# The Value of Calibration and Validation of Probabilistic Discretionary Lane-Change Models

**Victor L. Knoop**
**Christine Buisson**

## Abstract

This paper analyses methodologies to calibrate and validate probabilistic lane change models. We perform a calibration and validation on lane change models (microscopic and macroscopic) which take the most basic dependencies into account. The resulting model has reasonable parameters, and the goodness of fit for the validation set (hold back from the total set) is similar to the calibration. For two measures of validation the model hence is validated. However, in real world terms, the model performs quite bad. It is hence concluded that the model should be validated based on measures which have a clear physical interpretation, and based on those the quality should be judged.

## Introduction

- Lane changes are rare events (~1 lane change per 2 km)
- Many lane change models are probabilistic
- Probabilistic models are usually tested using log likelihood
- Calibration and validation are required

## Validation

1) Parameter values match the expected value
2) Quality of fit of validation is equal to quality of fit of calibration
3) The found model is good enough (purpose as base)

In order to to have an influence of day or location, we validate the model on the same site as the calibration takes place — we hence check the internal consistency of the model.

## Lane change model

Three base requirements

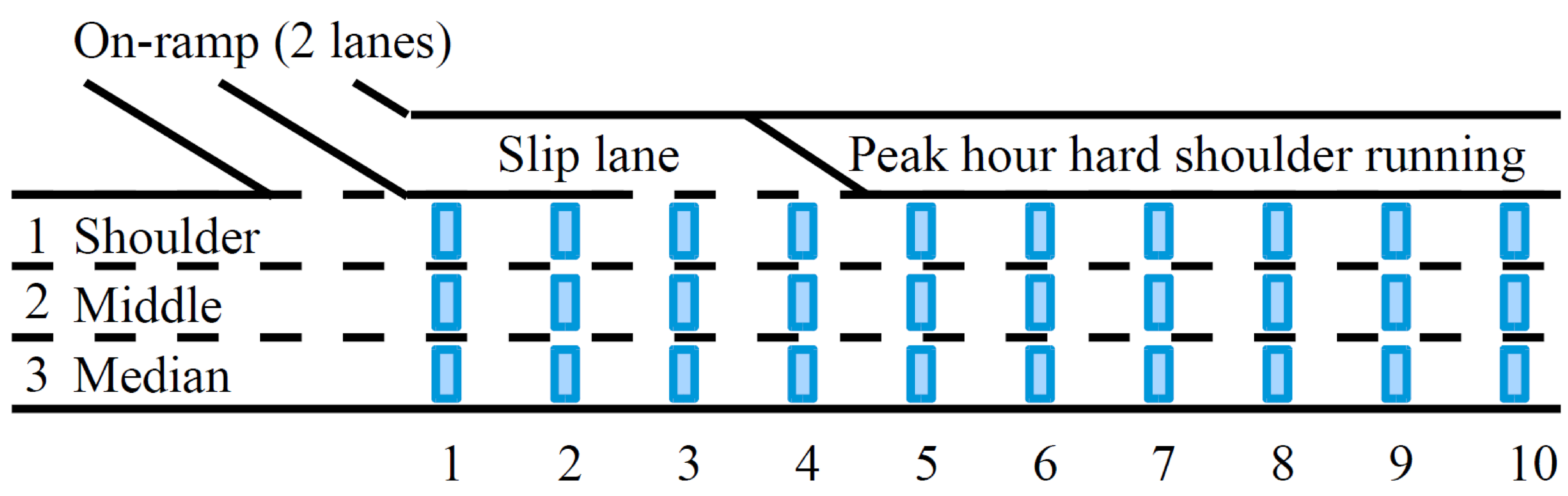
1) Desire for higher speed (binary, $f_1$)
2) Higher speed in other lane (linear with speed difference, $f_2$)
3) Availability of gap (speed dependent, $f_3$)

