Calibration of Traffic Simulation Models Using Vehicle Travel Times

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Abstract. In this paper, we propose an effective calibration method of the cellular automaton based microscopic traffic simulation model. We have shown that by utilizing a genetic algorithm it is possible to optimize various model parameters much better than a human expert. Quality of the new model has been shown in task of travel time estimation. We increased precision by more than *25 %* with regard to a manually tuned model. Moreover, we were able to calibrate some model parameters such as driver sensitivity that are extremely difficult to calibrate as relevant data can not be measured using standard monitoring technologies.

Keywords: traffic, simulation, cellular automaton model, calibration, travel time.

1 Introduction

A very important stage of development of any traffic model is its comparison with reality, namely calibration and validation. In [1], authors proposed an effective three-step process for the microscopic traffic model calibration. Another paper [2] gives some basic guidelines for calibration of microscopic simulation models in form of framework and applications. The developers usually calibrate and validate the model on their own using some data sets that they have access to and publish the results obtained. For example, in paper [3] authors tried to perform a simple calibration of ten microscopic traffic simulation models in a way that the models were calibrated and compared to each other with the GPS based field data from year 2004 in Japan. But it should be noted, that in almost all previous calibration approaches, some real data are desired in a form, which is generally not available. It was shown that it is important to find a few basic parameters for the model calibration [4]. Namely a driver sensitivity (e.g. reaction time), a jam density headway and free-speed (maximum speed when vehicle is not constrained) have to be determined. It was also stated that this process is neither a straight-forward nor an easy task. For example, while the free-speed is relatively easy to estimate in the field and generally lies between the

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speed limit and the design speed of the roadway, the jam density headway is more difficult to calibrate but typically ranges between 110 to 150 vehicles/km/lane. The driver sensitivity factor is extremely difficult to calibrate because it can not be measured using standard monitoring technologies (e.g. detection loops that work on magnetic-induction principle).

In this work we propose to utilize our cellular automaton (CA) based microscopic traffic simulation model, which was shown not only to be extremely fast to achieve multiple in real-time simulations (e.g. [6]), but also updated to eliminate unwanted properties of ordinary CA based models. The quality of this updated model has been previously evaluated by comparison with *Van Aerde* fundamental diagram [5]. Then we will also try to calibrate parameters of this model to field data that can be obtained from standard monitoring technologies. We will show, that it is possible to achieve a better precision on travel time estimation for a given road segment. Moreover, except CA model parameters, we will also optimize some parameters such as driver sensitivity which, as stated for example in [4], are extremely difficult to calibrate with other common techniques. The optimization/calibration will be performed by genetic algorithm (GA).

The rest of the paper is organized as follows. Section 2 introduces an updated cellular automaton based traffic simulation model. Then, in Section 3, the process of optimization of the model with selected GA is described in detail with all simulation model parameters. Experimental evaluations for our field data sets are then presented in Section 4. Finally, conclusions and suggestions for future work are given in the last Section 5.

2 Updated Local Transition Function

In our previous work [5], we updated the original local transition function [7] to a new form, where some brand new parameters can be found. The traffic simulation model is extended to eliminate unwanted properties of ordinary CA based models, such as stopping from maximum vehicle speed to zero in one time step. This is possible due to storing the previous (or the leading) vehicle velocity $v_v(i+1)$. When there is such vehicle, the following vehicle (i) is able to determine its positive or negative acceleration with $acc(i+1)$. According to Alg. 1, it is firstly determined, if investigated vehicle could accelerate (i.e. vehicle velocity $v_v(i)$ is not greater than maximal vehicles speed p_4 or given vehicle speed limit $v_{max}(i)$). If so, its speed-up is accomplished with probability p_7, so not all vehicles tend to always accelerate as in the original model [7]. Then, if there is a plenty of room for vehicle to get in (i.e. $gap(i) + acc(i+1) > v_v(i)$) or there is no previous vehicle in the same lane, collision avoidance mechanism is not performed. Similarly to the original CA local transition function, only deceleration based on probabilities could be applied in this situation. In case of small vehicle speeds $(v_v(i) < p_6)$, deceleration is performed with probability p_5, otherwise $(v_v(i) > p_6)$ with probability p_8.

