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# Traffic simulation models calibration using speed–density relationship: An automated procedure based on genetic algorithm

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ABSTRACT

This paper presents the first results of a research which applied a genetic algorithm to calibrate a microscopic traffic simulation model based on speed–density relationships. A large set of traffic data collected from the A22 Freeway, Italy, was used and a comparison was performed between the field measurements and the simulation outputs obtained for a test freeway segment by using the Aimsun microscopic simulator.

The calibration was formulated as an optimization problem to be solved based on a genetic algorithm; the objective function was defined in order to minimize the differences between the simulated and real data sets in the speed–density graphs. For this purpose, the genetic algorithm tool in MATLAB® was applied.

Keeping in mind the objective to automatize this process, the optimization technique was attached to Aimsun via a subroutine, so that the data transfer between the two programs could automatically happen. An external script written in Python allowed the MATLAB® software to interact with Aimsun software.

A better match to the field data was reached with the optimization parameters set with the genetic algorithm. In order to check to what extent the model replicated reality, model validation was also addressed. Results showed that a genetic algorithm is usefully applicable in the calibration process of the microscopic traffic simulation model. Beneficial effects are expected by applying the suggested optimization technique since it searches for an optimum set of parameters through an efficient search method.



## 1. Introduction

### 1.1. Literature notes

Numerous problems in science and engineering require the optimization of model performance by minimizing the error between the model outputs and observations of the real system (Pujol & Poli, 2004). As it is known the optimization problems consist in maximizing or minimizing an objective function, which expresses how far an observable variable is from its simulated value, constrained by the set of feasible values of the model parameters on which the simulated variable depends (Hourdakis, Michalopoulos, & Kottommannil, 2003; Ma, Dong, & Zhang, 2007). Parameter optimization represents, thus, a problem in which the objective is to set the system parameters so as to maximize its performance.

Microsimulation has been increasingly used in engineering applications, but various issues concerning the extent to which its outputs reproduce field data still need to be addressed (Barceló et al., 2010). In traffic modeling, microscopic simulation requires many different parameters to describe traffic flow characteristics, driving behavior, traffic control systems, and so on. Since some of calibration parameters, as for example those corresponding to the car-following and lane-changing models, are often difficult to collect on the field, it is common practice to use the default parameters provided by the microscopic simulation models. However, the simulation models under default calibration parameters may not accurately represent field conditions and usually produce unreliable results (Barceló et al., 2010; Park & Schneeberger, 2003; Vasconcelos, Seco, & Silva, 2014). In turn, the different kind of errors which could affect the outputs of the models limits the required accuracy of the model results (Vasconcelos, Seco, & Silva, 2009).

A proper calibration of the traffic model parameters has to be performed so as to obtain a close match between the simulated and the actual traffic measurements. In this perspective the calibration process could be a complex and time-consuming task because of

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the large number of unknown parameters (Toledo, Ben-Akiva, Darda, Jha, & Koutsopoulos, 2004). The formulation of the calibration process of a traffic model as an optimization problem is perhaps the most recommended practice (Barceló et al., 2010). However, increasing the number of variables and parameters, also the number of possible parameter values gets too large to handle without automation (Bukharov & Bogolyubov, 2015; Ma & Abdulhai, 2002). In order to solve the optimization problem, various automatic calibration methods and procedures have been used by researchers in the process of calibration of microsimulation traffic models. For the calibration of microscopic traffic simulation models some studies used sensitivity analysis and trial-and-error method which could be very resource-intensive and/or time-consuming (Moridpour, Sarvi, Rose, & Mazloumi, 2012; Park & Schneeberger, 2003); for calibration purposes some other studies used multistart algorithms (Ciuffo, Punzo, & Torrieri, 2008), neural networks (Otković, Tollazzi, & Šraml, 2013) and genetic algorithm for input parameters of the simulation model (Camilleri & Neri, 2014; Kim, Kim, & Rilett, 2005; Menneni, Sun, & Vortisch, 2008; Onieva, Milanés, Villagra, Pérez, & Godoy, 2012; Park & Qi, 2005). However, the search for an effective solution to the calibration problem cannot be exhausted by the choice of the most efficient optimization algorithm. The use of available information concerning the phenomenon could allow calibration performance to be enhanced, for example, by reducing dimensions of the domain of feasible solutions (Ciuffo et al., 2008; Vasconcelos et al., 2009). According to Hale et al. (2015), this reduction in domain could allow use of different optimization methods.

