

# Data-driven Microscopic Traffic Modelling and Simulation using Dynamic LSTM

## 1 INTRODUCTION

This document contains supplementary materials of our paper, "Data-driven Microscopic Traffic Modelling and Simulation using Dynamic LSTM", submitted to SIGSIM conference on PADS (2021) under Association of Computing Machinery (ACM).

## 2 APPENDICES

### 2.1 Appendix A

According to [1, 2], Krauss car-following model is governed by the following equations.

At time  $t$ :

$$vel_{safe}^f = vel^l + \frac{gap - vel^f \tau}{2 decel_{max}^f} + \tau \quad (1)$$

$$vel_{desire}^f = \min(vel_{max}^f, vel^f + accel_{max}^f \Delta t, vel_{safe}^f) \quad (2)$$

$$vel_{next}^f = \max(0, vel_{desire}^f - \sigma) \quad (3)$$

where  $vel$  is velocity of follower( $f$ ) or leader( $l$ );  $gap$  is net front gap distance w.r.t leader;  $\tau$  is driver's desired time headway;  $accel_{max}$  and  $decel_{max}$  are follower's maximum desired acceleration & deceleration respectively;  $vel_{max}$  is follower's maximum desired velocity;  $\Delta t$  is time step length;  $\sigma$  is driver's imperfection; next is next time step  $t + \Delta t$ . We use a Genetic Algorithm (GA) as shown in Figure 1 to calibrate Krauss car-following model. The calibration process is defined as an optimization problem and the objective is to minimize the performance index  $O$  (or fitness value) in Equation 4 & 5. Optimization variables are  $accel_{max}^f$ ,  $decel_{max}^f$ ,  $\tau$ ,  $\sigma$ ,  $vel_{max}^f$ .

$$O = (1 - \beta)RMSE_{vel} + \beta RMSE_{pos} \quad (4)$$

$$RMSE_k = \sqrt{\frac{1}{N} \sum_{i=1}^N (k_i^{act} - k_i^{est})^2}, k \in \{vel, pos\} \quad (5)$$

where  $act$  and  $est$  are actual and estimated respectively,  $N$  refers to total number of samples used for calculating the fitness value,  $\beta$  is configurable parameter and can only take a value within the range  $[0,1]$ .  $vel$  and  $pos$  are follower's velocity and longitudinal  $x$  position respectively. Stopping conditions are either when the best set of parameters do not change for the last 5 generations or reach the chosen maximum number of generations. We use uniform crossover operator for it is known to mitigate premature convergence. Mutation is carried out on  $M$ -randomly-selected genes via diversification by means of adding small perturbations drawn from uniform random distribution. When performing mutation on offspring's genes, two constraints are imposed on modified values of  $\tau$  and  $\sigma$  as shown in the figure.

The optimization variables are initialized using uniform random distribution. Various ranges of  $accel_{max}^f$ ,  $decel_{max}^f$ ,  $\tau$ ,  $\sigma$ ,  $vel_{max}^f$  are  $[0,3.41]$ ,  $[-3.41,0]$ ,  $[0,1]$ ,  $[0,1]$ ,  $[0, vel_{max}^{type}]$  respectively.  $vel_{max}^{type}$  is