Collision avoidance occurs only when there is no free room for vehicle i in the same lane to get in (i.e. $gap(i) + acc(i+1) <= v_v(i)$). Two basic situations may

Algorithm 1. Updated local transition function

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if $v_v(i) < p_4$ and $v_v(i) < v_{max}(i)$ then
    $v_v(i) := v_v(i) + 1$ with probability $p_7$
end if
if $(gap(i) + acc(i + 1)) > v_v(i)$ then
    if $v_v(i) < p_6$ then
        $v_v(i) := v_v(i) - 1$ with probability $p_5$
    else
        $v_v(i) := v_v(i) - 1$ with probability $p_8$
    end if
else
    if $acc(i + 1) > 0$ then
        $v_v(i) := 1/p_9 \times (gap(i) + acc(i + 1))$
    else
        $v_v(i) := 1/p_{10} \times (gap(i) + acc(i + 1))$
    end if
end if
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Ensure: Each vehicle i is advanced $v_v(i)$ times and $v_{prev}(i) := v_v(i)$.

occur. If the leading vehicle tends to accelerate $(acc(i+1) > 0)$, the actual vehicle speed $v_v(i)$ is reduced to $1/p_9 \times (gap(i)+acc(i+1)$. Otherwise, $(v_v(i+1) <= 0)$, actual vehicle speed $v_v(i)$ is reduced more strictly to $1/p_{10} \times (gap(i)+acc(i+1)$. It can be seen that these two parameters are more driver-based parameters than model oriented. We will try to find out if these ones could be determined statistically for a given road segment. Finally, each vehicle is advanced $v_v(i)$ sites and velocity updates must be also performed.

3 Optimization of the Model

Genetic algorithms (GA) are widely used in various areas of science and engineering to find solutions to optimization and design problems [8]. The main idea is to evolve a population (set) of candidate solutions to find better ones. A candidate solution is encoded as a chromosome which is an abstract representation that can be modified with standard genetic operators such as mutation and crossover. In this work, GA is used to find all parameters of the CA model in order to maximize the precision of the traffic simulator.

3.1 Parameters Encoding

In order to simplify GA, all simulation model parameters, which will be optimized, are encoded in binary form. In case of real numbers from a given interval (e.g. $[1, 0]$), the interval is divided into the N pieces of the same size. The value N depends on the number of bits used for encoding of the parameter.

Using a 6-bit value and the minimal length of the cell 0.125 m the maximal cell length is 8 m (64×0.125). The cell length is the first model parameter – p_1. One vehicle always occupies as many such cells as it fits into the 5.5 m (or nearer, but not smaller). For example, for the smallest cell length (0.125 m) it is exactly 44 cells. Bigger vehicles, such as trucks, occupy only two times bigger place (11 m). The second model parameter, p_2, is the simulation time-step (also the reaction time) with the minimal value of 0.05 and maximum value of 3.2 seconds encoded again using 6 bits. The cell neighbor, p_3, is encoded using 12 bits (e.g. when the cell length is at minimum then the maximum neighbor is $0.125 \times 4096 = 512$ m). The next parameter is maximal vehicles speed p_4 (encoded on 11 bits, i.e. 2048 possible values for a chosen reaction time and cell lenght) giving, as in the original model [7], the number of cells per simulation step. The probability of slowing down is represented by p_5 (encoded on 8 bits) and slow speed boundary is encoded as p_6 ($1 - 512$ cells per simulation step on 9 bits). Then, the speed-up probability is denoted as p_7. The parameter p_8 is probability of vehicles slowing down in case of a vehicle speed greater than the slow speed p_6. Further model constants p_9 and p_{10} are coefficients of vehicle approximation in case of previous vehicle acceleration and previous vehicle slowing-down. Both parameters have minimal value of 1 and maximal value of 32 (encoded on 5 bits). All parameters with their respective minimal values, maximal values and step, are briefly summarized in Tab. 1.

Table 1. CA model parameters and values

	Bits used [#]	Min. value	Max. value	Step
p_1	6	0.125	8.000	0.125
p_2	6	0.05	3.20	0.05
p_3	12	p_1	$2^{12} \times p_1$	p_1
p_4	11	p_1/p_2	$2^{11} \times p_1/p_2$	p_1/p_2
p_5	8	0.00392	1.00000	0.00392
p_6	9	p_1/p_2	$2^9 \times p_1/p_2$	p_1/p_2
p_7	8	0.00392	1.00000	0.00392
p_8	8	0.00392	1.00000	0.00392
p_9	5	1	32	1
p_{10}	5	1	32	1
p_m	10	0.00097	1.00000	0.00097
p_c	4	0.06667	1.00000	0.06667

3.2 Chromosome

The proposed GA has an auto-evolution or also self-adaptation capability, which means that parameters of the algorithm (the probability of mutation p_m and crossover p_c) are also part of the chromosome. Hence the user is not forced to set them. The whole set of parameters is represented using one 92-bit number. It is important to note that each parameter of the chromosome is encoded using *Gray* *encoding* to ensure that the maximal Hamming distance between two successive values is only one. This setup does not allow big jumps between values in case of a single bit change. The first population ($X(0)$) consists of 60 such chromosomes ($|X(0)| = 60$) generated randomly.

