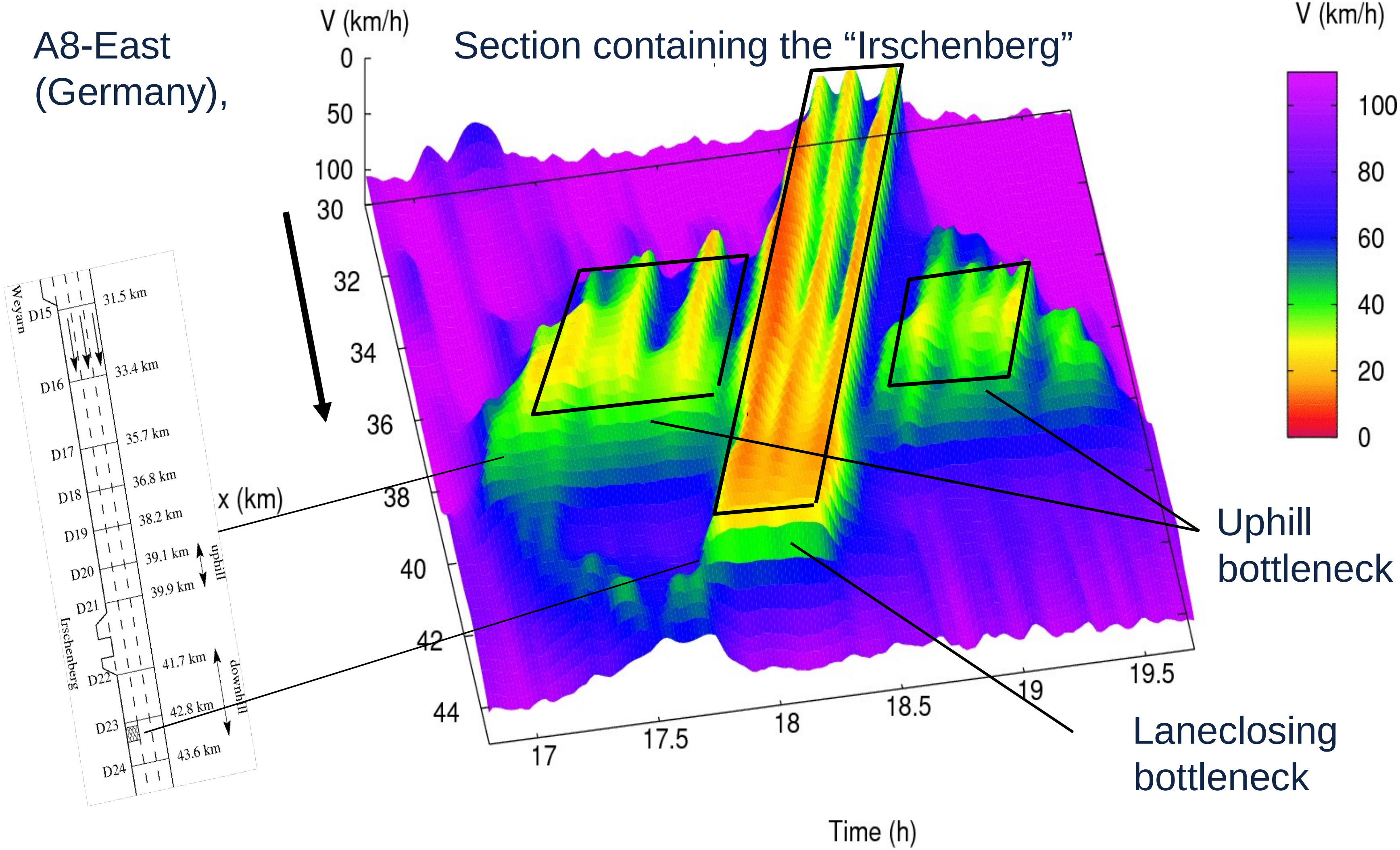
Validation: Apply to another congestion on the other direction

Congestion on the A5-South with LWR prediction as calibrated by the A5-North jam of the previous slides

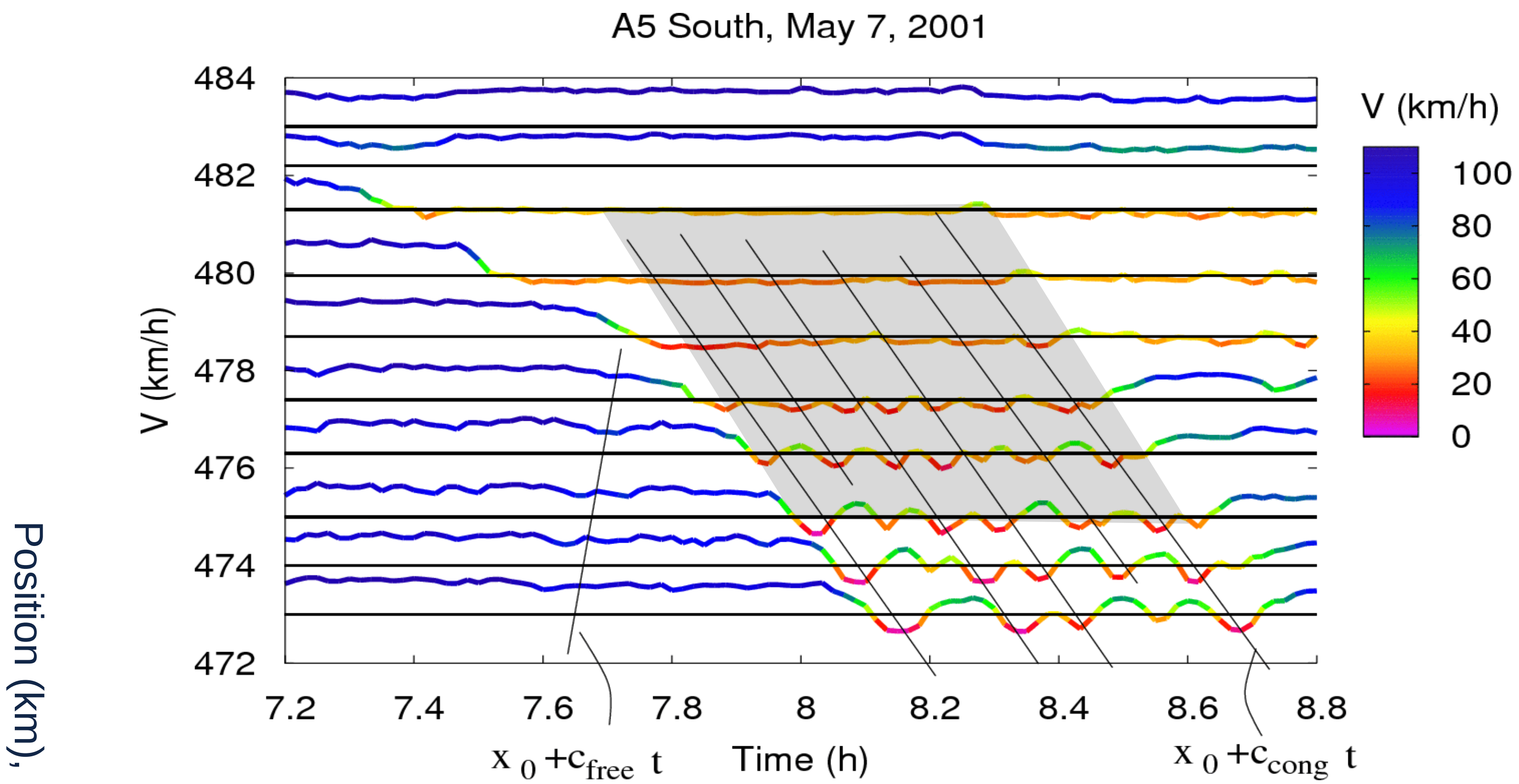


Calibrating macroscopic features II: traffic wave dynamics as a function of the bottleneck strength

A8-East (Germany),

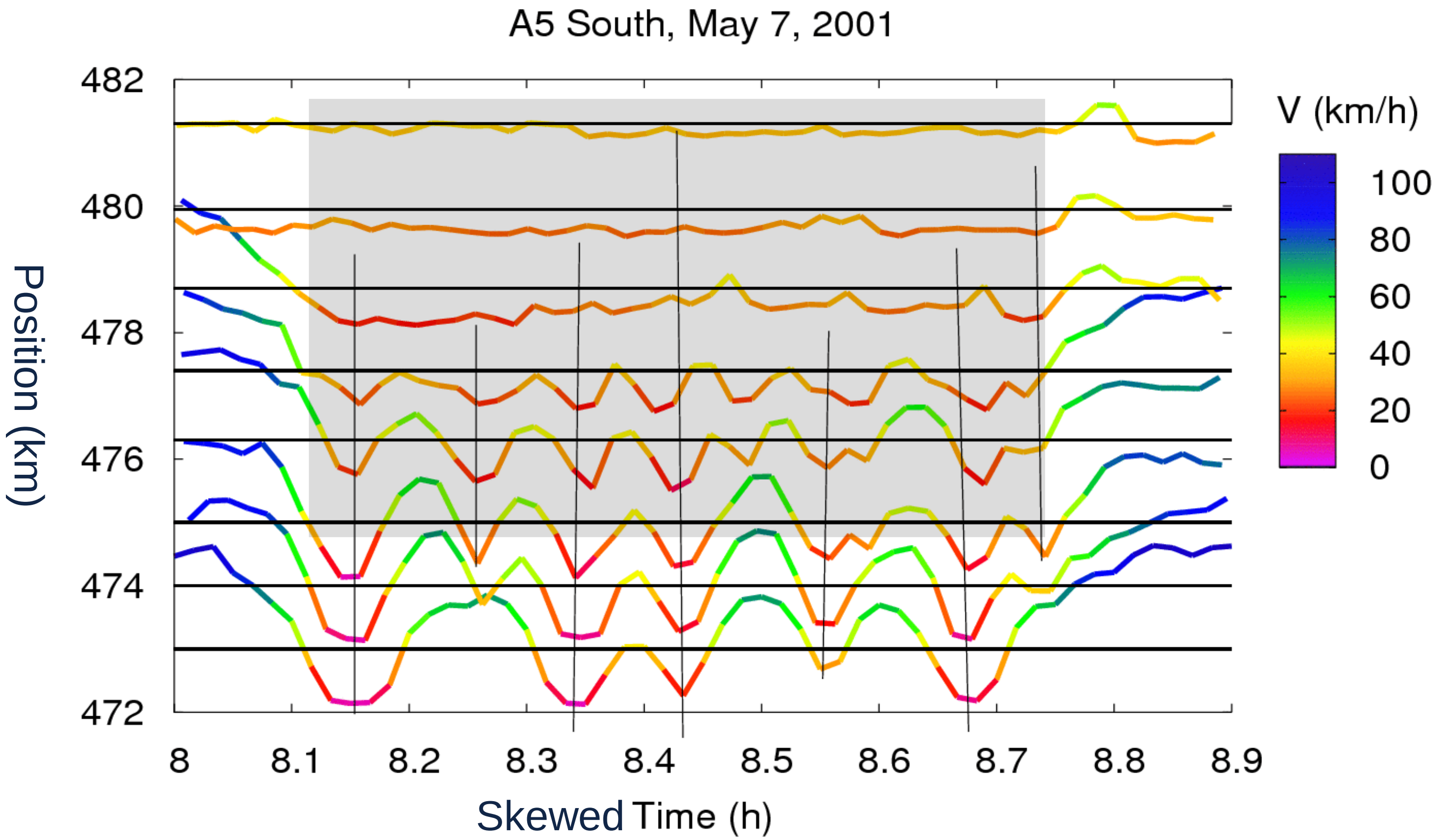


Wave property I: propagation velocity



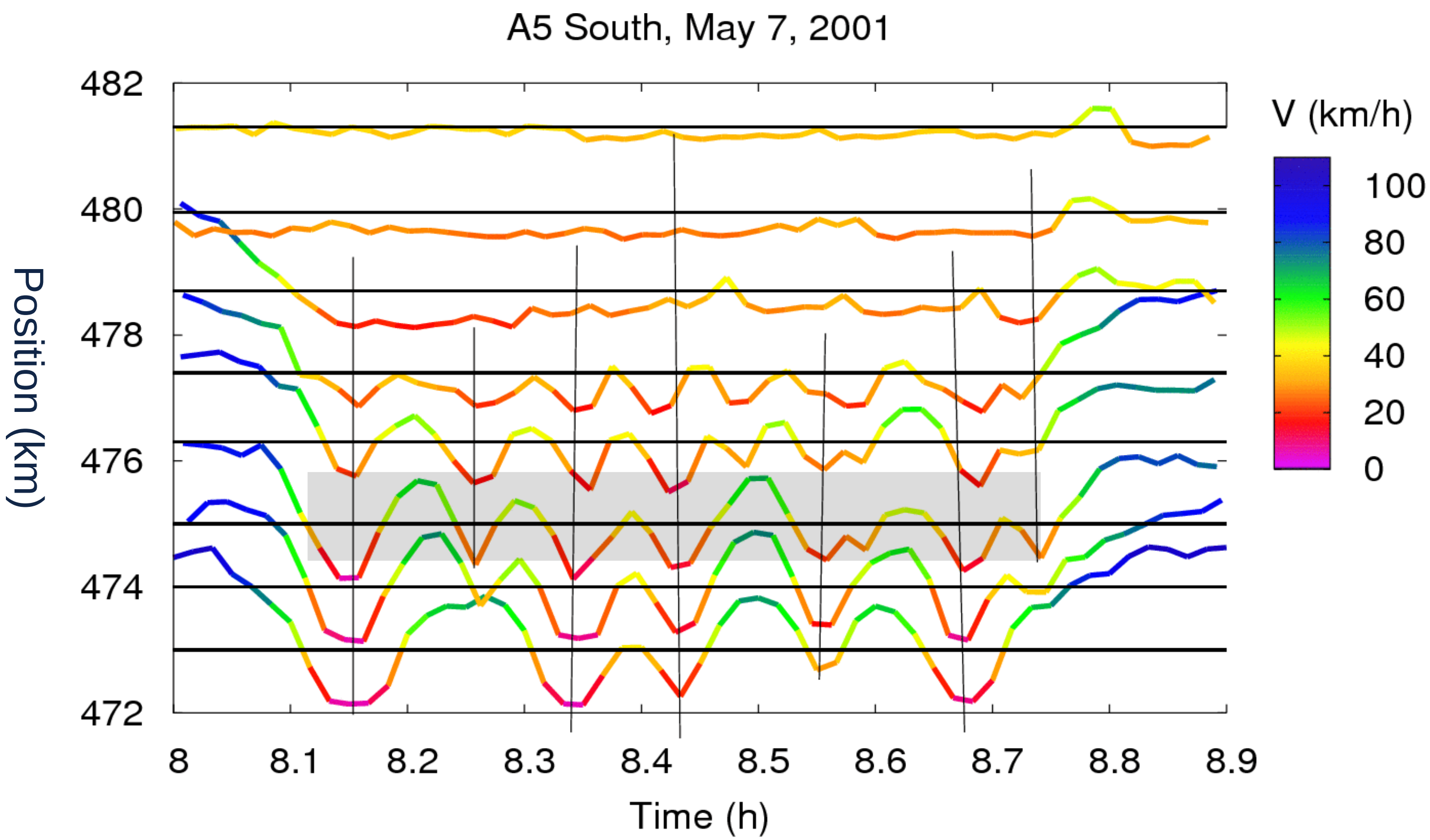
$$c_{\text{cong}} = \arg\max_c \sum_i \sum_{j>i} \text{Corr}\left[V_i(t), V_j\left(t + \frac{x_i - x_j}{c}\right)\right]$$

Wave property II: Growth Rate



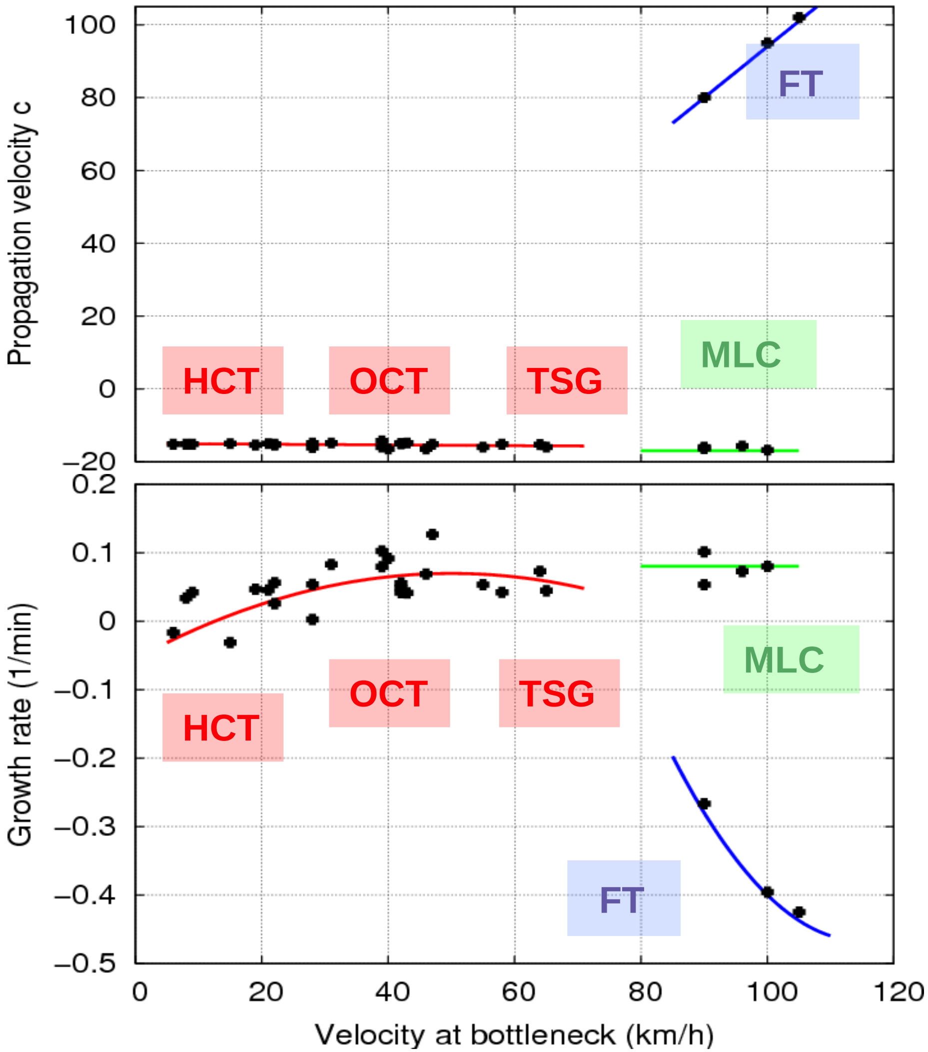
- Spatial growthrate: $$\tilde{\sigma} = \frac{\sum_i x_i \ln|A_i| - n\bar{x}\,\overline{\ln|A_i|}}{\sum_i x_i^2 - n\bar{x}^2}$$ (generally <0)
- Temporal growthrate: $\sigma = c_{\text{cong}}\tilde{\sigma}$ (generally >0)