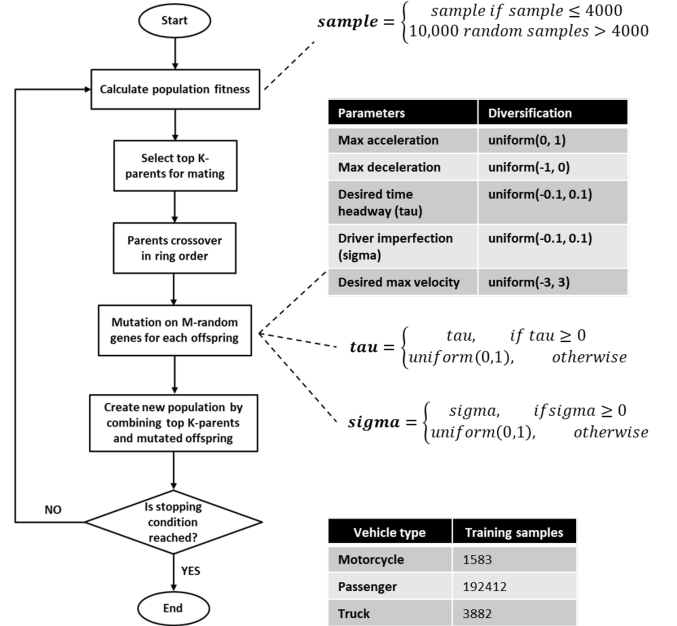


Figure 1: Genetic Algorithm

maximum desired velocity based on vehicle type and inferred from training data samples. Other GA parameters are population=100; number of mating parents=50; gene mutation count=3;  $\beta = 0.5$  and generations=500. The GA is run separately for each vehicle type. The optimal values are reported in Table 1 after running the GA for 10 times and taking the average of the results.

Table 1: Parameters of Krauss car-following model calibrated using GA

Parameters	Motorcycle	Passenger	Truck
$accel_{max}^f$	1.203	0.9167	0.9466
$decel_{max}^f$	0.8256	0.1259	0.0951
$\tau$	1.9905	0.9621	0.5845
$\sigma$	0.1027	0.0835	0.0726
$vel_{max}^f$	23.9579	24.2845	19.3276

### 2.2 Appendix B

This section is related to dynamic Krauss mobility model. Although data associated with passenger car trajectories are dense, only sparse data is available for trucks and motorcycles. Thus, we only perform dynamic calibration on passenger cars during real-time simulation. The following range of values are used for population initialization by adding perturbations to optimally calibrated values in Table 1. Different ranges of  $accel_{max}^f$ ,  $decel_{max}^f$ ,  $\tau$ ,  $\sigma$ ,  $vel_{max}^f$ ,

which are used to draw from uniform distribution, are  $[0,1]$ ,  $[-1,0]$ ,  $[-0.0005,0.0005]$ ,  $[0,0.00005]$ ,  $[-3,3]$  respectively. Other parameters are: Population size =50, number of mating parents=25, mutated gene count=3,  $\beta=0.5$ , generations=30, sample size=100 (used to calculate fitness value). Samples are drawn from recently arrived data up to window size of  $k$ . The following range of values are used for diversification during mutation operation by adding small perturbations to offspring's genes. Range for  $accel_{max}^f$ ,  $decel_{max}^f$ ,  $\tau$ ,  $\sigma$ ,  $vel_{max}^f$ , are  $[-1,1]$ ,  $[-1,0]$ ,  $[-0.0005,0.0005]$ ,  $[-0.00005,0.00005]$ ,  $[-0.1,0.1]$  respectively.

### 2.3 Appendix C

The estimated follower's velocity by dynamic LSTM is only used as preferred velocity. Thus, even when using dynamic LSTM, we also need to set parameters for underlying Krauss car-following model that is used to determine safe driving behaviours of vehicles in SUMO. The parameters are inferred from Dataset 1 and 2 by taking the average of observed values and shown in Table 2.

**Table 2: Parameters of Krauss car-following model used to revise the preferred velocity**

Parameters	Motorcycle	Passenger	Truck
$accel_{max}^f$	1.075	0.785	0.785
$decel_{max}^f$	1.24	1.19	1.225
$\tau$	1	1	1
$\sigma$	0	0	0
$vel_{max}^f$	24.395	29.05	22.24

### REFERENCES

- [1] Stefan Krauss. 1998. Microscopic modeling of traffic flow: investigation of collision free vehicle dynamics. *Forschungsbericht - Dtsch. Forschungsanstalt fuer Luft - und Raumfahrt e.V.* 98-8 (1998).
- [2] M. Pourabdollah, E. Bjärkvik, F. Fürer, B. Lindenberg, and K. Burgdorf. 2017. Calibration and evaluation of car following models using real-world driving data. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. 1–6. <https://doi.org/10.1109/ITSC.2017.8317836>