3.3 Fitness Function

All chromosomes from population X_i are separately evaluated using the same fitness function. Firstly, a candidate CA road segment is constructed using the parameters obtained from a candidate chromosome. Then simulation is performed for that model. Incoming vehicles are generated depending on their time of arrival based on measurements from the field. Vehicles outgoing from the simulated road segment are simply removed and their travel time is recorded. Depending on the facility type, various vehicle types could be generated where possible. Whole simulation is executed until the same number of simulated vehicles as the number of vehicles in the field data is reached (N_x). After that, the fitness function F (see Eq. 3) is calculated as a sum of two functions. The error function E is defined as

$$E = \sum_{i=1}^{M} \left(\frac{\left| x_{mi} - x_{f_i} \right|}{x_{f_i}} \right), \tag{1}$$

where M is time interval (e.g. travel times of 50 to 51 seconds – in the scope of 1 second), x_{mi} and x_{f_i} are frequencies (or occurrence) of i-th travel time measured from the calibrated model and from the field data respectively. Then the penalty function P is

$$P = (cel\_length)^{-8}. \tag{2}$$

This penalization ensures that the solutions where the cell length is very small are not preferred due to noticeable slower simulation runtime. Moreover, it is multiplied by the number of vehicles – N (to add a constant error to every vehicle). Thus the fitness function is

$$F = E + (N \times P). \tag{3}$$

Finally, GA tries to minimize this fitness function F as better solutions are always with lower fitness value.

3.4 Creating a New Population

Selection: After evaluation of all chromosomes from the population $X(i)$ is complete, some of them are selected for next operations using a tournament selection with base 2 giving a new population $X_S(i)$, where $|X_S(i)| = 30$.

Crossover: Two-point crossover is applied between two randomly selected individuals giving a new set $X_C(i)$ (where $X_C(i) \subset X_S(i)$ and $|X_C(i)| = 30$). The first point of crossover operation is between the p_3 and p_4 parameter and the second one right after p_{10} parameter, to allow alternation of the model and the GA parameters individually. This operator is applied with the average probability calculated from two chosen chromosomes (p_c).

Mutation: On all chromosomes from $X_C(i)$ a mutation operator (i.e. changing bit $0 \rightarrow 1$ or $1 \rightarrow 0$) is applied with the probability (p_m) taken from evaluated individual, which gives a brand new population $X_M(i)$ of the same size.

Population Recovery: Finally, a new population of 60 individuals $X(i+1)$ is selected from the previous population $X(i)$ and the $X_M(i)$ population. This ensures that the best solution will always survive (i.e. elitism is present) [8].

4 Experimental Results

4.1 Field Data

In order to evaluate proposed method, field data have been utilized. Our field data comes from 2431 meters long road segment between two bigger villages in the Slovak Republic with a maximum allowed speed of 50 km/h. This segment is a bit crocked one and there is no allowance for another vehicle advancement due to the local restrictions. The particular segment is on the way to the country seat, so the road is utilized mostly by drivers going to work and back on ordinary business days, but traffic is not strictly homogenous here. This road segment is also a part of the route between two biggest cities in the region and statistically given 5% of traffic comes from bigger vehicles (e.g. busses, trucks, etc.).

Data set was obtained using standard monitoring technology (i.e. detection loops and detection cameras) for every day and night of the year 2010. Therefore, it was possible to measure travel time for vehicles on given road segment. To be able to get frequency of individual travel times (that is used for model comparison), we decided to round these travel times to 1 second scope. Based on this, it is possible to get frequencies of travel times for different intervals (e.g. morning travel times, one day travel times, week travel times, etc.). We utilized two such data sets, where travel time for every single vehicle is present. Frequencies of travel time from ordinary business day (Tuesday, 18/5/2010) (1) and from the last business day (Friday, 21/5/2010) (2) of the same week has been selected. First data set (1) has average travel time of 197.74 seconds for 6702 vehicles (N_1). Second data set (2) has about 11.21 seconds greater average travel time for 8511 vehicles (N_2). It is also important to note that there were sometimes short-term traffic jams during the second selected day. Both data sets for different week day are shown in Fig. 1.