Wave property III: Period/Wavelength



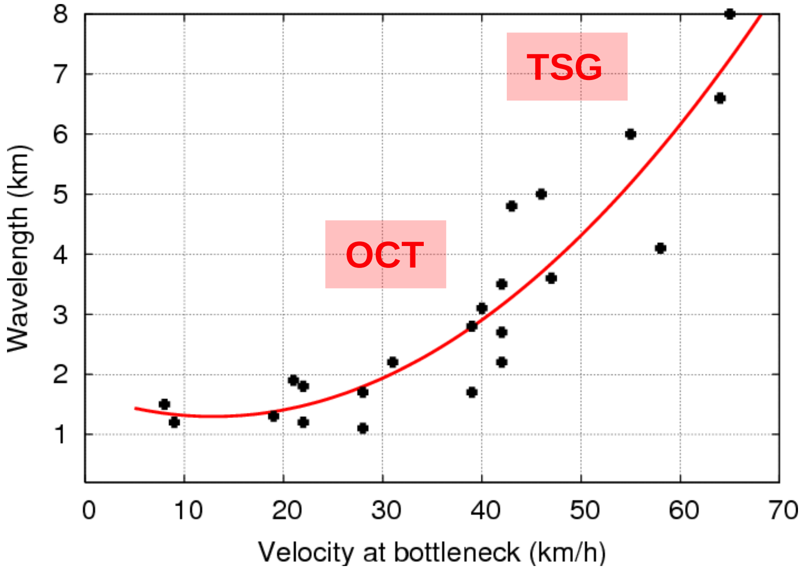
- Average period: $\tau = \arg\max_{\tau'} \text{Corr}\left[V_i(t)V_1(t+\tau')\right]$
- Wavelength: $L = |c|\tau$

Systematic Investigation for the A5 South



(Measure of the bottleneck strength)

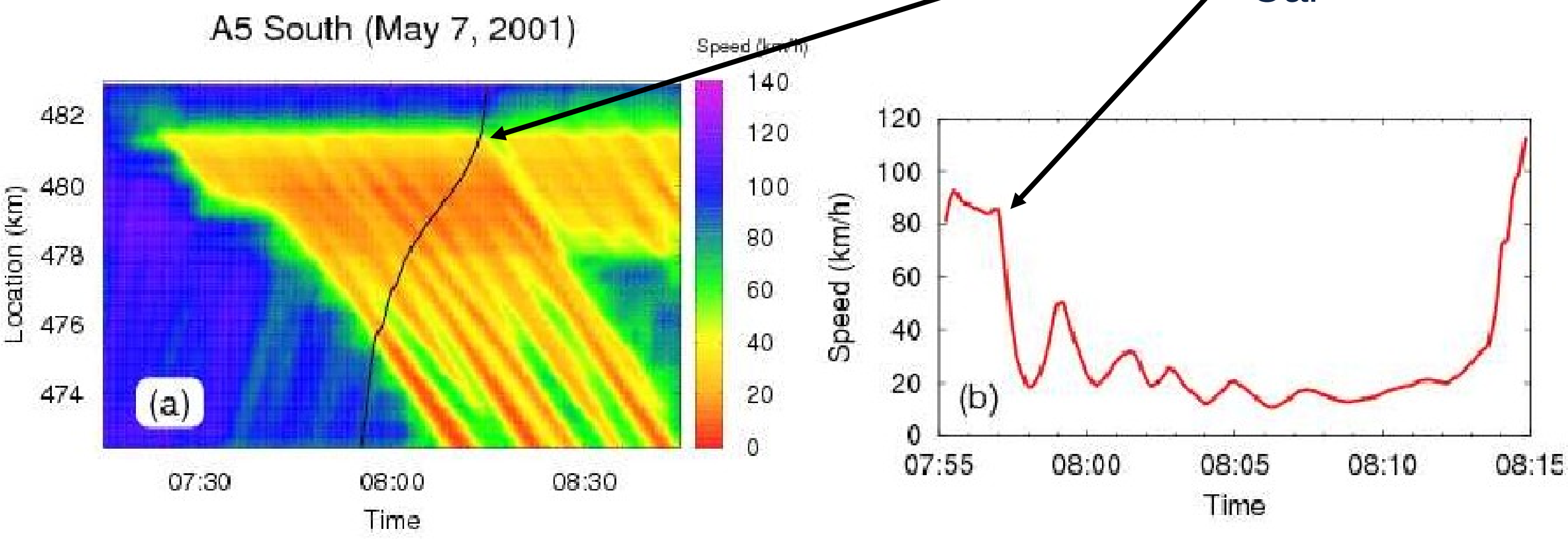
- Depends on the “bottleneck strength”
- Shorter in urban environment (NGSIM=>J. Laval)



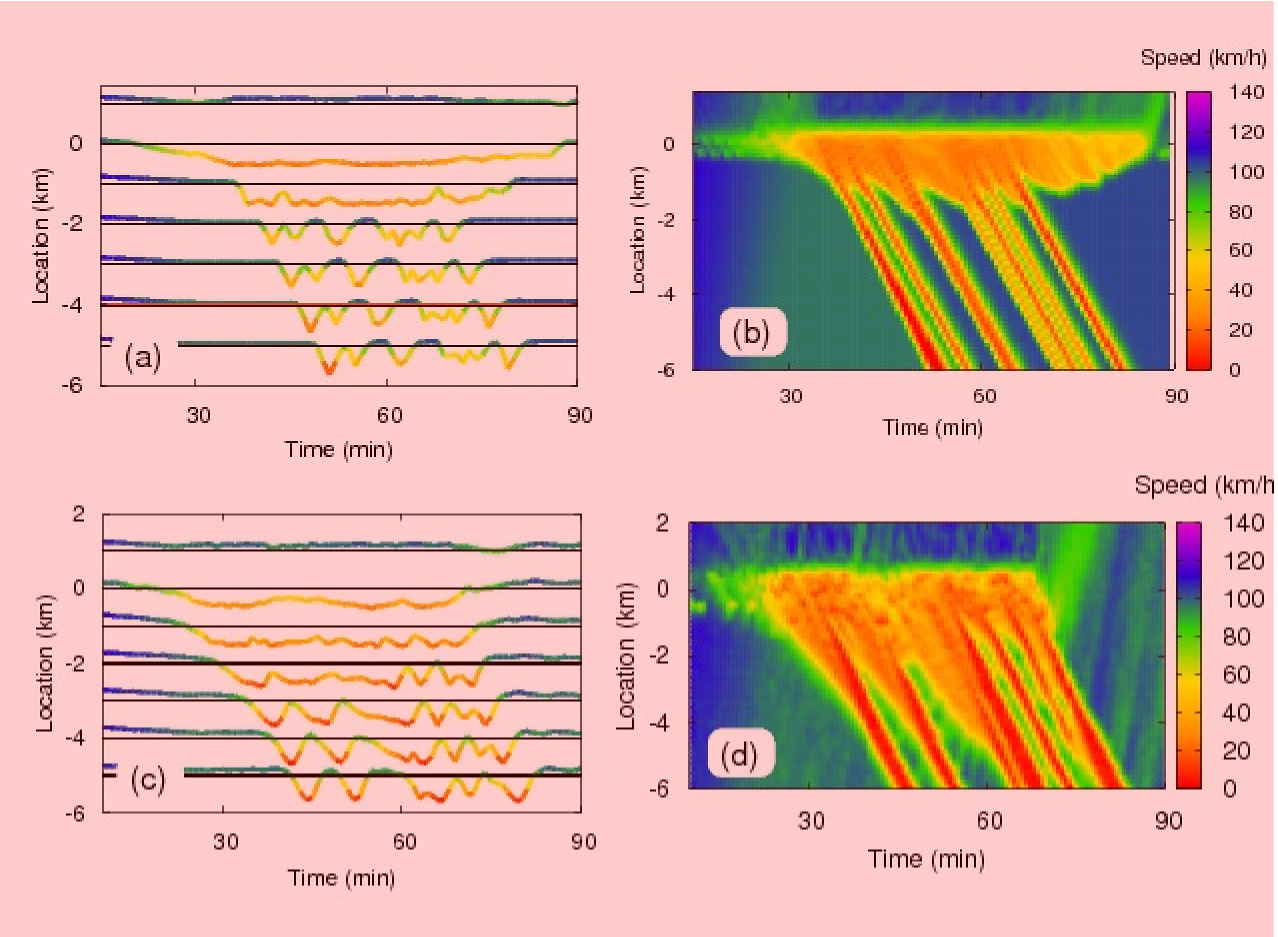
Extraction of wave properties from FCD instead of stationary detector data (SDD)

$$\tau_{\rm FC} = \tau \left(\frac{|c|}{|c| + \bar{V}_{\rm FC}} \right)$$

Floating Car



Application to microscopic models



- Calibrated Intelligent-Driver Model:

Propag. Velocity: OK

Growth rate: Too high

Period: Too low

- Calibrated Human-Driver Model:

Propag. Velocity: OK

Growthrate: OK

Period: OK

- Reaction time and multi-anticipation seem to play a role!

Calibrating car-following aspects: methods/objective functions

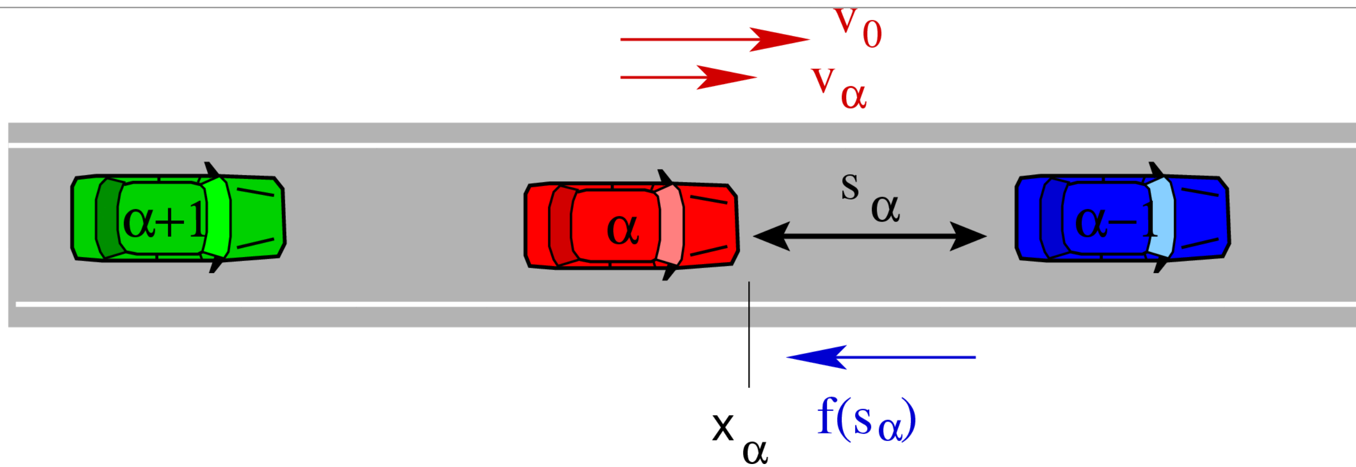
- **Local (point-to-point) calibration** using maximum likelihood for the speed/positional data => Log-likelihood is proportional to the sum of squared acceleration differences

- **Global calibration along a trajectory** using LSE for absolute gaps (absolute measure)

- **Global calibration along a trajectory** using LSE for the logarithms of gaps (relative measure)

- **“Super-global” calibration of a complete platoon** => better use macroscopic criteria

Example: the Intelligent-Driver Model (IDM)



- Equations of motion:

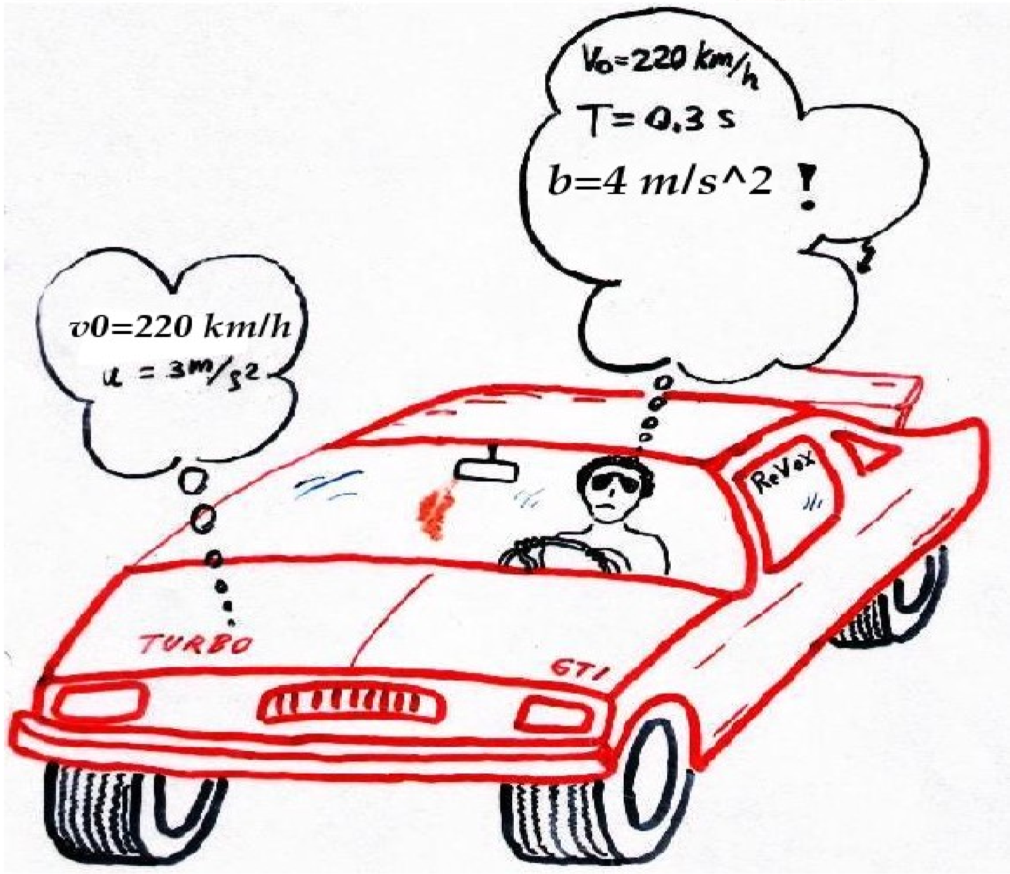
$$\dot{x}_\alpha = v_\alpha,$$

$$\dot{v}_\alpha = a \Bigg[\underbrace{1 - \left(\frac{v_\alpha}{v_0}\right)^\delta}_{\text{Beschleunigung}} \underbrace{- \left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2}_{\text{Bremsverzögerung}} \Bigg]$$

- Dynamic desired distance

$$s^*(v, \Delta v) = \underbrace{s_0}_{\text{Mindest-abstand}} + \underbrace{vT}_{\text{“Sicherheits”-abstand}} + \underbrace{\frac{v \Delta v}{2\sqrt{ab}}}_{\text{dynamischer Teil}}$$

Parameters to Adapt the Driving Style



Relaxed drivers …
… or aggressive drivers …

… are characterized by the IDM parameters:

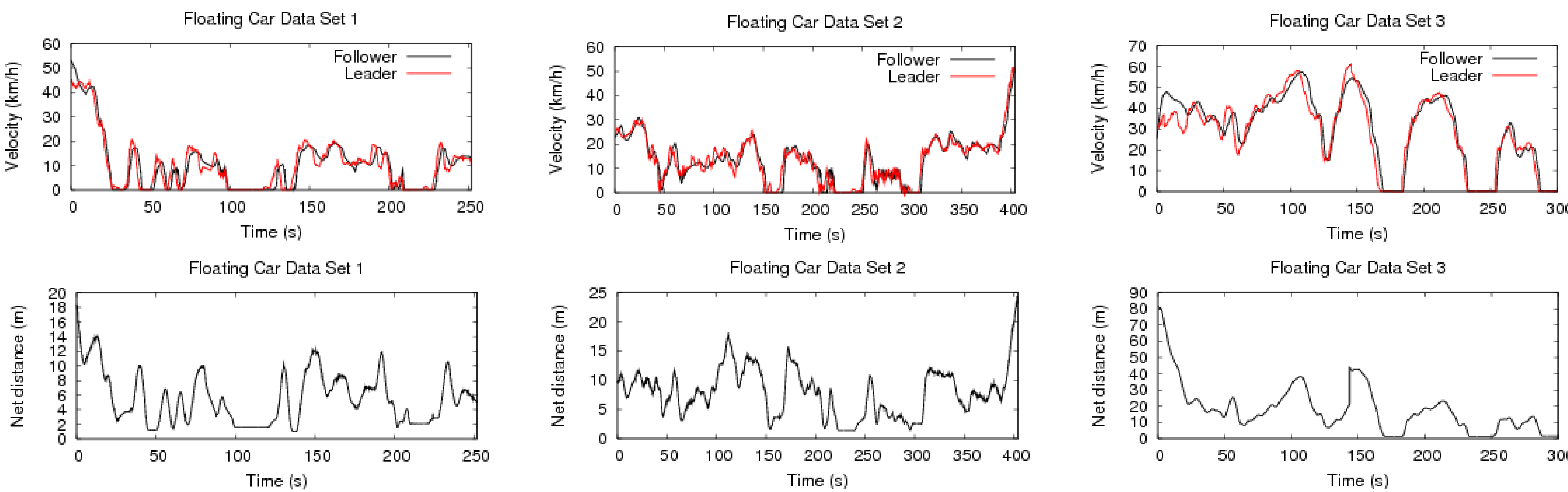
Parameter	**Typical Value**
Desired velocity **v0**	120 km/h
Desired headway **T**	1.5 s
Desired acceleration **a**	0.3-2.5 m/s^2
Desired deceleration **b**	2.0 m/s^2
Minimum gap **s0**	2 m
Gap contribution **s1**	5 m

Data Set I: a small set

- Recorded in 1995 by Bosch on one-lane road in Stuttgart
- Radar sensor provides relative speed and distance to leading vehicle
- Three sets of durations between 4 – 7 min including stops to standstills due to traffic lights

Follower

Leader



• Publicly available data: DLR Clearing house, http://www.dlr.de/cs/

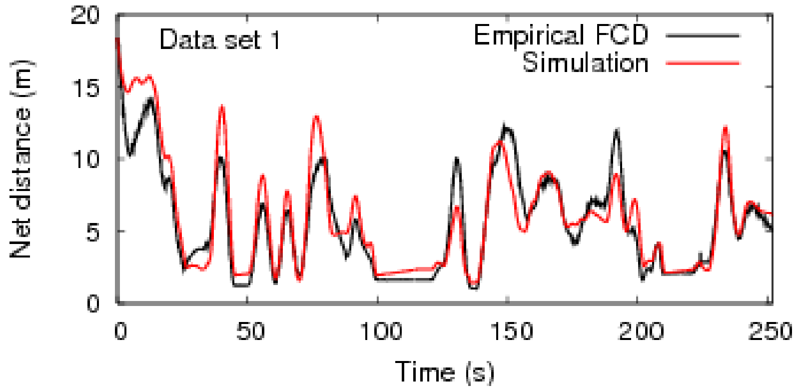
Martin Treiber
martin@mtreiber.de

Calibrated Parameters for three data sets

- Results of nonlinear optimization (with genetic algorithm):

IDM	FCD set 1			FCD set 2			FCD set 3		
Measure	$\mathcal{F}_{\mathrm{rel}}[s]$	$\mathcal{F}_{\mathrm{mix}}[s]$	$\mathcal{F}_{\mathrm{abs}}[s]$	$\mathcal{F}_{\mathrm{rel}}[s]$	$\mathcal{F}_{\mathrm{mix}}[s]$	$\mathcal{F}_{\mathrm{abs}}[s]$	$\mathcal{F}_{\mathrm{rel}}[s]$	$\mathcal{F}_{\mathrm{mix}}[s]$	$\mathcal{F}_{\mathrm{abs}}[s]$
Error [%]	24.1	20.8	20.7	28.7	26.2	25.7	18.0	13.0	11.2
T [s]	1.08	1.12	1.03	1.52	1.44	1.23	1.30	1.31	1.35
s_0 [m]	2.39	2.35	2.59	2.62	2.79	3.50	1.60	1.52	1.25
a [m/s^2]	1.01	1.23	1.43	0.953	0.973	1.09	1.58	1.56	1.55
b [m/s^2]	3.23	3.10	3.91	0.590	0.993	1.17	0.761	0.626	0.605
v_0 [m/s]	69.9	70.0	70.0	70.0	70.0	68.9	16.0	16.1	16.2

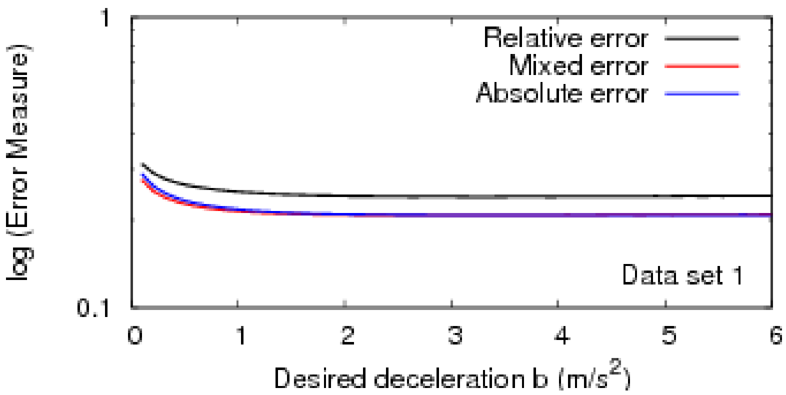
- Calibration error between 10 -- 30%
- T, s_0 and a in expected range
- b and v0 more difficult to calibrate
- Consistency between different error measures!

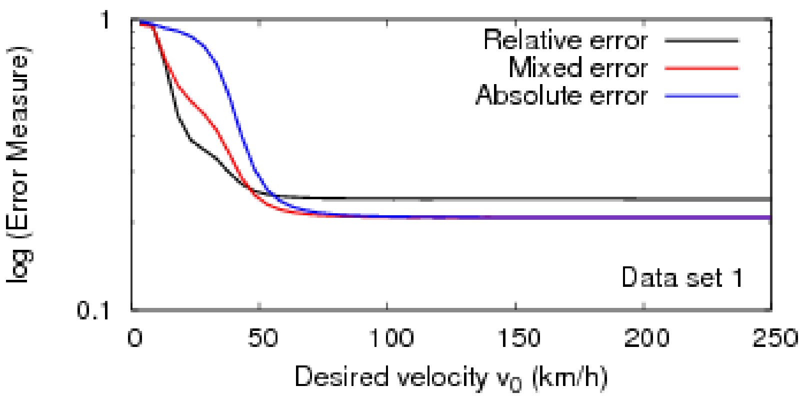


Sensitivity with respect to deceleration b and desired speed v0 for Set 1 (only congestion)

For data sets 1 and 2:

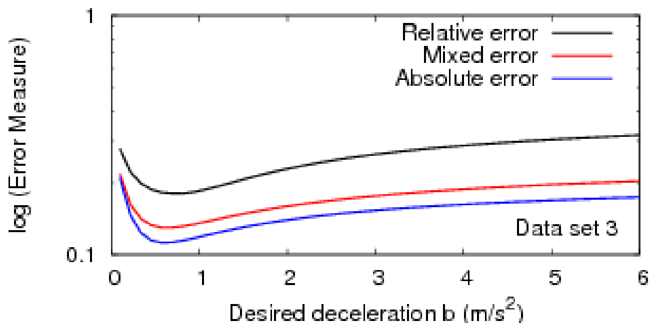
- Desired deceleration *b* nearly without minimum
- Desired velocity v_0 only sensitive to low speeds due to leader
- Neither *b* nor v_0 are identified by this data!

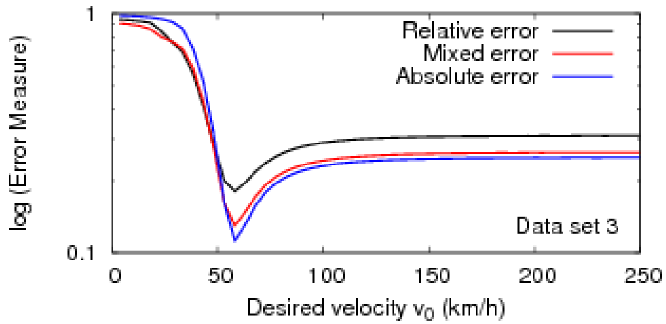




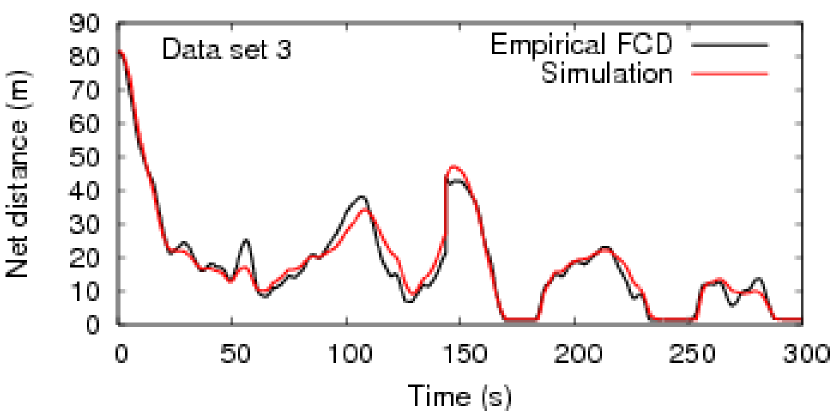
Sensitivity with respect to deceleration b and desired speed v0 for Set 3 (also free traffic)

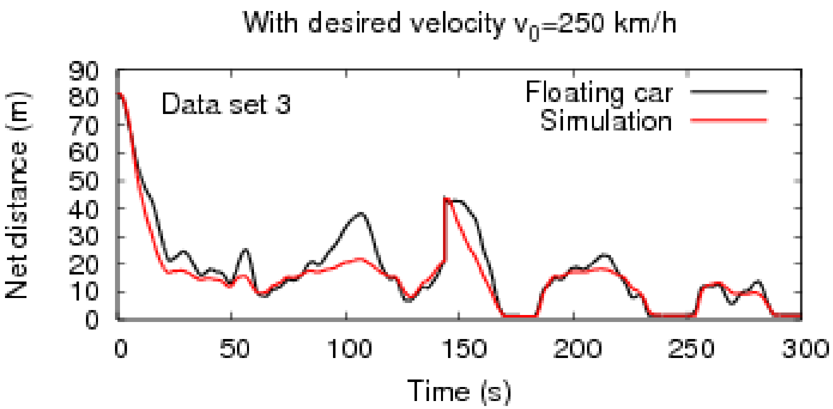
- Data set 3: Distinct minima also for b and v_0:





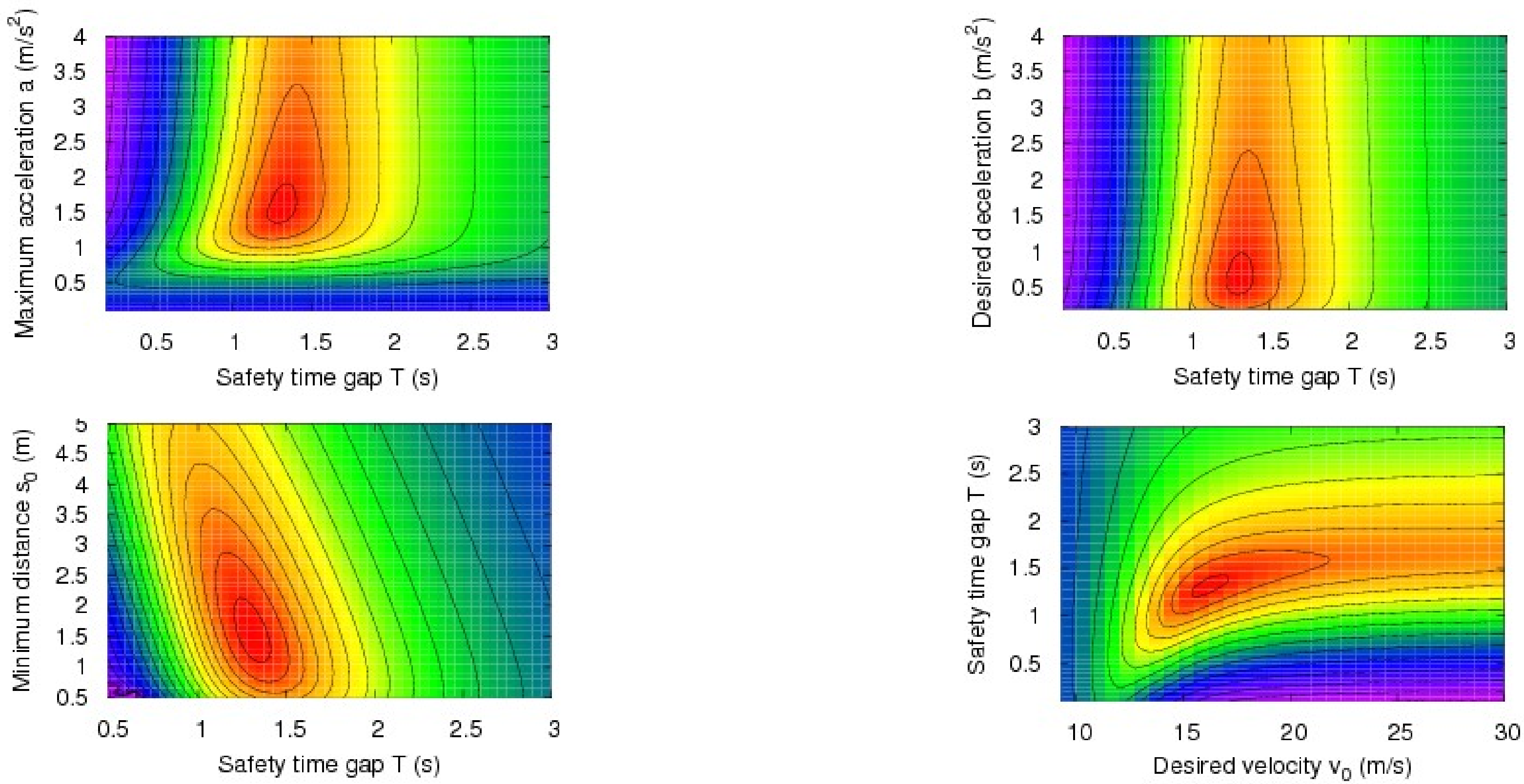
- Compare optimal desired velocity v_0=58 km/h with maximum of v_0=250 km/h:





Martin Treiber
martin@mtreiber.de

Simultaneous variation of Two Parameters: Colinearity?

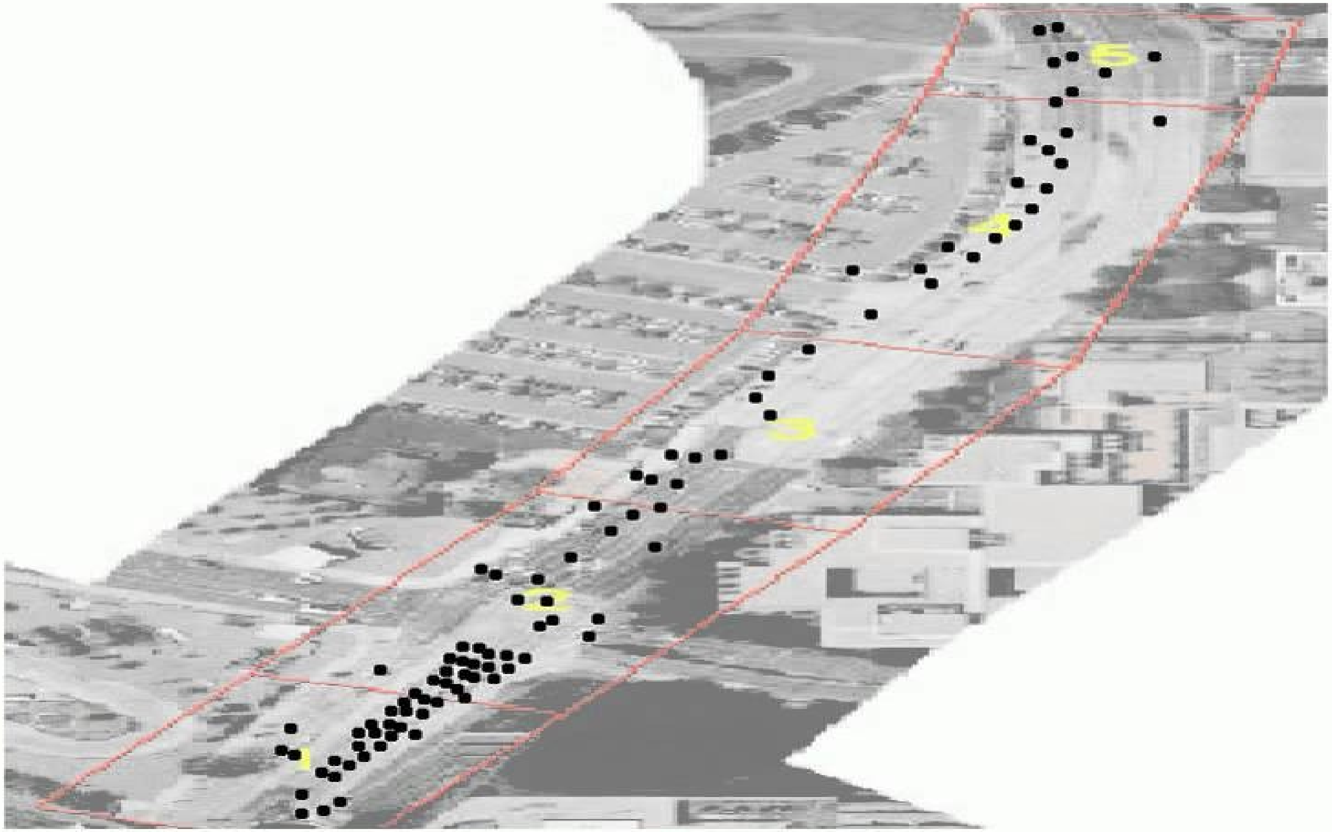


- Safety time gap T is the most important parameter
- IDM parameters typically have small correlations
- Correlation between s0 and T is explained by $s^*(v, \Delta v = 0) = s_0 + vT$