All need to be fulfilled, so multiply for probability

Besides: rest probability ($\alpha$)

$$P(\text{lane change}) = \alpha\left(f_1 * f_2 * f_3\right) + (1-\alpha)$$

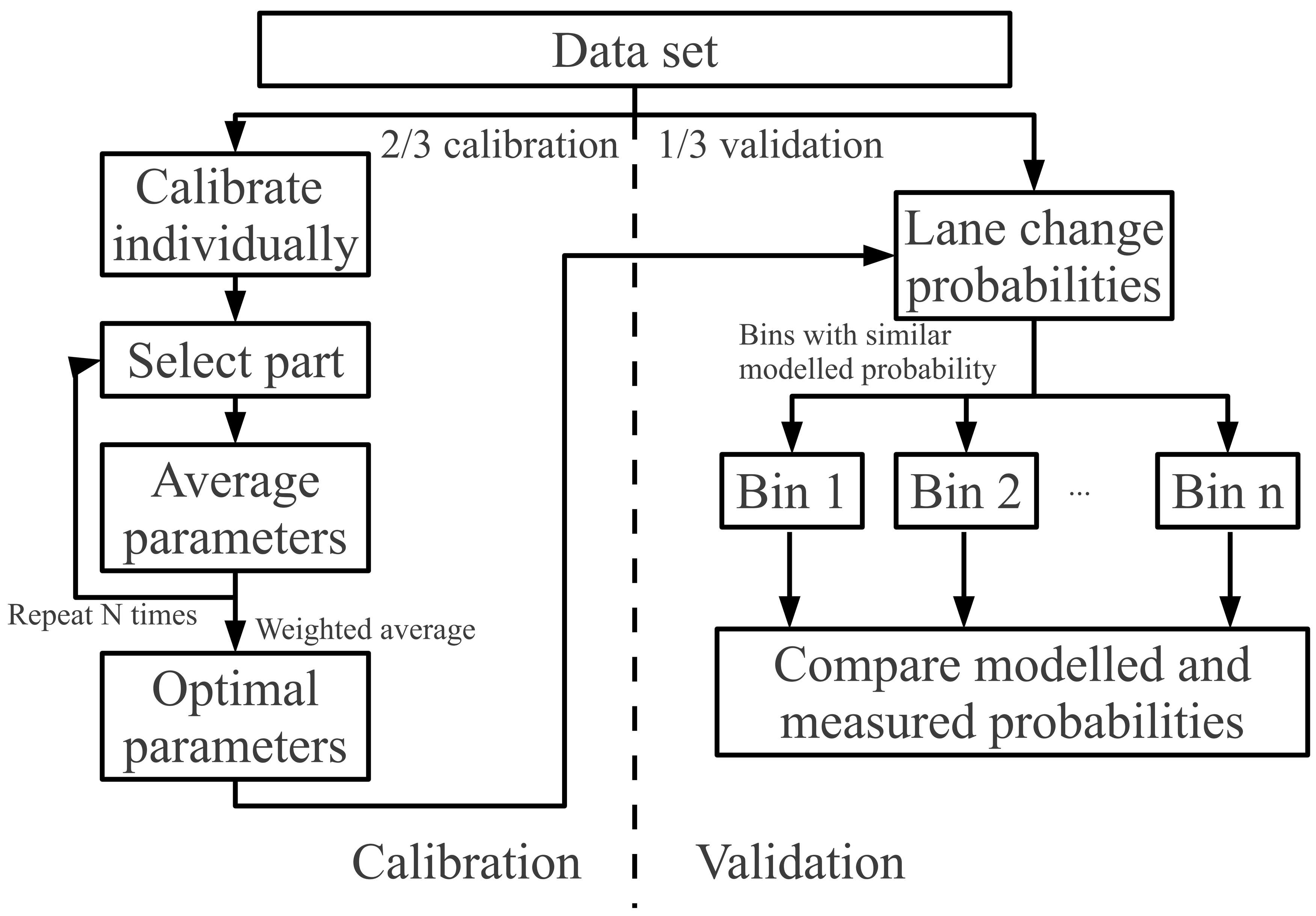
This microscopic lane change probability is translated into a probability to observe N lane changes in an observation interval of T seconds and X meters. We use the fundamental diagram per lane to make this dependent on the densities in each lane