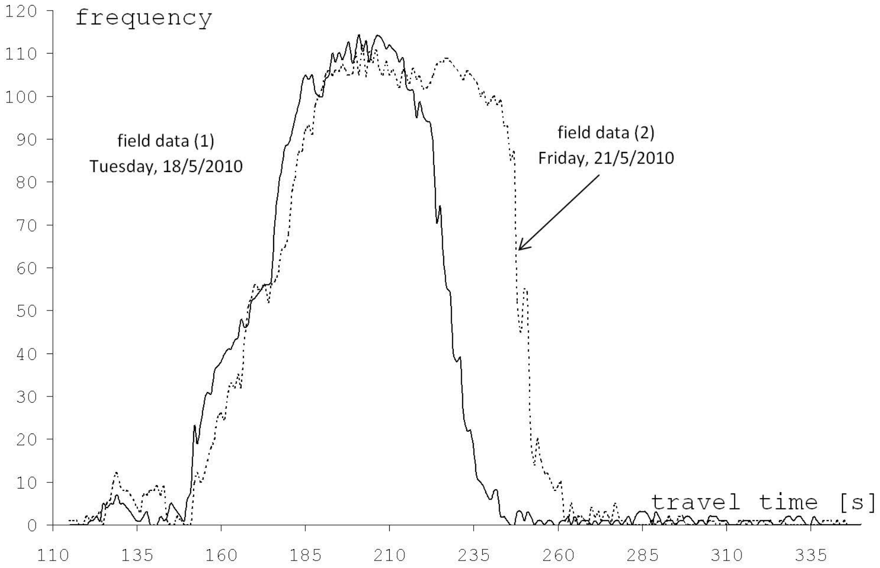

Fig. 1. Frequencies of travel times for two days

4.2 Calibrated Model

All parameters of the CA based microscopic traffic simulation model ($p_1 \dots p_{10}, p_m$ and p_c), which were evolved for our data sets separately are shown decoded as real values in Tab. 2. All come from the best solution of the last generation (220 000) of GA. Tab. 2 also shows parameters of our previously manually tuned and updated CA model as introduced in [5] and in [6] (in the first column of the table). Some of those manually updated values, are generally not available (GA parameters) or have a bit different meaning in our previous model. Such an example is the low speed boundary value p_6, which is identical with maximal vehicles speed p_4. This is caused by absence of the first parameter in the updated model, because slowing down was performed for all available vehicles (with probability p_5). Also all vehicles in the updated model tend to always accelerate, so $p_7 = 1.0$.

In order to check whether all evolved values are not only a result of stochastic nature of GA we made a simple convergence test and it was discovered, that all parameters tend to evolve to one particular value during generations of GA. Due lack of space we do not illustrate this test results here.

The cell length parameter (p_1) is nearly 2 times less in contrast to our previously manually updated model. This also means that single vehicle is represented using two such cells. The evolved reaction time (p_2) of 1.5 seconds corresponds to the minimal increment of 7.43 km/h (p_1/p_2 as seen in Tab. 1). This parameter is also slightly different compared to our previous model. However, very important finding is that these parameters (p_1 and p_2) converged to the same value for both data sets as they are strictly model oriented. All other parameters ($p_3 \dots p_{10}$)

Table 2. Parameters and errors for updated model and models evolved for data sets

	Updated model	Model for (1)	Model for (2)
p_1	5.500 m	2.375 m	2.375 m
p_2	1.200 s	1.15 s	1.15 s
p_3	60.5 m	194.75 m	166.25 m
p_4	181.5 $\frac{km}{h}$	81.78 $\frac{km}{h}$	89.22 $\frac{km}{h}$
p_5	0.3000	0.1059	0.4118
p_6	181.5 $\frac{km}{h}$	29.74 $\frac{km}{h}$	59.48 $\frac{km}{h}$
p_7	1.00000	0.8314	0.7569
p_8	n/a	0.1451	0.4549
p_9	12	2	2
p_{10}	12	2	3
p_m	n/a	0.00196	0.00293
p_c	n/a	0.66667	0.66667
E_t on (1)	28.19%	**7.63%**	15.21%
E_t on (2)	36.40%	19.23%	**6.35%**

are a bit different in between two given data sets. The first such parameter is cell neighbor (p_3). It is 194.75 m (i.e. 82 cells) for the first data set (1) and 166.25 m (i.e. 70 cells) for the second data set (2). The maximum allowed speed (p_4) is for both models higher than a local speed restrictions. This represents the real situation at the road segment as some drivers do not keep the maximum speed limit here.