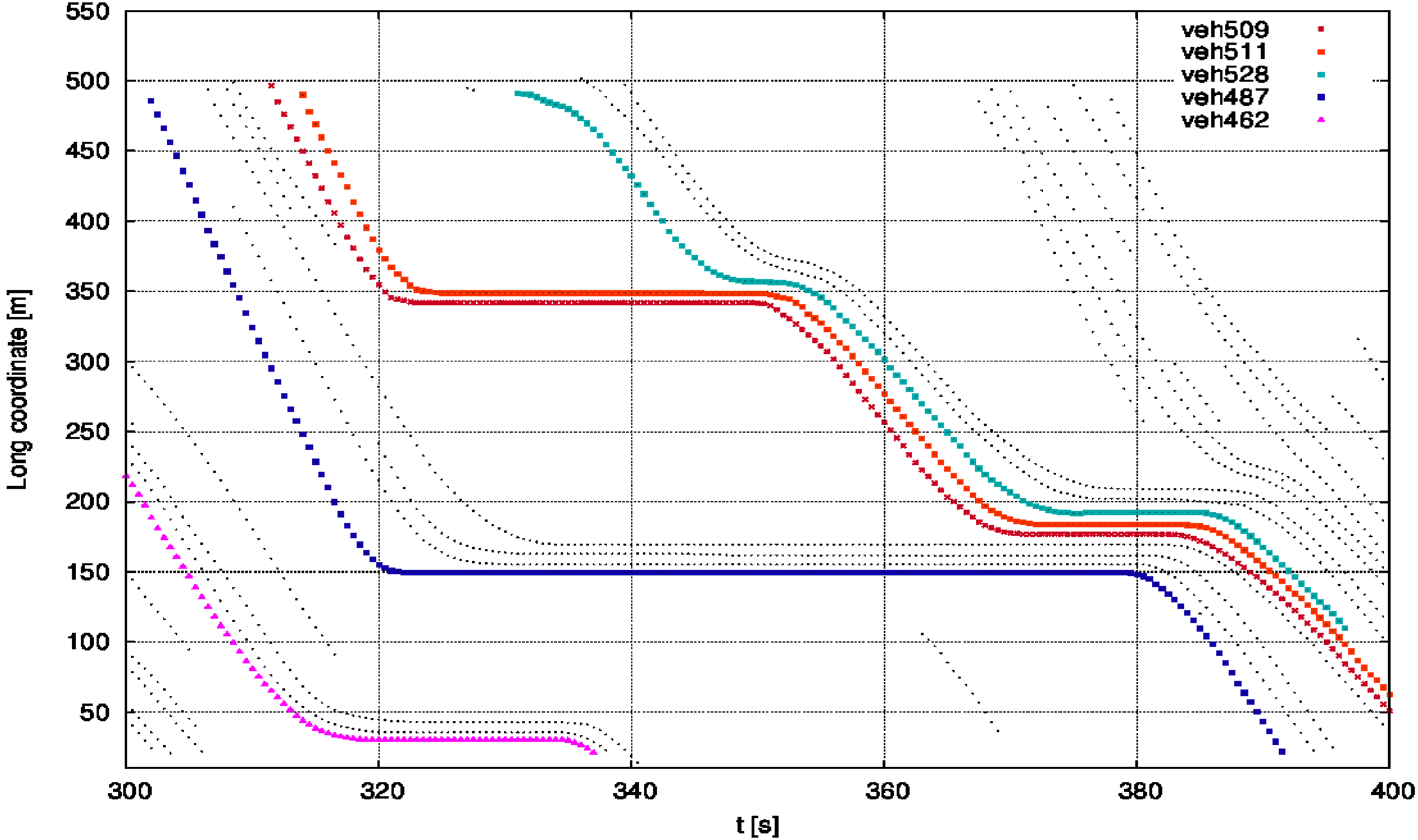
Data Set II: a big set (NGSIM, Lankershim Blvd)

- Recorded by the NGSIM initiative
- The Lankershim Blvd is a city arterial with intersections/traffic lights

Time: 08:47:39

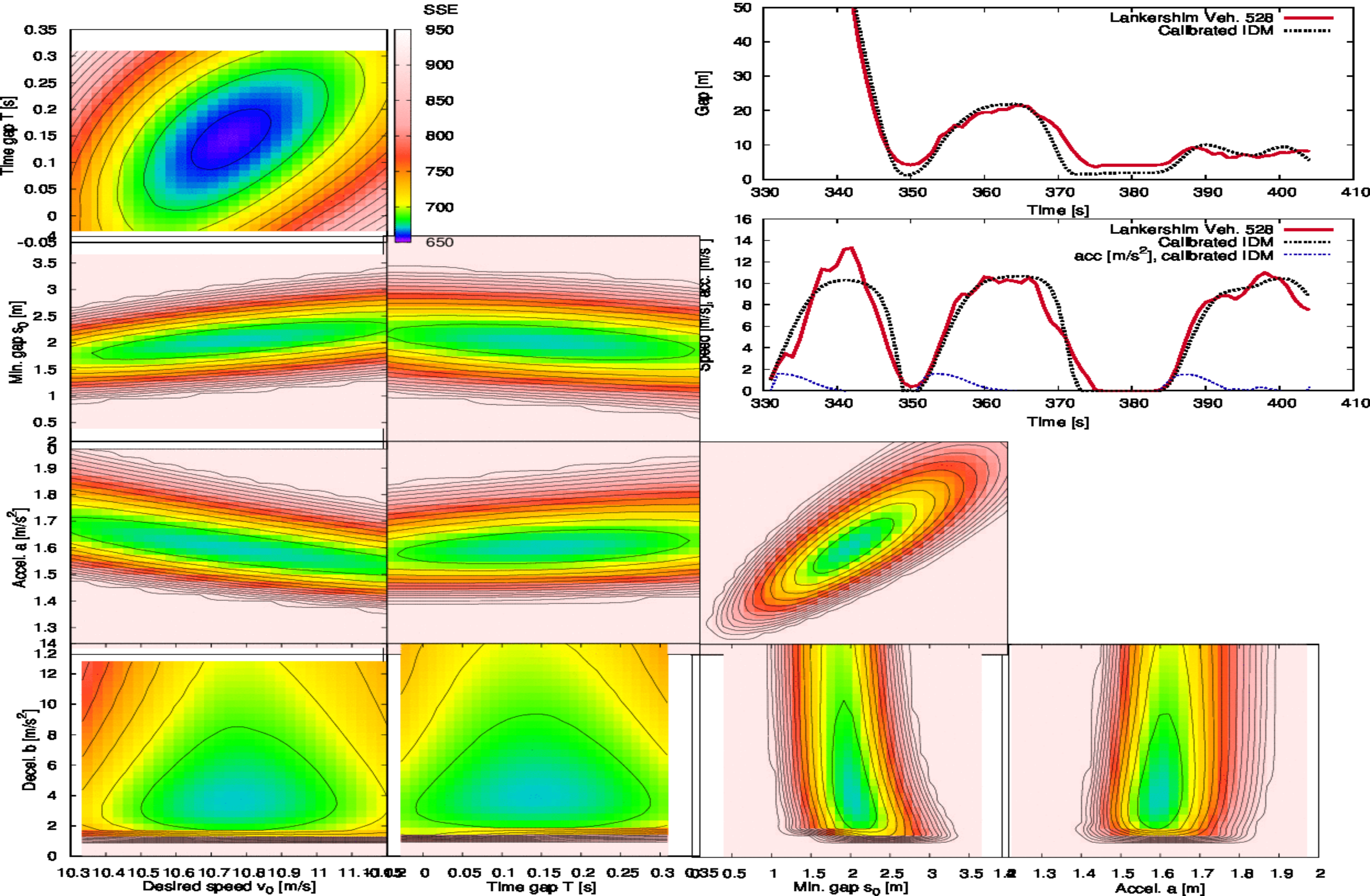


NGSIM, Lankershim Blvd: example trajectories

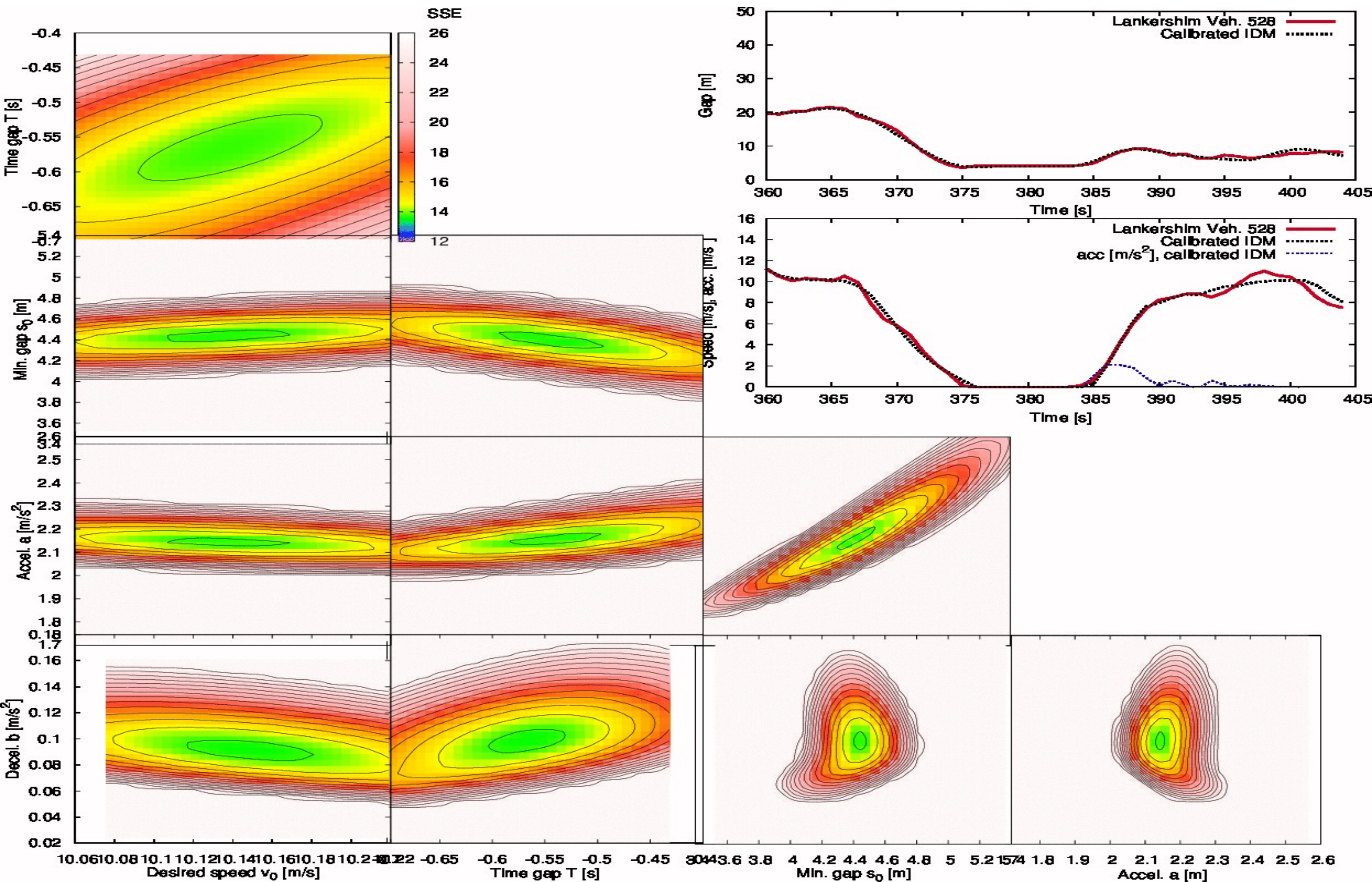


TECHNISCHE UNIVERSITÄT DRESDEN

(1) Dependence on the data: Calibration of the complete Trajectory 528 (global, absolute gaps)

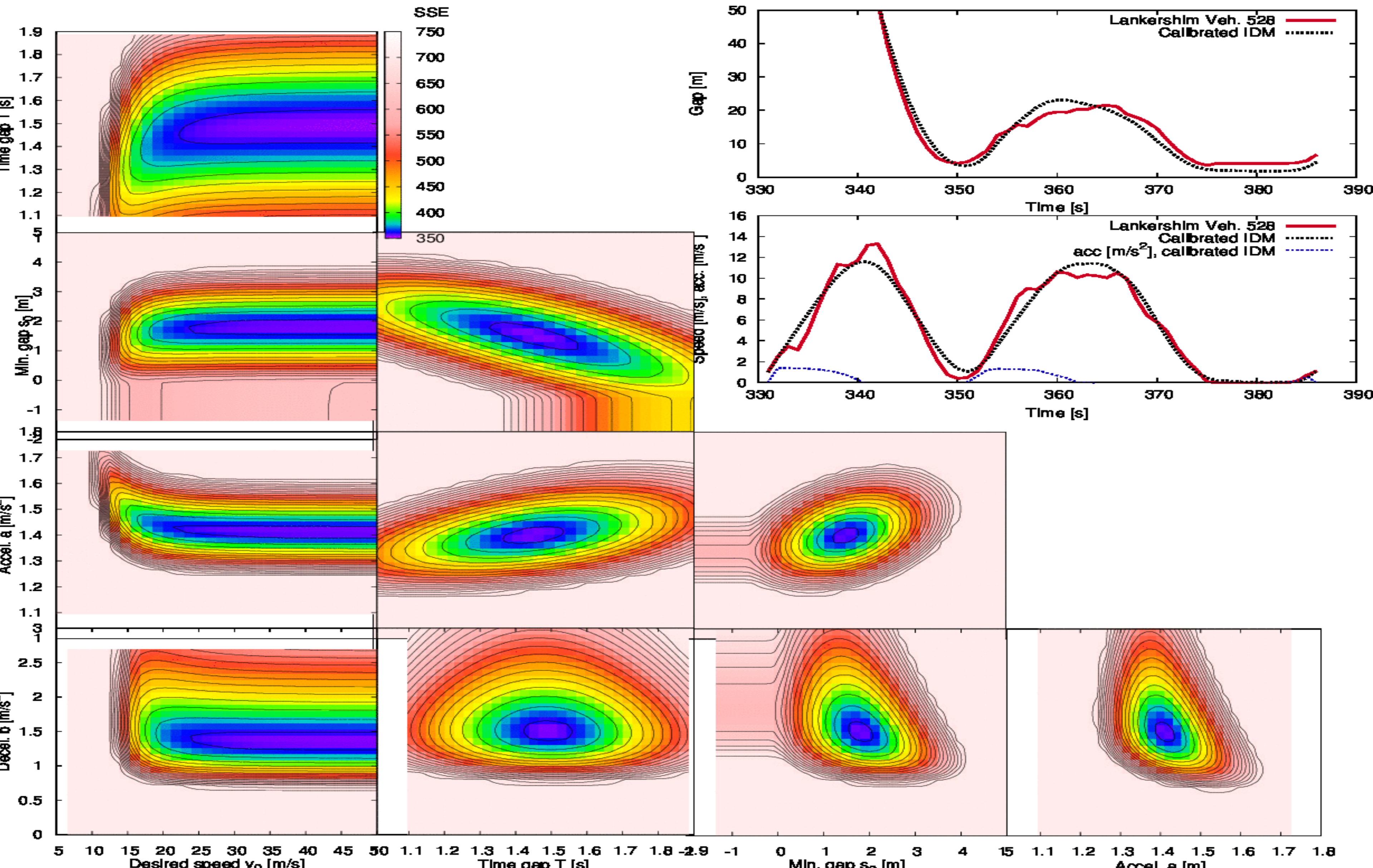


(1b) Calibrating only the second part of Trajectory 528: negative time gaps!