## Data

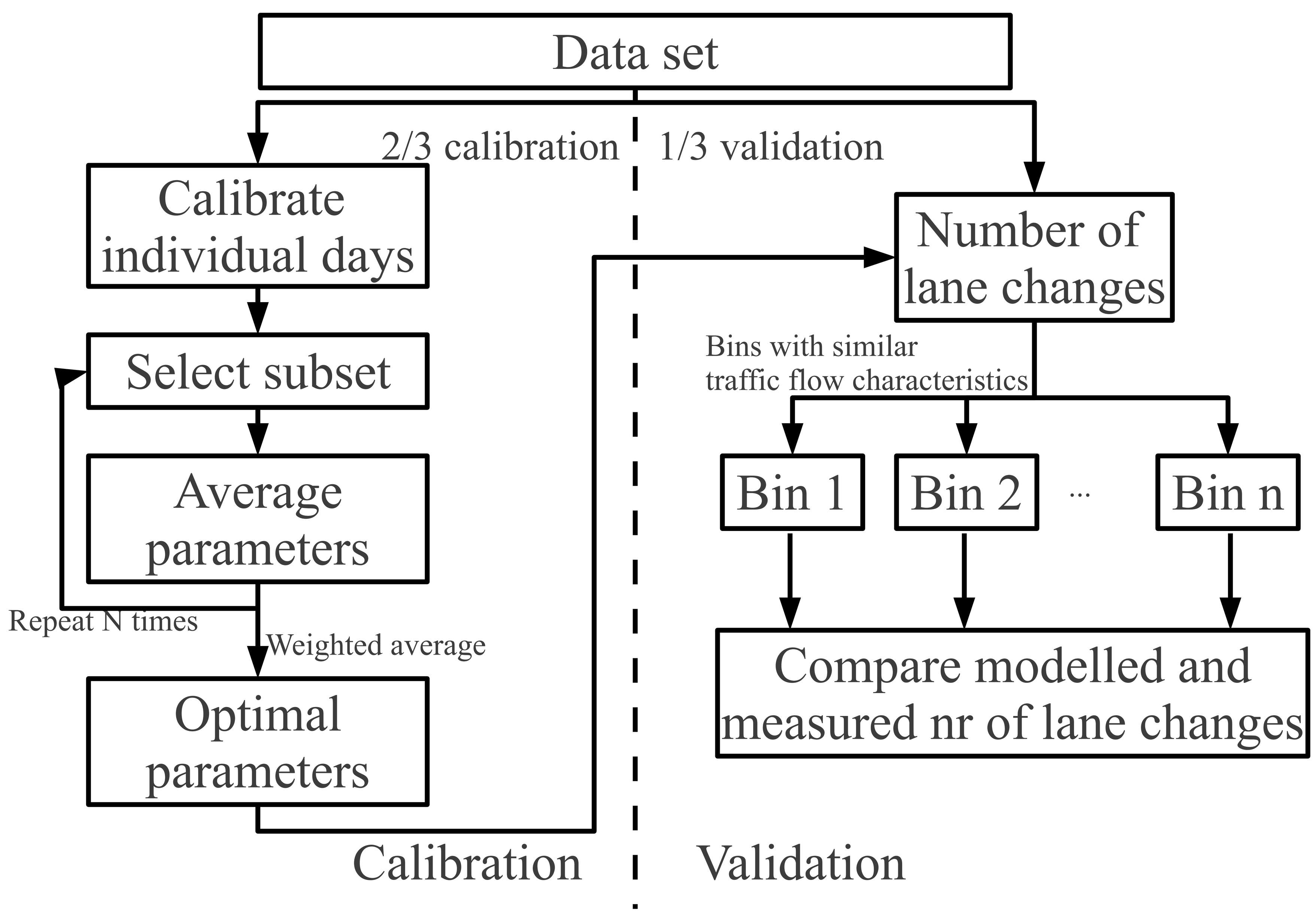
- M42 motorway near Birmingham, UK, 3 lanes
- 1 km individual loop data,
- Vehicles re-identified from site to site
- Used: 500 meters as far downstream as possible from ramp
- Considered: lane changes from middle to median lane

## Methodology: microscopic model




In calibration: optimize the likelihood that the model predicts all lane changes and not lane changes correctly.