For the model calibrated to (1), the probability of slowing down (p_5) is 0.1059 for vehicle speeds lower than the evolved boundary (p_6) of 29.74 km/h. The same slowing down (in case of speed lower than 59.48 km/h) occurs for 41.18% in the model calibrated to (2). On the other hand, the probability of acceleration (p_7) is higher for (1). The parameter (p_8) of slowing down in case of speeds greater than the evolved boundary speed (p_6) is nearly the same as the previous one (p_5). This could indicate that it would be possible to somehow interoperate both of these parameters and simplify the simulation model.

Parameters p_9 and p_{10} are surprisingly very small and also quite similar. However, based on their convergence tests, we claim that these parameters (i.e. driver sensitivity) can be also statistically obtained for a desired road segment and/or time.

Tab. 2 also shows the average travel time error E_t for one time interval computed as

$$E_t = \frac{E}{M}, \tag{4}$$

where M is the number of time intervals for a given data set. We also measured this error for our manually updated model with additional maximal speed re-adjustment for exact local conditions (e.g. maximal speed). It can be seen that all three new calibrated models, which were obtained using described GA, are significantly better on a particular data set in comparison to our manually updated model (compared previously only with fundamental diagrams). Moreover, all new models are also better when compared to different data sets. This finding is very important for future travel time estimation using simulations.

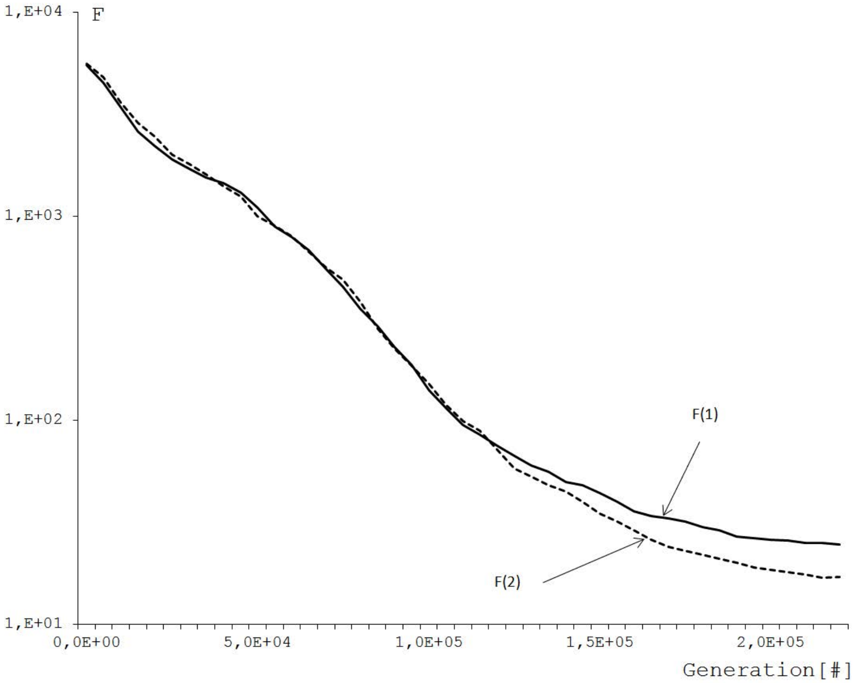

Fig. 2. Fitness $F(1)$ and $F(2)$ in all generations as an average value out of 50 independent runs when calibrating to data set (1) and (2) respectively

It is also important to note, that completing all runs for one data set (50 runs of 220 000 generations) takes more than three days running at *Intel Xeon CPU5420 @ 2.5 GHz* due to need for performing simulations. Fig. 2 shows the average fitness value $F(1)$ and $F(2)$ for 50 successive runs and for data set (1) and (2) respectively. Note that y-axis is in the logarithmic scale. It can be also seen, that quality tends to increase (lower fitness) during evolution of 220 000 generations which is ensured by elitism. After that number of generations, the quality of population is not changing dramatically. Our genetic algorithm was tuned to always find a reasonable solution after this number of generations. The whole tuning process will be described in the forthcoming paper.

5 Conclusions

In this work, we proposed an effective calibration method for a simple microscopic traffic simulation model. The proposed model is based on the cellular automaton, which can easily be accelerated. We utilized genetic algorithm for model parameters optimization, that was able to find all parameters of the CA model for a given field data. We increased the precision of simulator in average by more than 1/4 in comparison with our previously updated and manually tuned model. Furthermore, new evolved models have better stability compared to original model (i.e. model calibrated to (1) utilizable for (2) and vice versa). Therefore, the proposed methods seem to be promising for calibration in the task of travel time estimation of pre-selected road segments of interest.

In our future work, it would be very interesting to derive how much data has to be used for a proper model calibration in the case when a sufficient amount of data is not available. This could be very important in the travel time estimation using such calibrated cellular automaton based models.

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