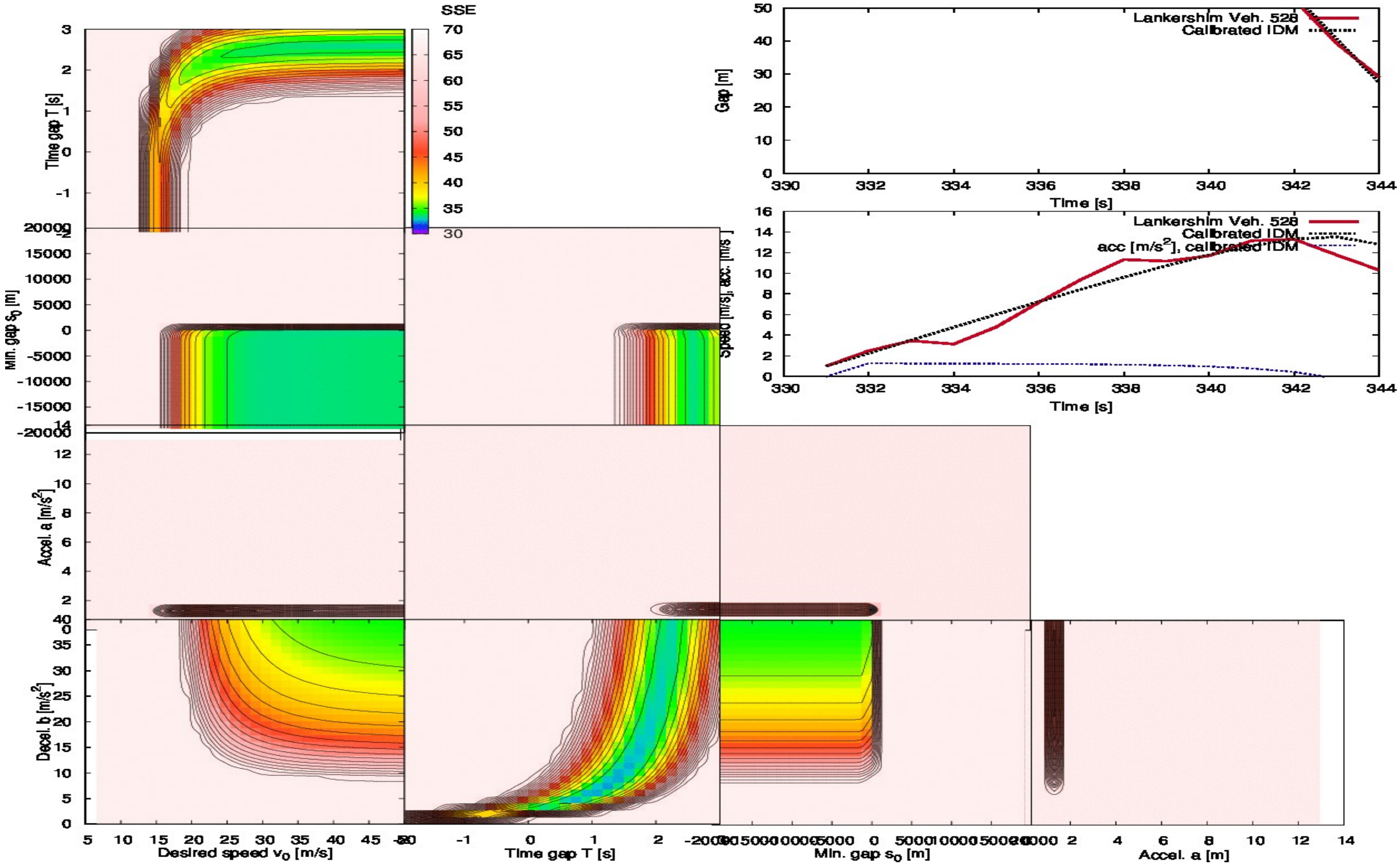


TECHNISCHE UNIVERSITÄT DRESDEN

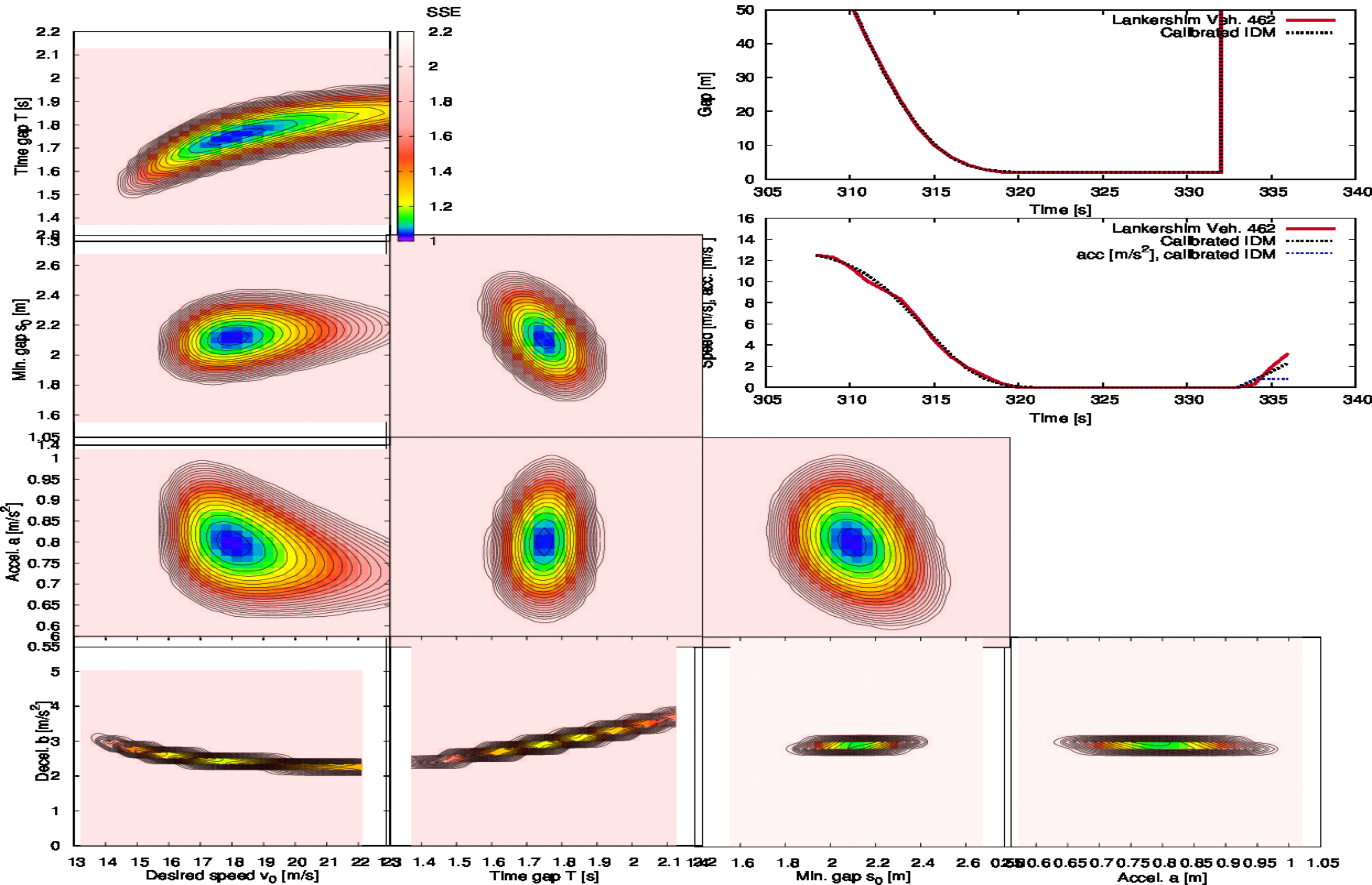
(1c) Omitting the last seconds of Trajectory 528: Everything is plausible and well-defined!



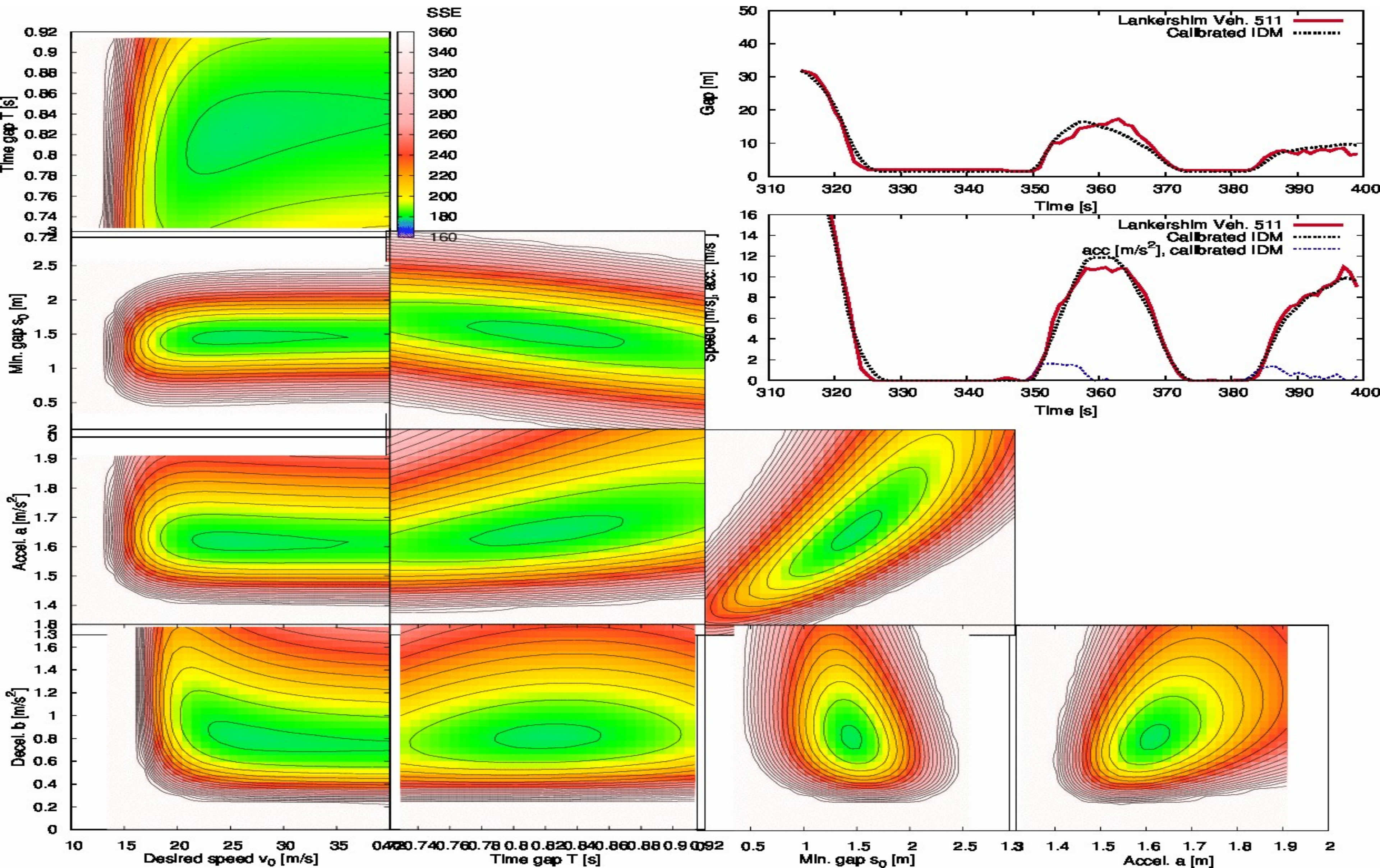
(1d) Only the acceleration phase of Trajectory 528: The acceleration is the only identifyable parameter!