## Methodology: macroscopic model




In calibration, optimize the likelihood that the model predicts the correct number of lane changes.

IFSTTAR

Sponsored by: NWO Netherlands Organisation for Scientific Research

Project: there is plenty of room in the other lane

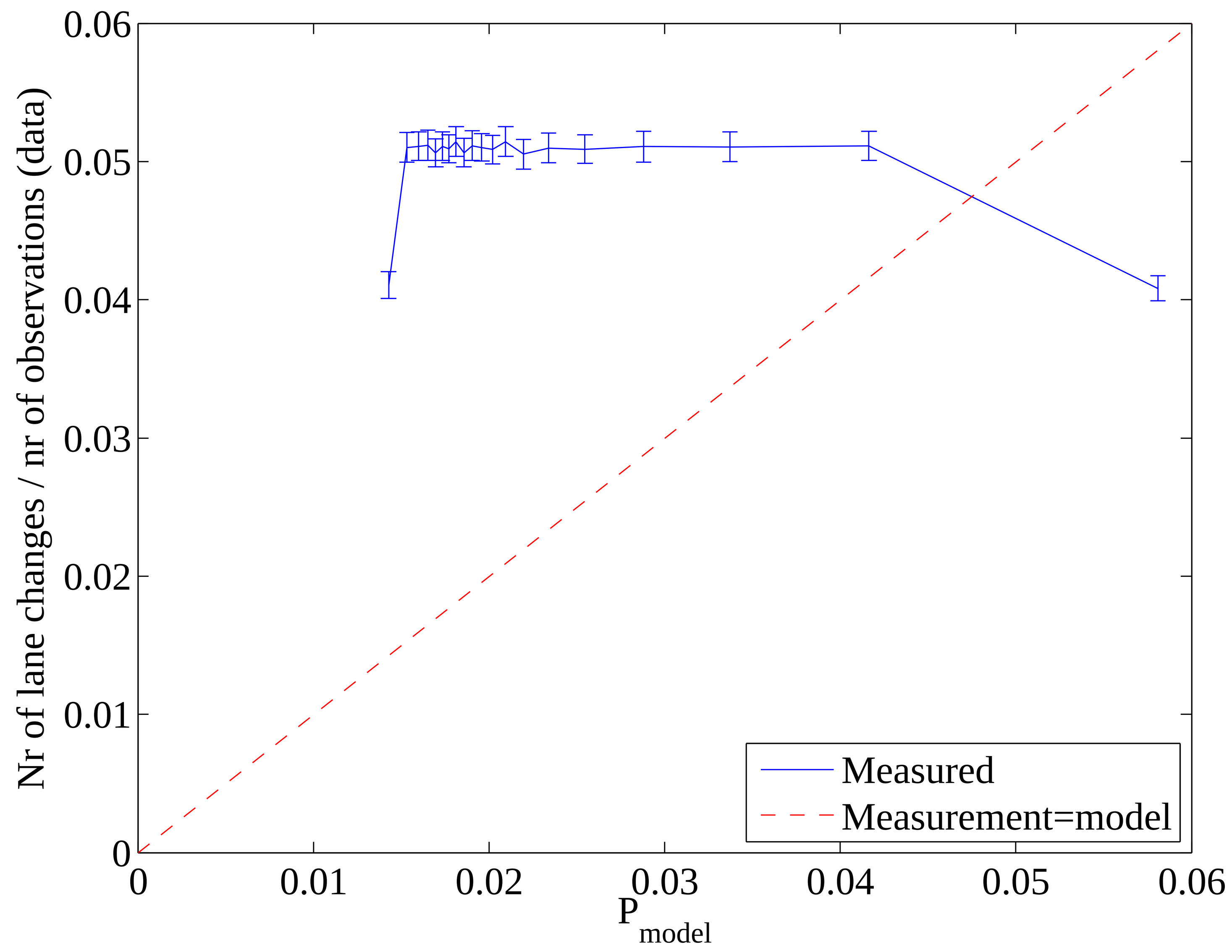
TU Delft
Delft University of Technology
Transport & Planning