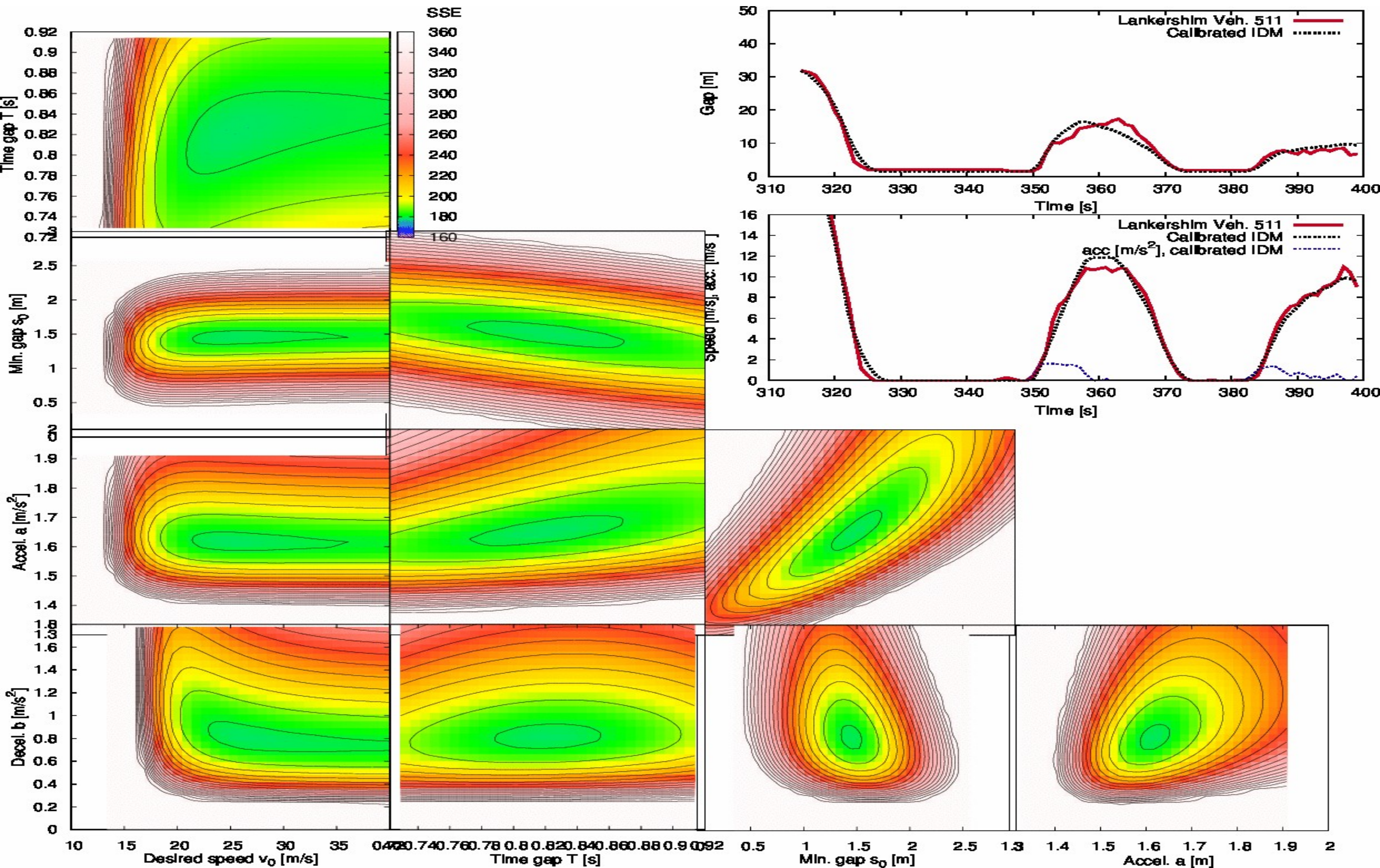
(1e) Trajectory 462



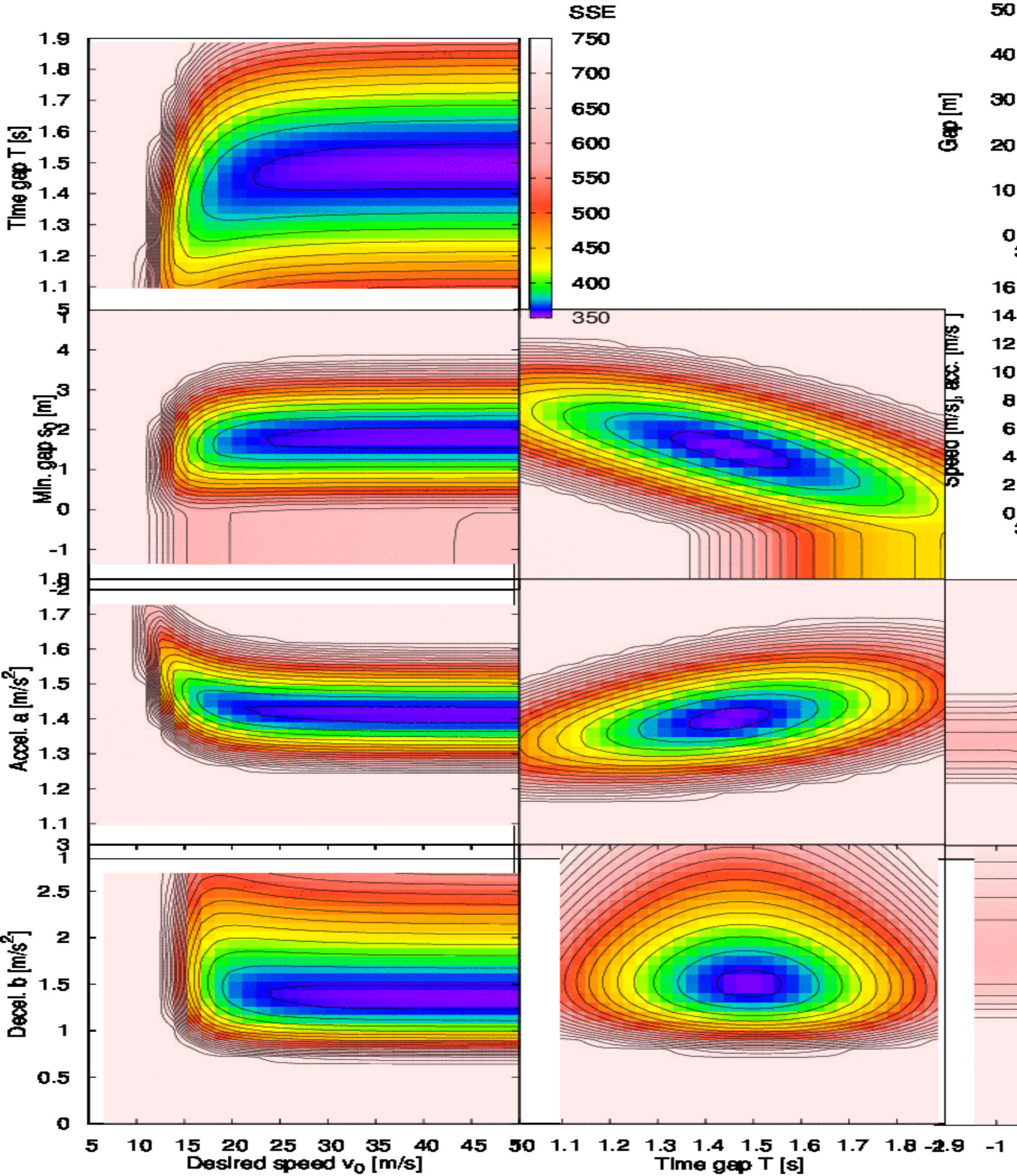
(1f) Trajectory 511

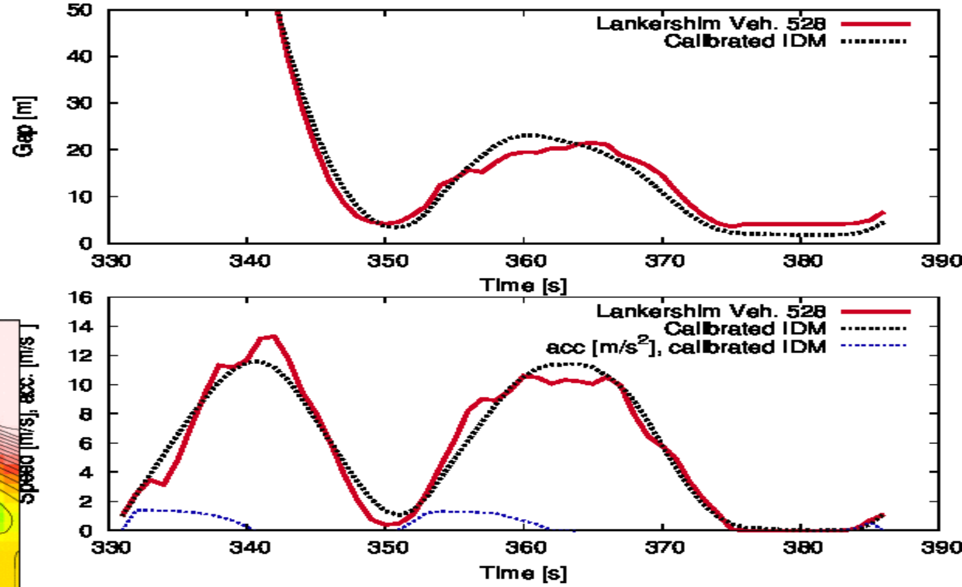


(1f) Trajectory 511



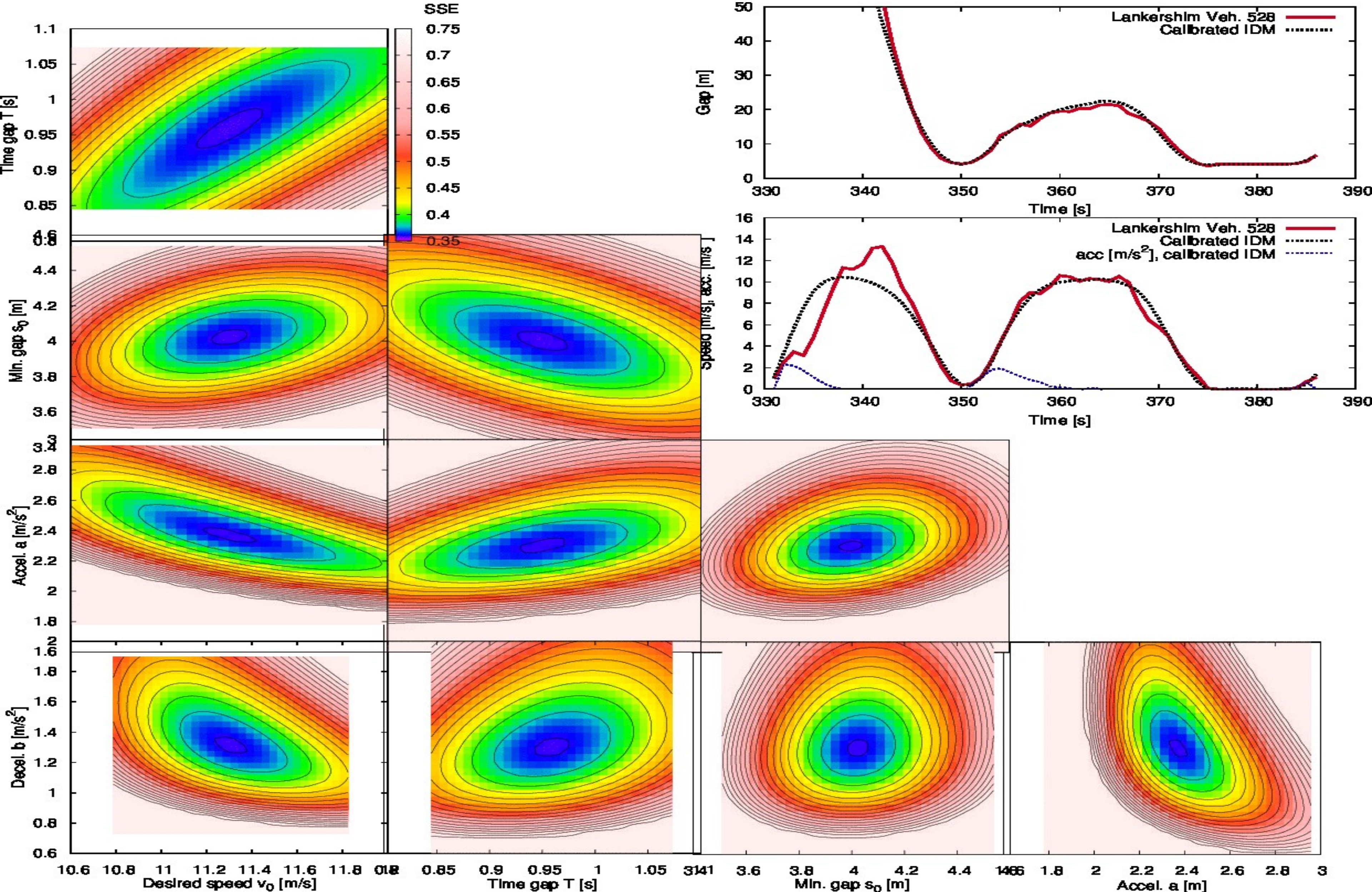
(2) Dependence on the calibration method: Reference (Trajectory 528 w/o the last seconds, absolute gaps)



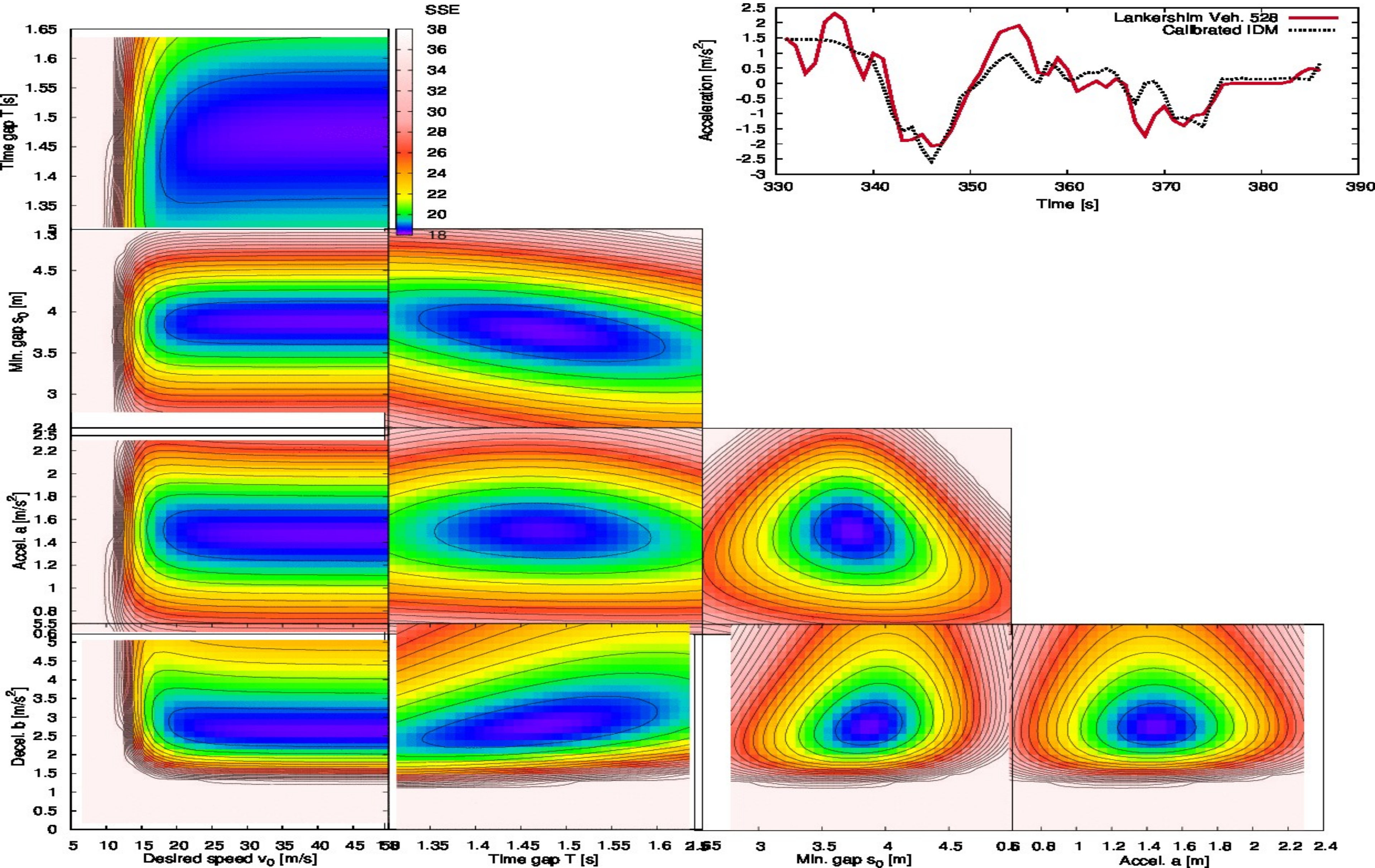


TECHNISCHE UNIVERSITÄT DRESDEN

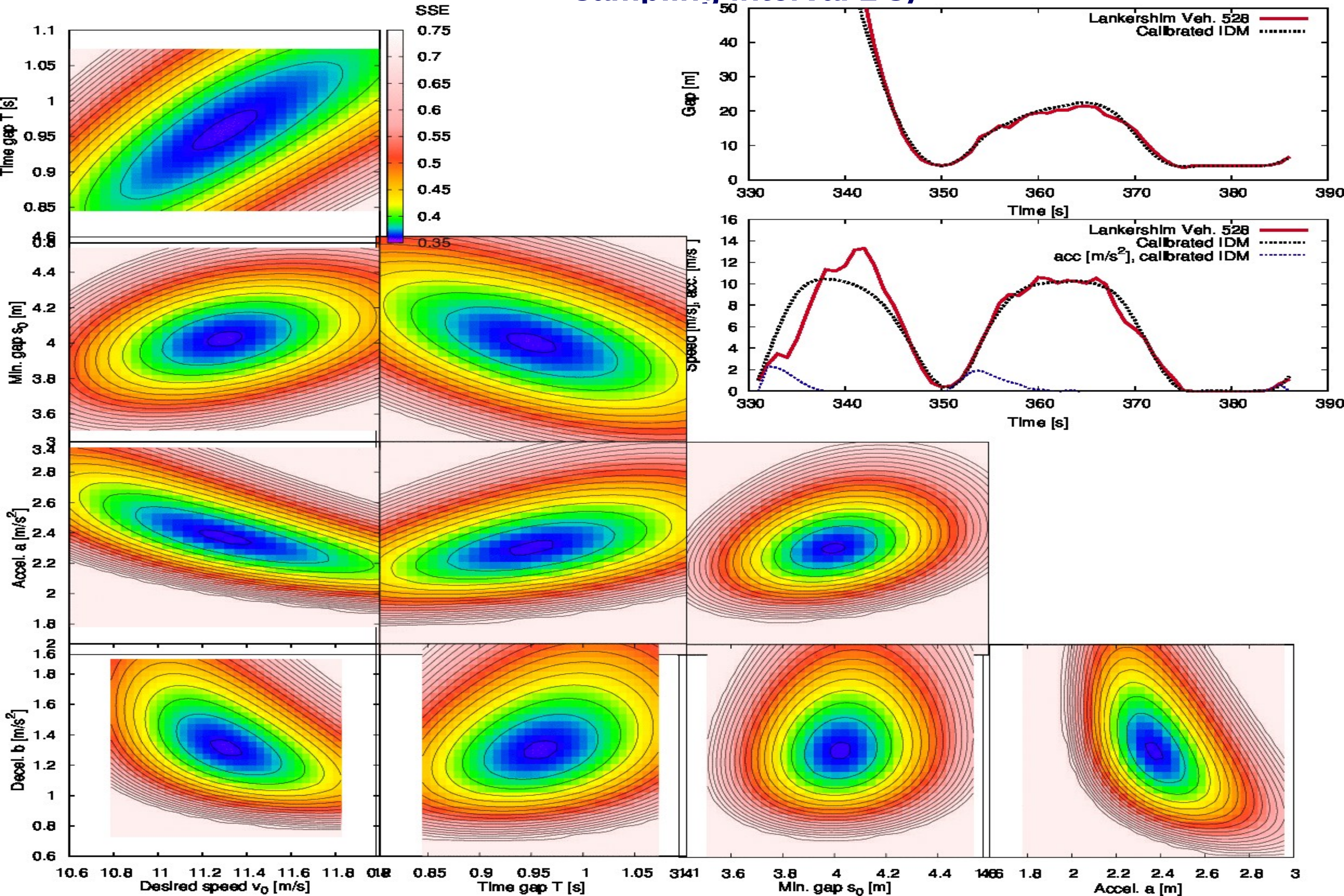
(2b) global LSE, relative instead of absolute gaps