Transportation Research Board
91th Annual Meeting,
January 13-17, 2014
Paper nr. 14-0103
www.victorknoop.eu/research

Victor L. Knoop, PhD
TRAIL Research School
Delft University of Technology
Transport & Planning
v.l.knoop@tudelft.nl

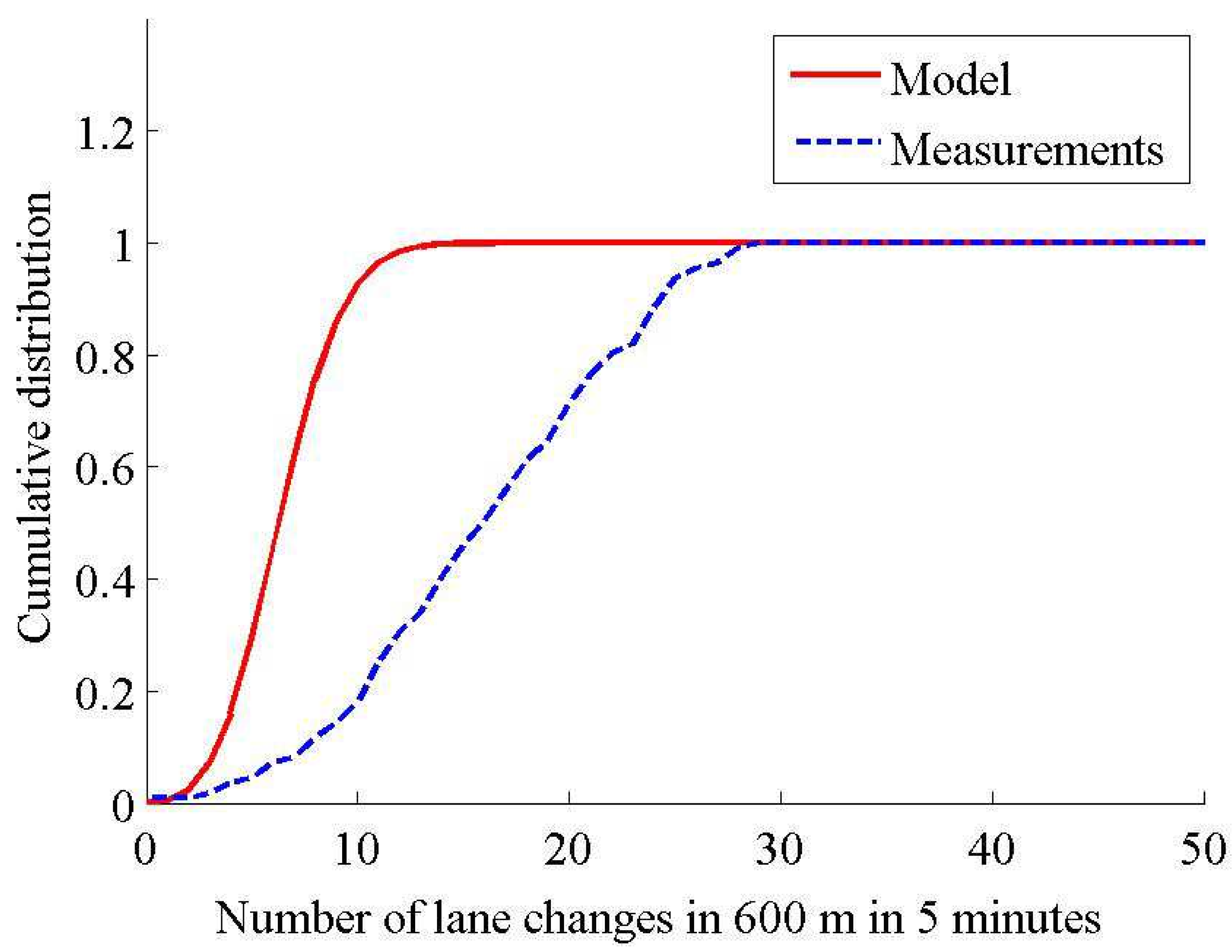