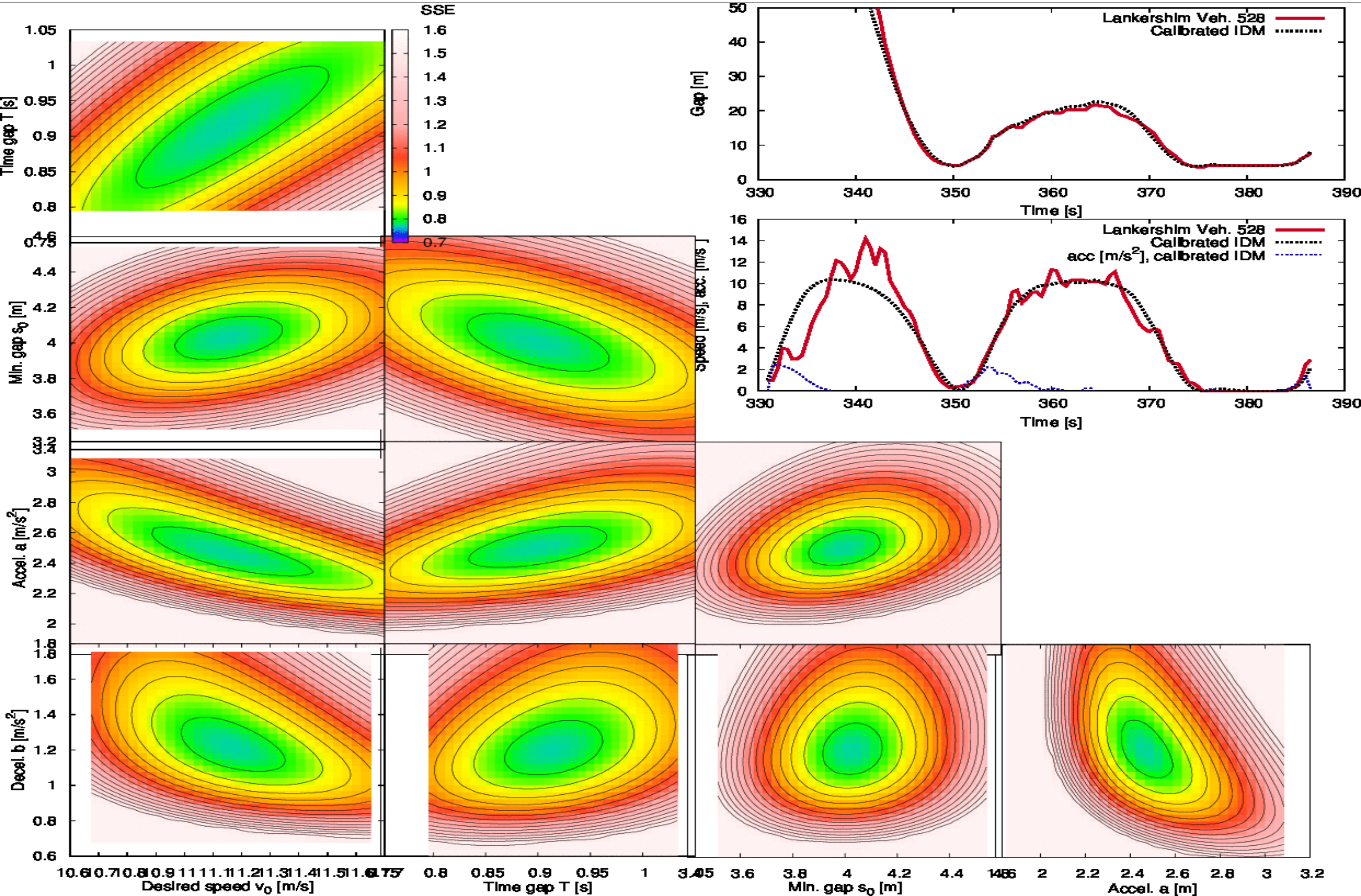
(2c) local MLE, pointwise accelerations



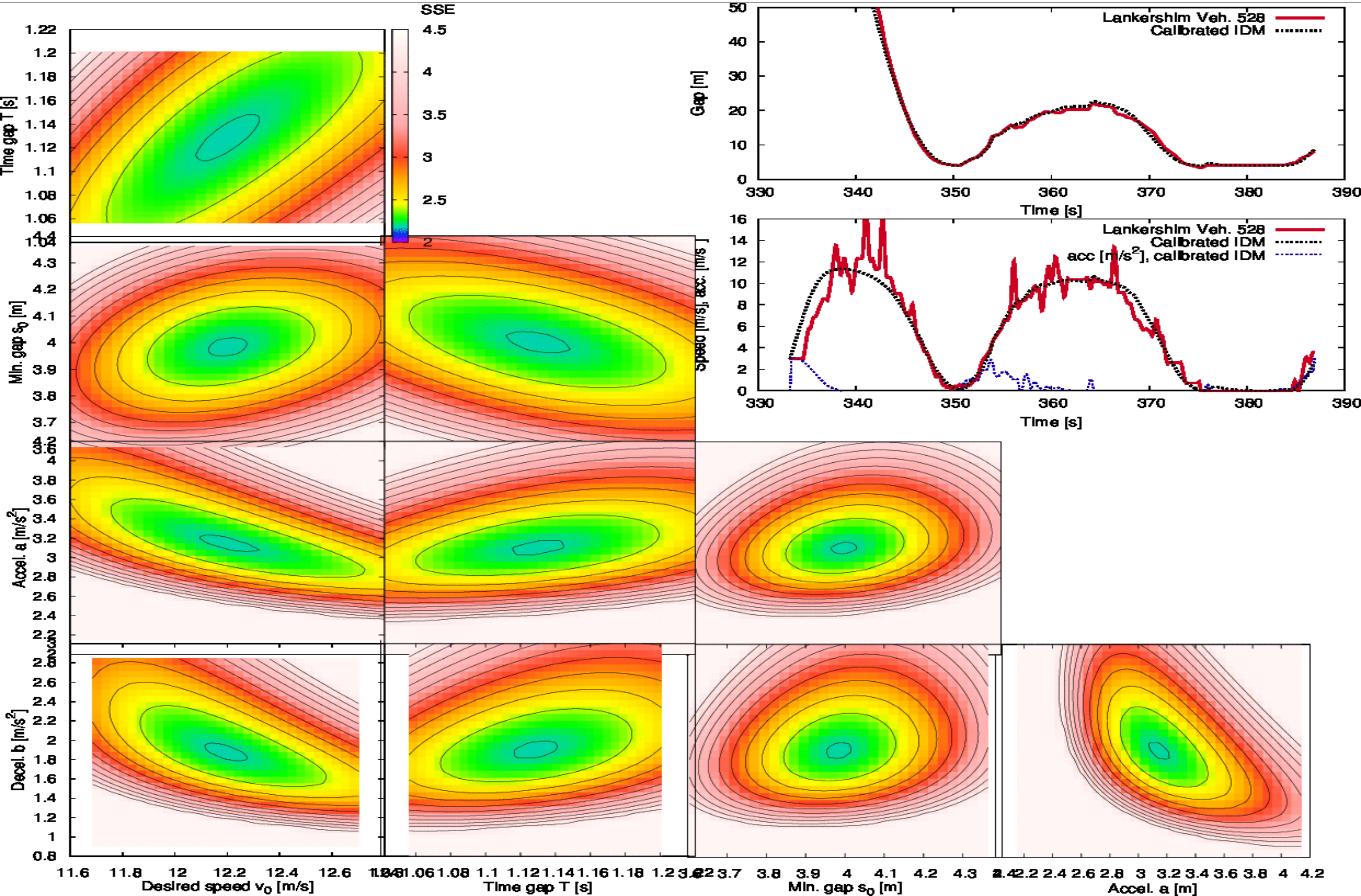
(3) Dependence on the sampling rate: Reference (Traj 528 w/o the last seconds, relative gaps, sampling interval 1 s)



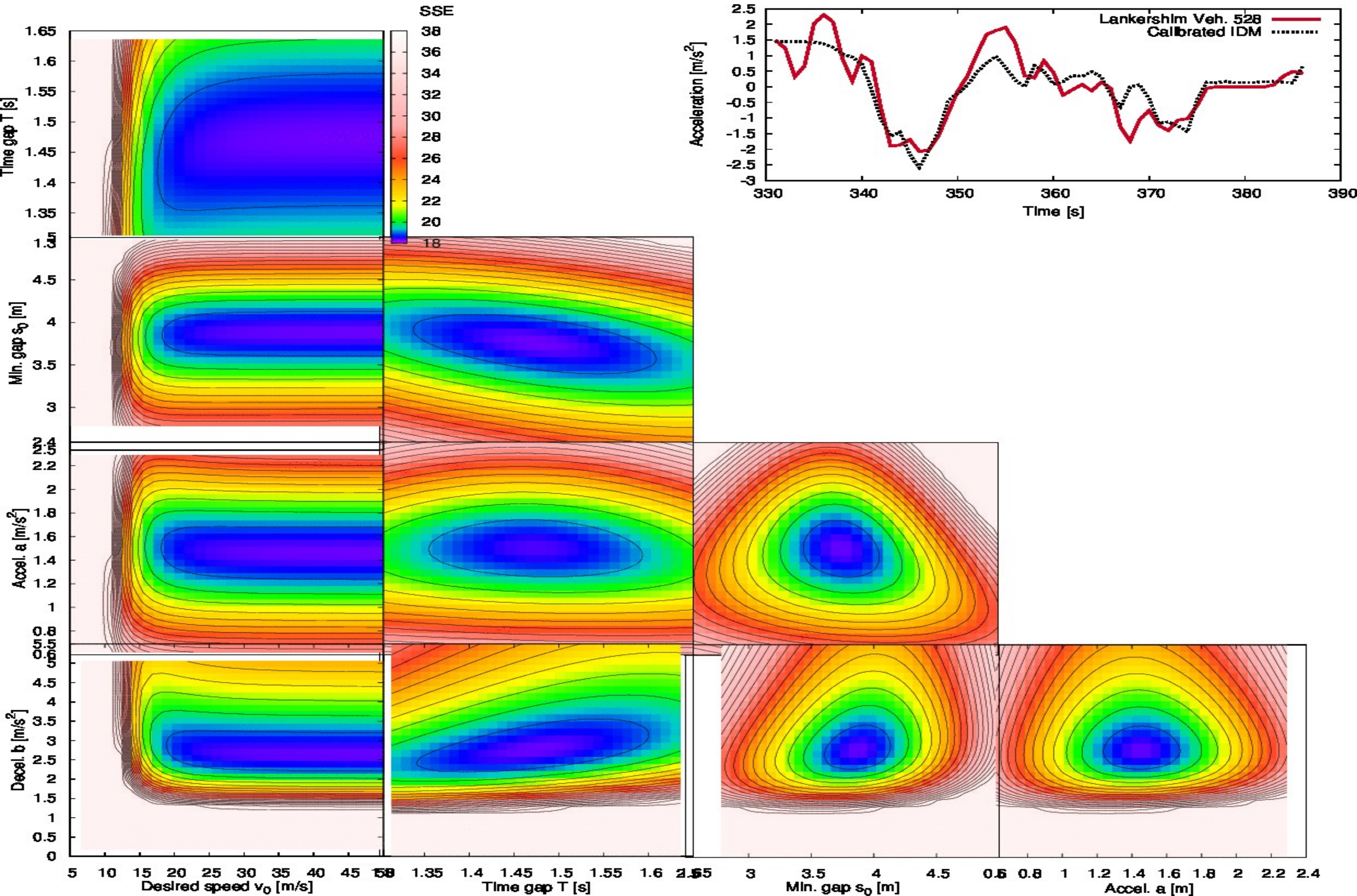
(3b) Relative gaps, sampling interval 0.5 s)



(3c) Relative gaps, sampling interval 0.1 s)

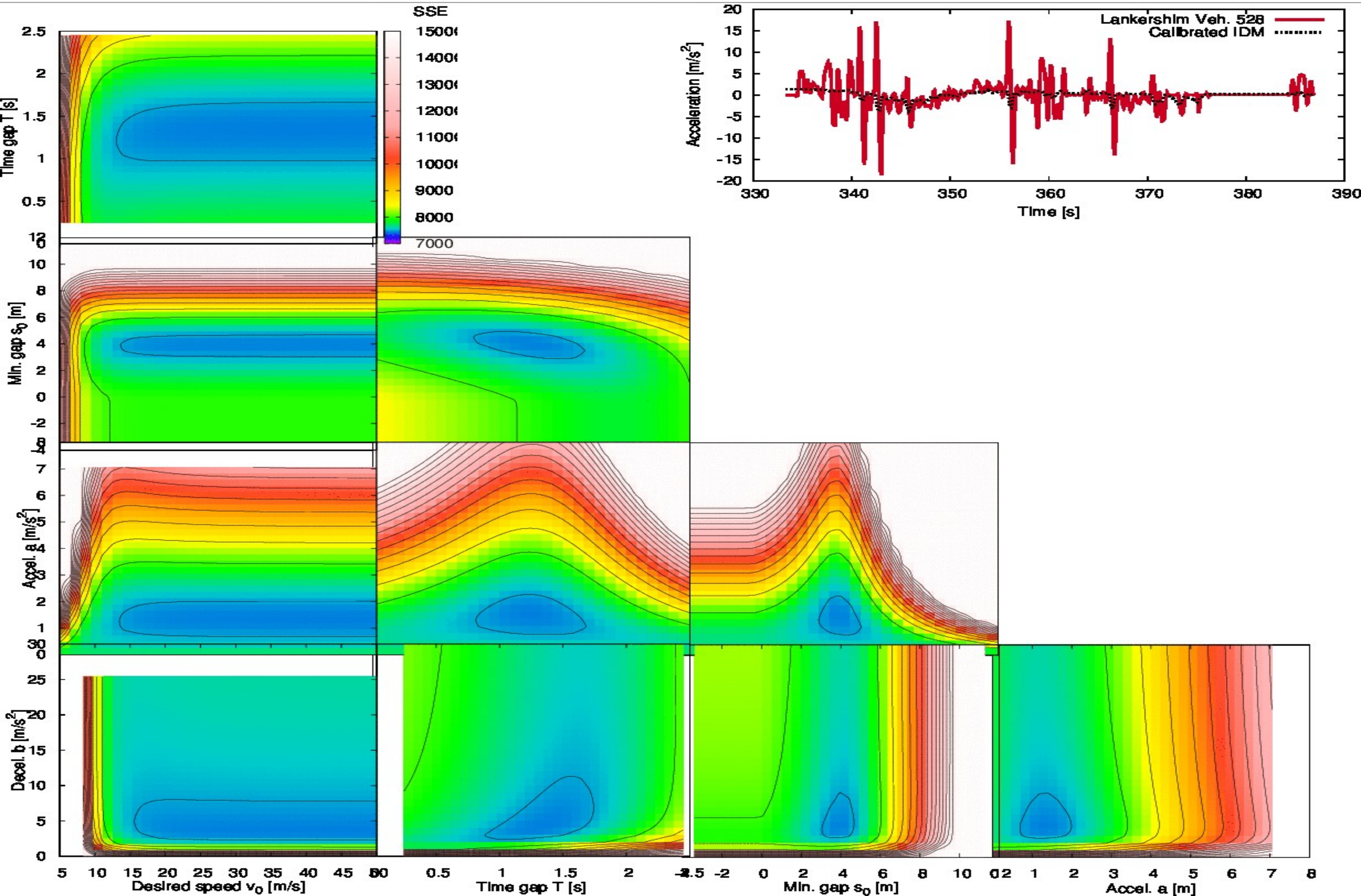


(3d) Reference 2: Traj 528 w/o the last seconds, local MLE calibration, sampling interval 1 s)

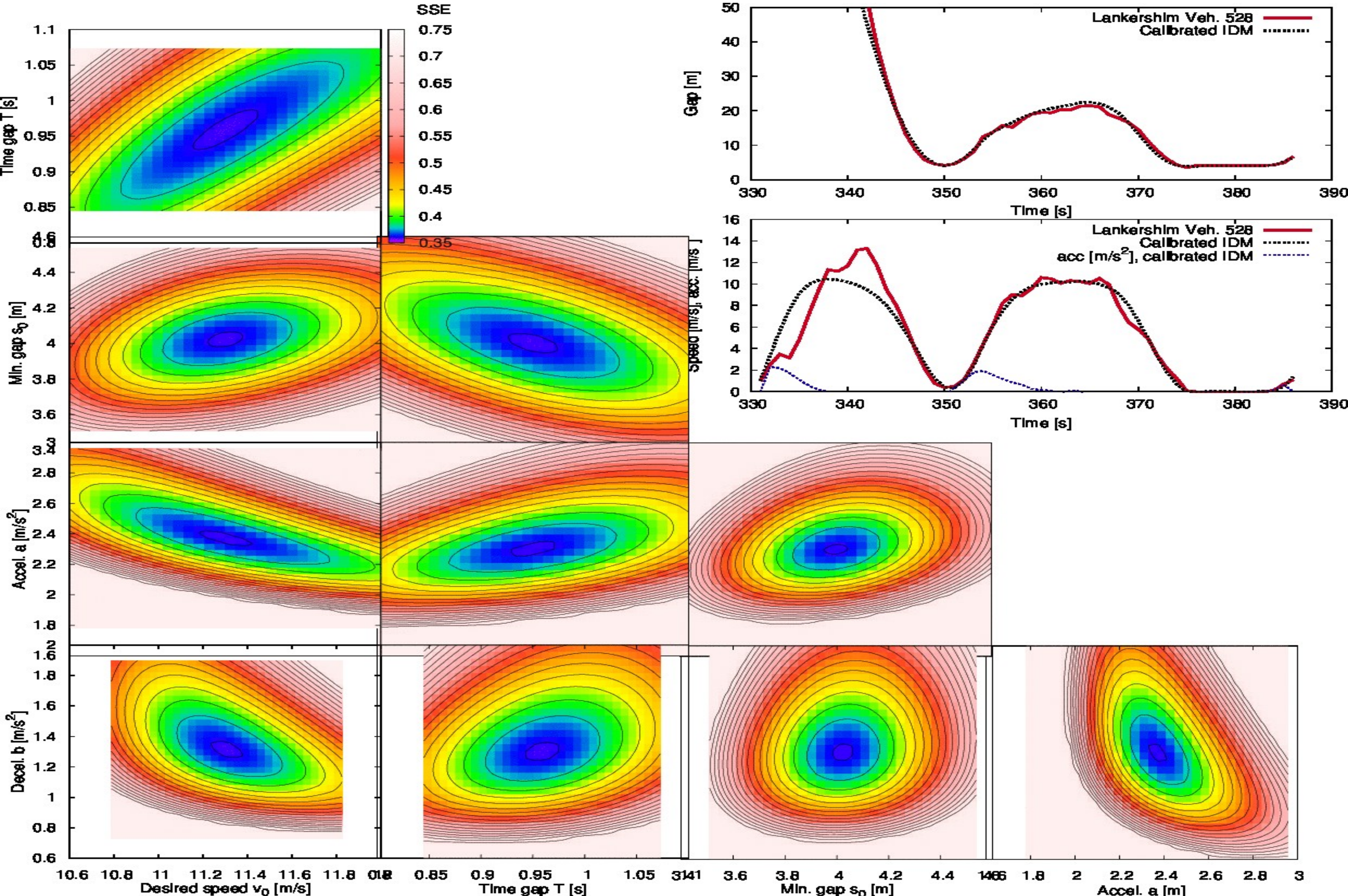


TECHNISCHE UNIVERSITÄT DRESDEN

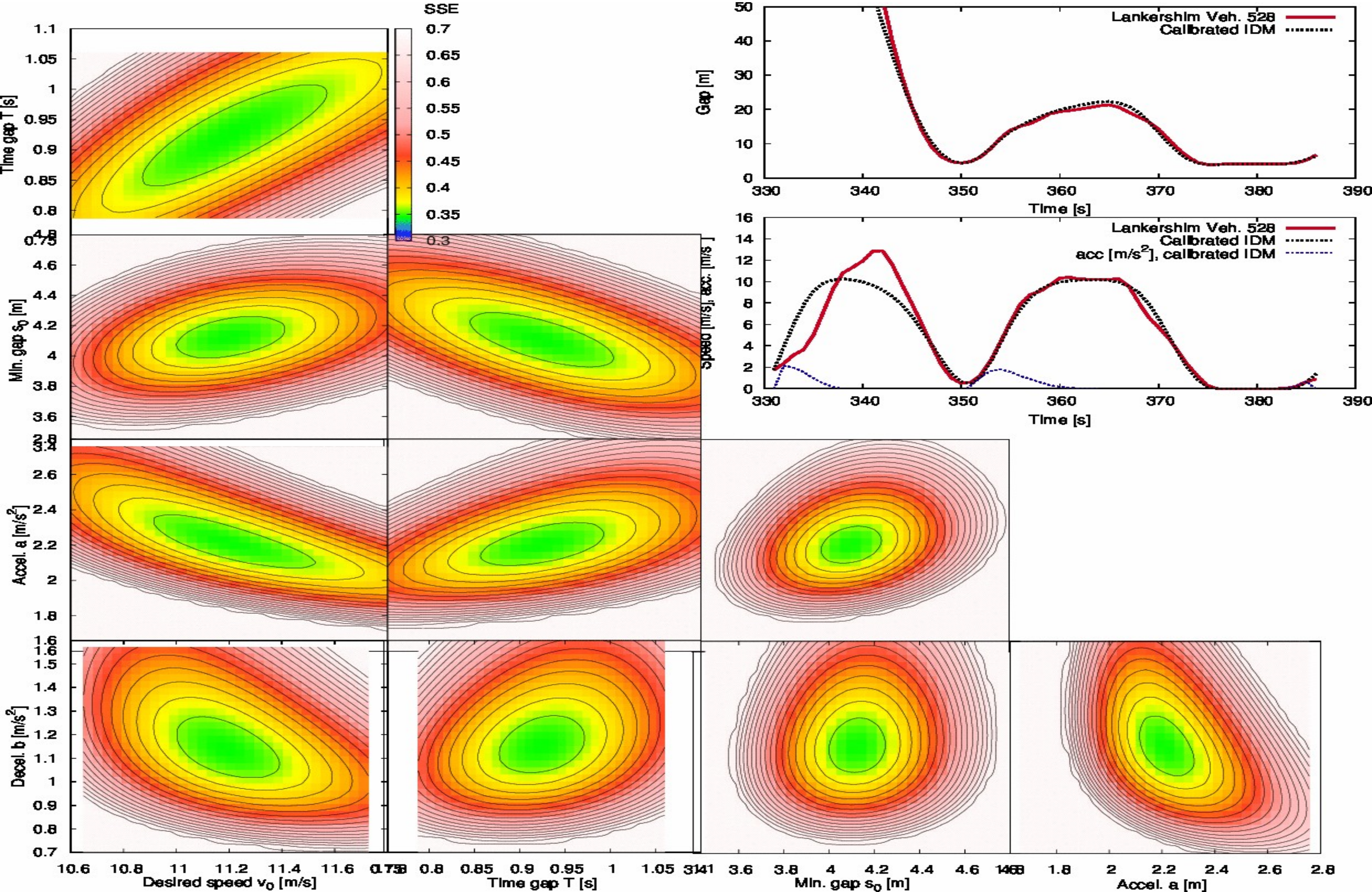
(3e) Sampling interval 0.1 s instead of 1 s