## Check on model quality - microscopic

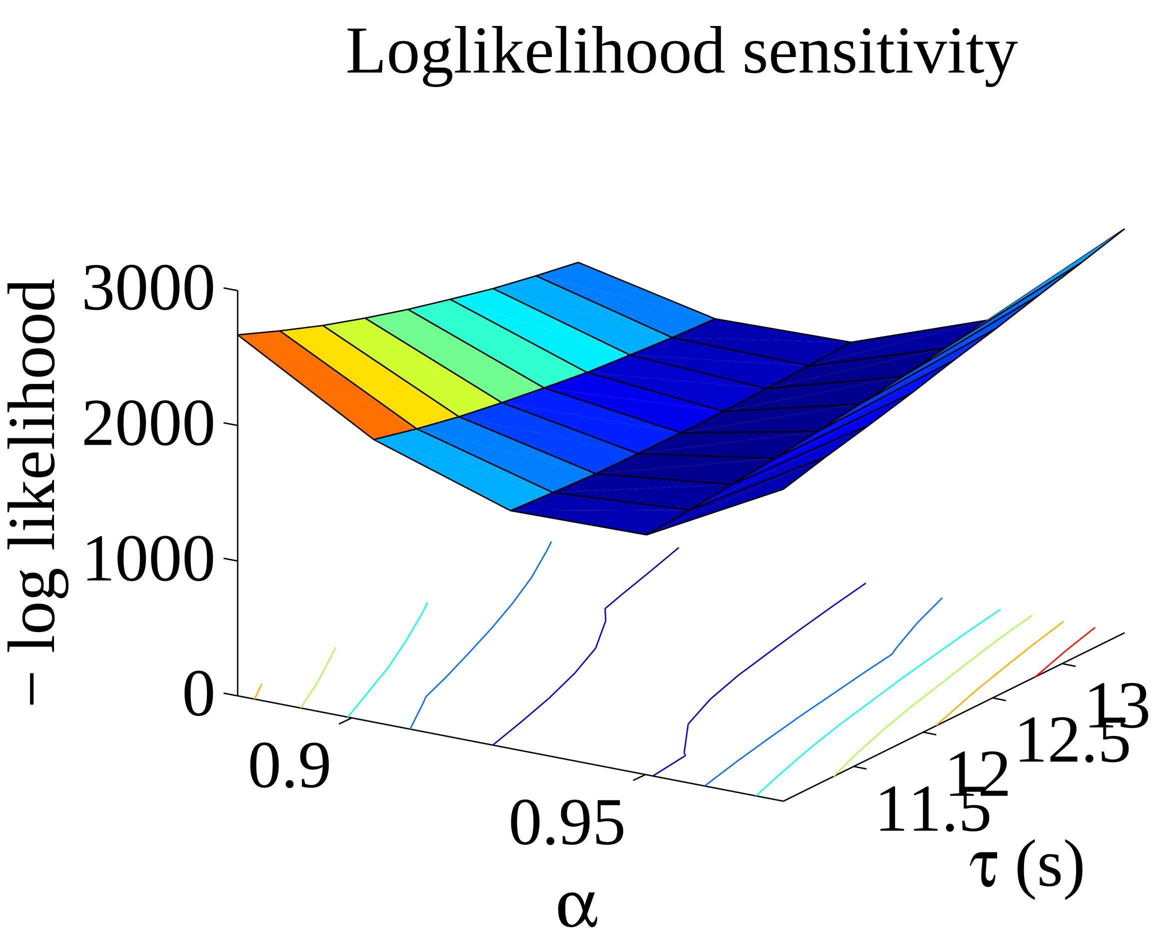
- Lane change probability for each vehicle for each time
- Categorize all time step events in bins for which the predicted lane change probability is the same
- Check per bin whether the average lane change is the same
- It is not — not even close:

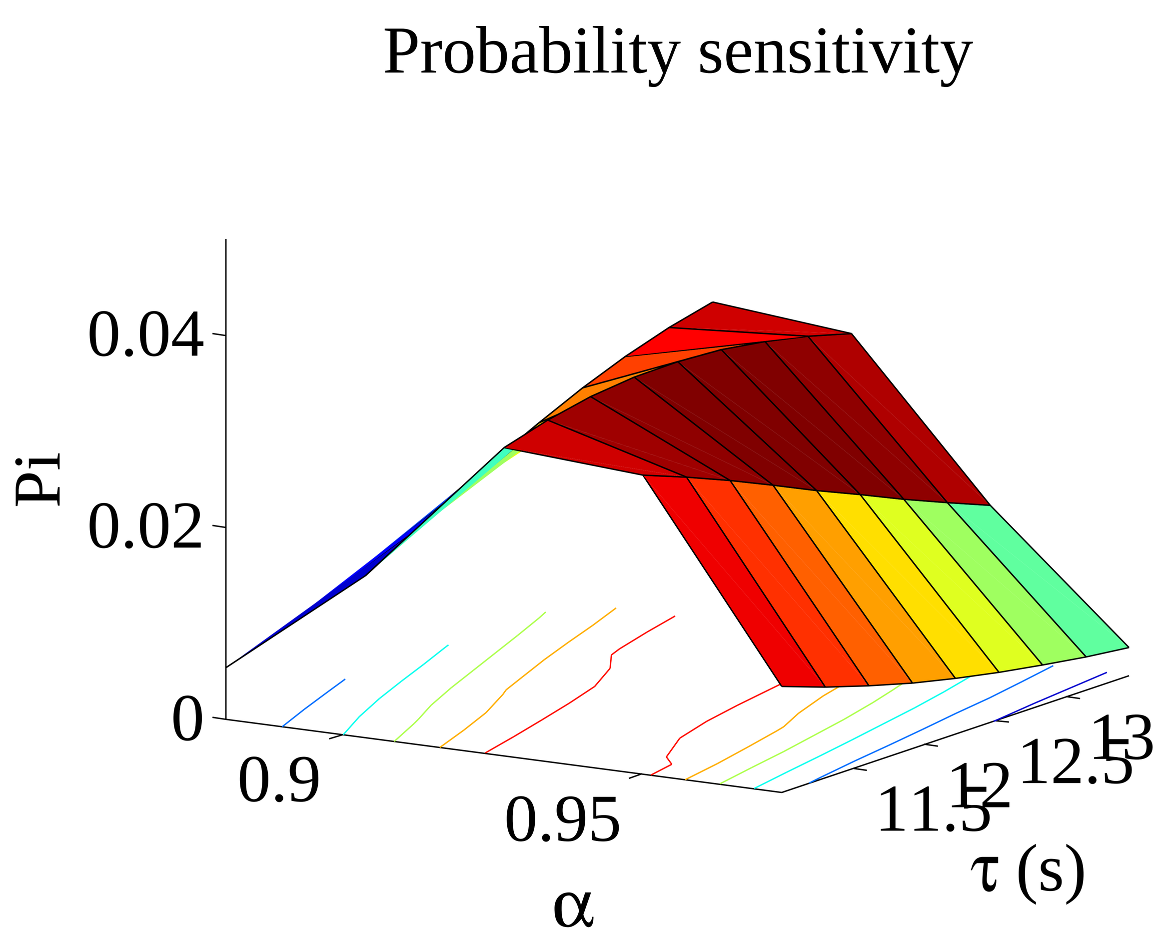


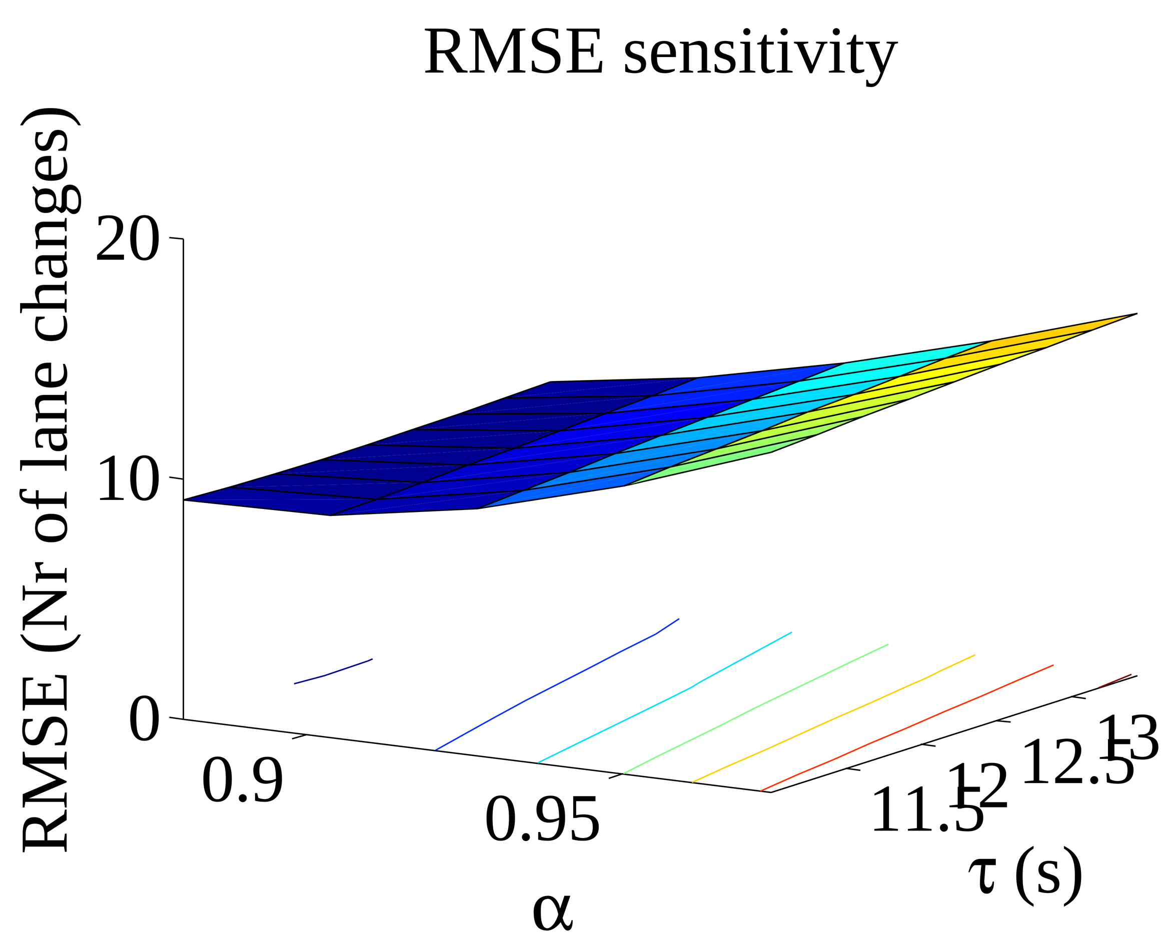

## Check on model quality - macroscopic

- Lane change rates depend on the densities
- Categorize traffic states in bins with similar density in origin and target lane
- Determine the distance between the distribution of the prediction and the observation in each category
- It is not the same:




## Discussion

- Loglikelihood is very insensitive to the correct probabilities for rare events
- Probability sensitivity (average probability per event that the prediction is correct) is much more sensitive
- The model P(lane change)=0 results in a better likelihood!
- Optimizing on RMSE of number of lane changes results in **a different best parameter set**

## Conclusions

We considered the calibration and validation of a probabilistic lane change model. Following the state of the art, optimal parameters were found by maximizing the log likelihood. The parameters were reasonable and the for the validation the log likelihood value (corrected for the number of observations) was approximately the same. Nevertheless, the predicted number of lane changes was quite far off the observed number. Hence we conclude that all models must be calibrated using sound physical measures which have a clear interpretation.

IFSTTAR

The Netherlands Research School for Transport, Infrastructure and Logistics
TRAIL

TU Delft
Delft University of Technology
Transport & Planning