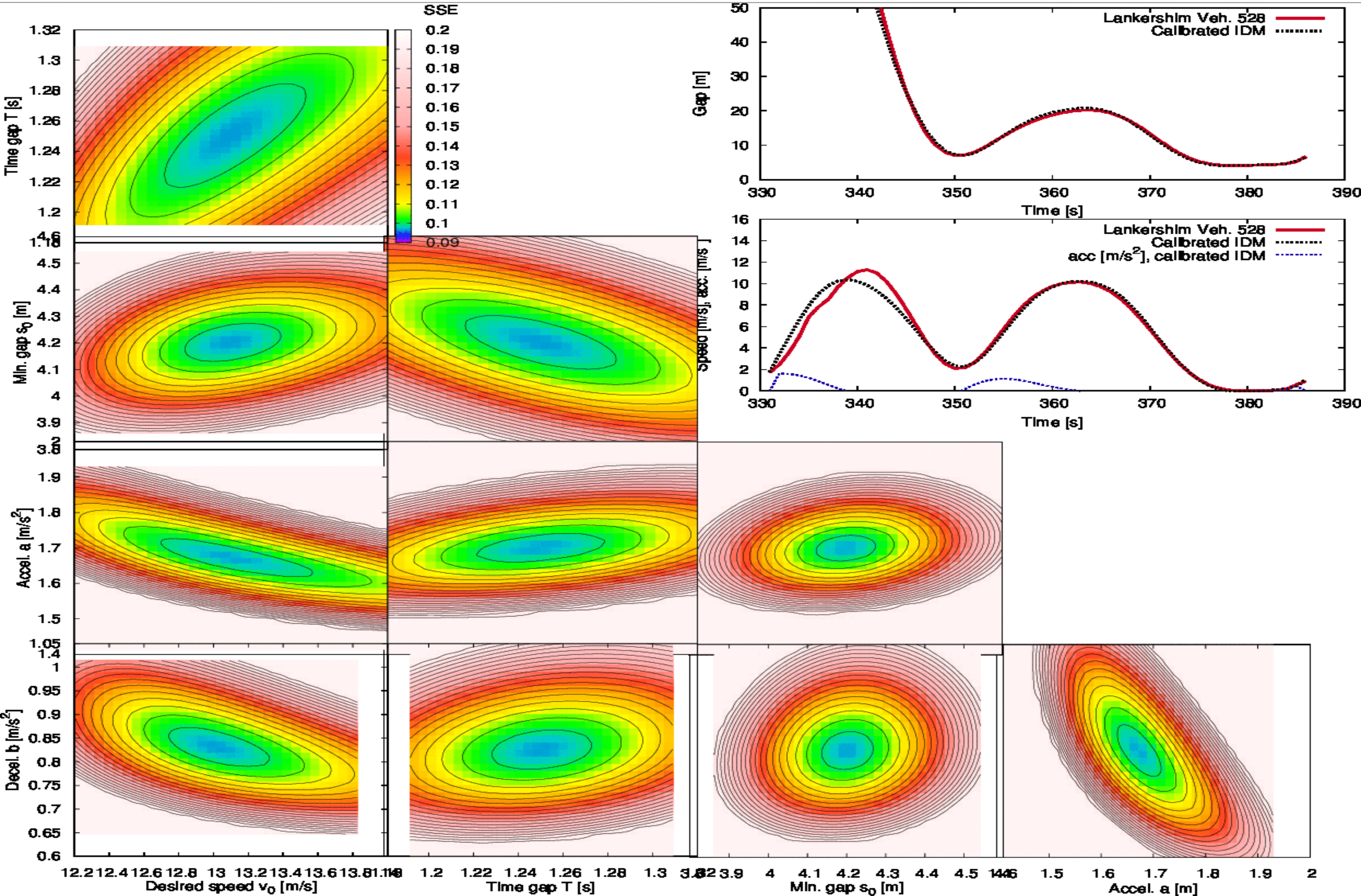
(4) Dependence on the data preparation: Reference (Traj 528, relative gaps, no smoothing)



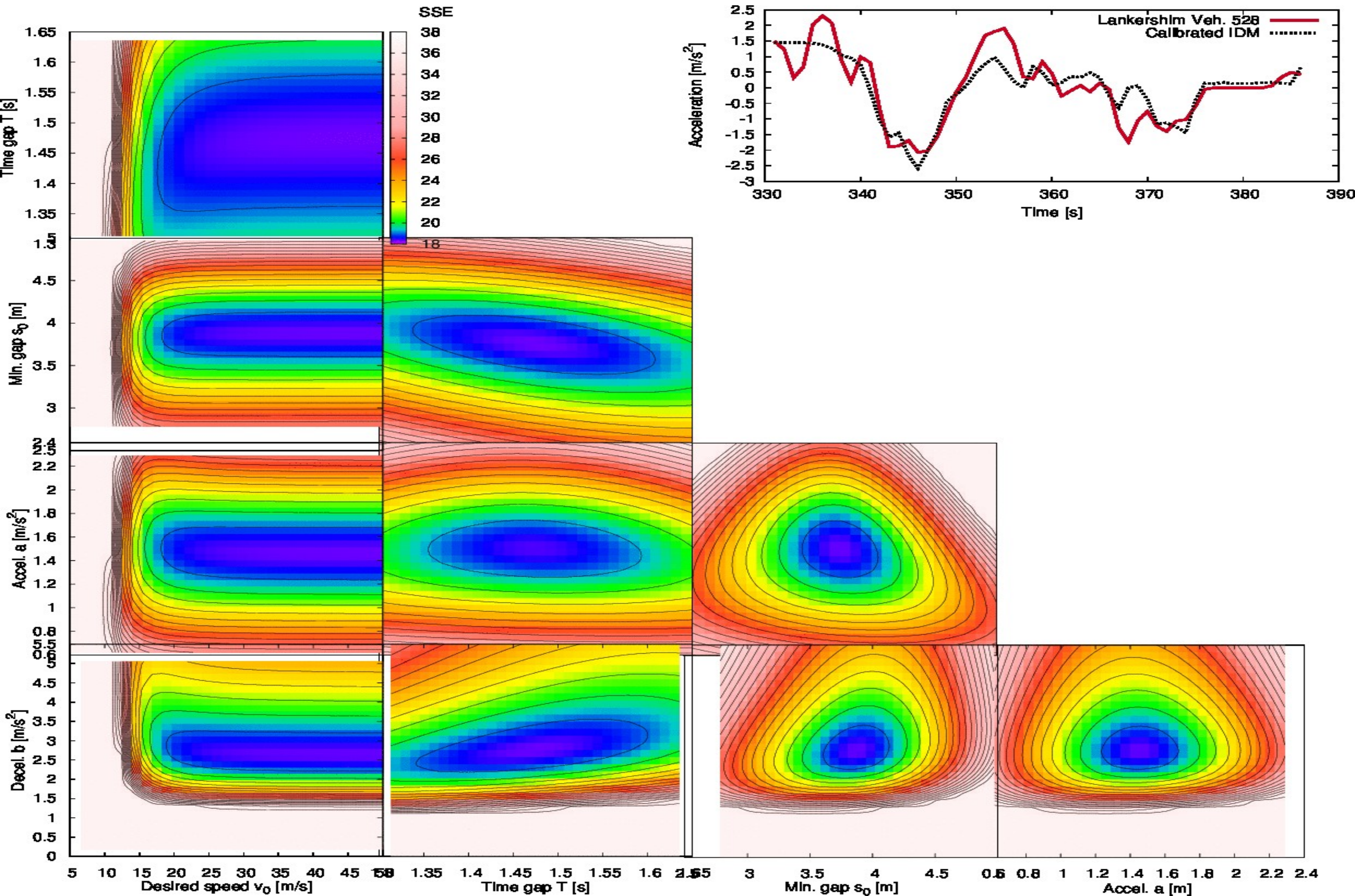
(4b) Smoothing with double-exponential kernel, 1 s



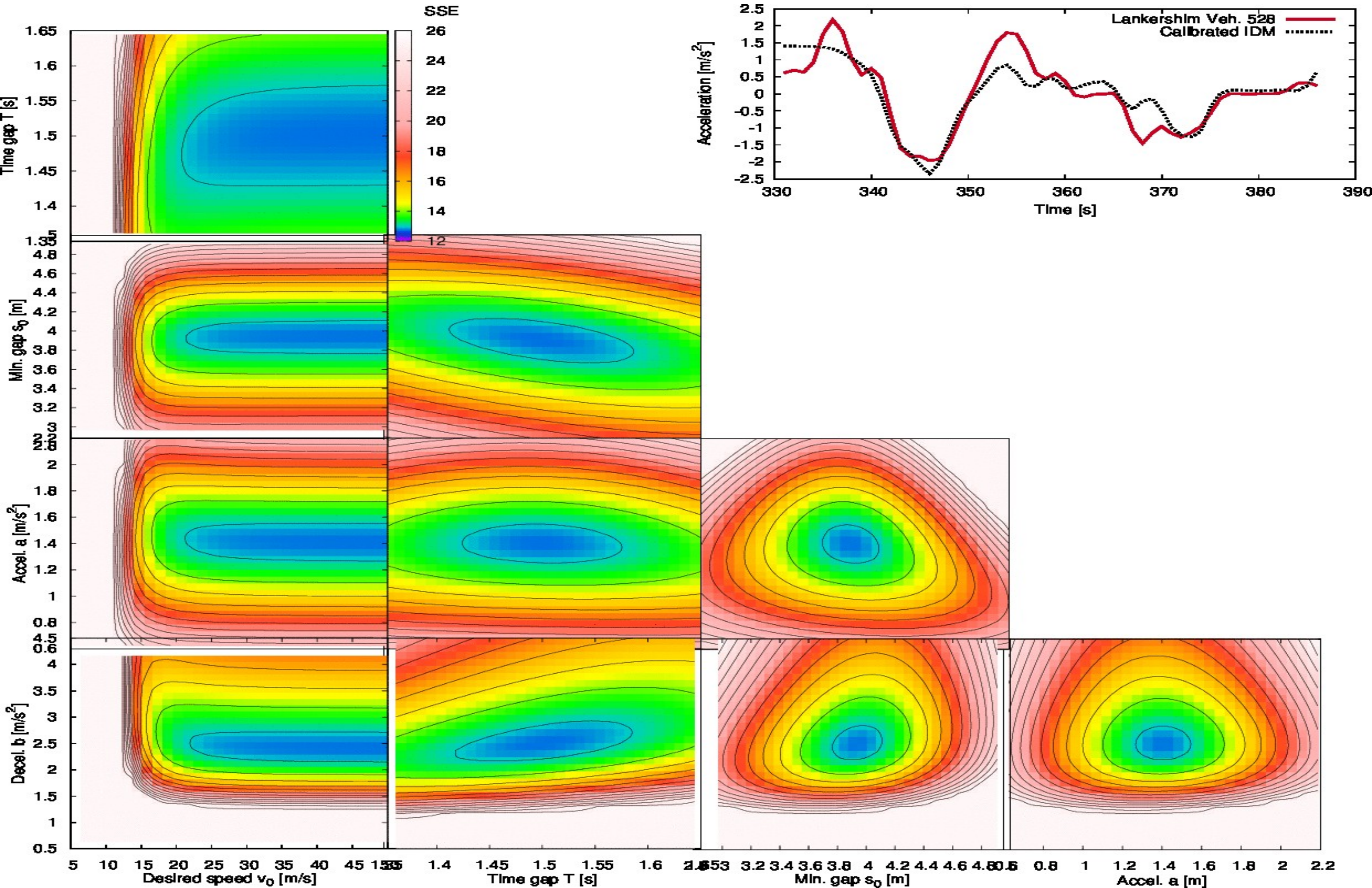
(4c) Smoothing with double-exponential kernel, 5 s



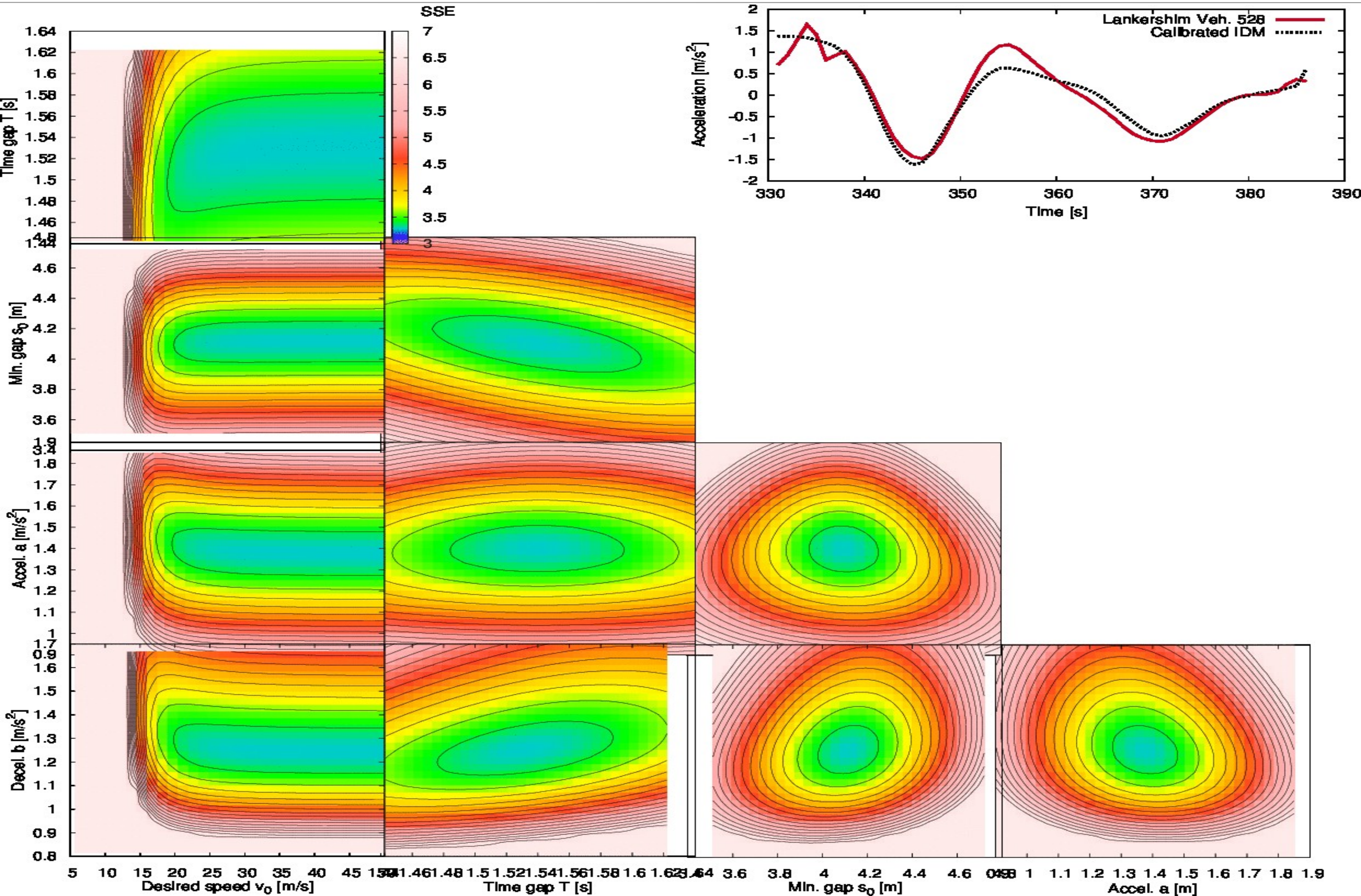
(4d) Reference 2: Traj 528 w/o the last seconds, local MLE calibration, no smoothing)



(4f) Local MLE calibration, smoothing 1 s)



(4g) Local MLE calibration, smoothing 5 s)



Conclusions

- When calibrating **macroscopic/collective aspects**, simple LSE calibration of local fields (speeds, densities) will not do. Instead, one calibrates for collective properties directly (jam extensions, propagations, wave speeds etc)

- When calibrating **the bahavior of individual drivers**, the selection of suitable data is crucial, e.g. omitting periods around lane changes. Otherwise, non-identifications, or inconsistent values, will be likely

- The choice of **the calibration method and/or objective function** is of lesser importance when calibrating driving behavior. Most differences are to be expected

- Remarkably, **data preparation/manipulation** such as smoothing, changing the sampling rate, or “reconstructing” the data, has little effect.

Let's discuss ...