### 1.2. Research aims and specific objectives of the paper

For the purpose of calibrating a microscopic traffic simulation model, a reliable calibration process must include: (1) the definition of a criterion to evaluate the performance of a model in terms of an objective function; (2) the selection of the parameters that will be calibrated; (3) an appropriate algorithm to minimize or maximize the objective function; (4) the test of calibration results against new data sets. Starting from these considerations, the study presents a calibration methodology that was implemented and tested on the A22 Brenner Freeway, Italy, based on a real traffic data set. A macroscopic approach was followed in order to compare the field measurements with the corresponding simulated outputs obtained by using the microscopic traffic simulation package AIMSUN for a test freeway segment under congested and uncongested traffic conditions.

This paper shows the first results obtained by applying a genetic algorithm in the microsimulation traffic model calibration process. The calibration was formulated as an optimization problem in which the objective function was defined to minimize the differences of the simulated measurements from those observed in the speed–density diagram.

The Genetic Algorithm tool in MATLAB®was applied for calibrating the simulation models. In order to implement this process, the optimization technique was attached to Aimsun via a subroutine that allowed the data transfer between the two programs. The MATLAB®software acted as an interface with Aimsun via external scripting written in Python.

Taking in consideration the best combination of the Aimsun parameters resulted from the genetic algorithm, the simulation with optimized parameters generated a satisfactory fit to the field data in comparison with the simulation using the default parameters. The results also indicated that the procedure gave a good fit both in the calibration and validation sections.

The organization of the paper is as follows: Section 2 presents the data gathering process and discusses the calibration issues for the A22 Freeway. Section 3 presents the methodology, and describes the formulation and the solution of the calibration problem for which a genetic algorithm as implemented in MATLAB®was used. Finally, simulation results are discussed in Section 4, whereas conclusions will be presented in Section 5.

## 2. Data gathering and calibration issues

This section sets out not only how data were gathered on different segments of the A22 Brenner Freeway, Italy, but also the study efforts initially made to investigate the methodological issues associated with the calibration of the microsimulation model parameters for the A22 Brenner Freeway, Italy. Preliminary results from the comparison between the empirical measurements of speed–density values, and the simulated pairs of speed–density as generated by Aimsun, using the default values for the parameters of the model, will be also presented.

### 2.1. Data gathering process

The data needed for this study were obtained from a series of experimental surveys carried out at different observation sections on the A22 Brenner Freeway and multiple days in 2003, 2005, and 2007 (Mauro, 2007). The A22 Brenner Freeway refers to a major European trunk route, which connects Innsbruck in Austria to Modena in northern Italy. High traffic volumes up to 40,000 vehicles per day (of which up to one-third are heavy vehicles) move on the freeway, with high seasonal tourist flows during holiday times; however, all vehicle categories on the A22 Freeway are growing similarly to the national trend.

Details about the issues regarding the experimental data collection and the treatment of traffic data surveyed at specific observation sections along the A22 Freeway are also available in Mauro, Giuffrè, and Granà (2013). The summary on the characteristics of the observation stations which were selected far enough from merging or diverging operations near the on–off ramps is reported in Table 1; the same table shows the ratios of the peak hour traffic volume, both in the 30th and 100th peak-hour, to the annual average daily traffic (AADT) for each location.

The traffic data were measured at specific stations (Adige, Rovereto and S. Michele) on the A22 Freeway and were processed for the purpose of deriving the fundamental diagram of traffic flow, namely the flow–density–speed relation; thus the relationships between flow and density, $Q = Q(D)$, speed and density, $S = S(D)$, speed and flow, $S = S(Q)$, were developed for the roadway, the right lane and the passing lane. The measurements of traffic flows, $Q$, were expressed in passenger car units/hour, by homogenizing the traffic flows, measured at 15 min intervals, with the site specific values of passenger car equivalent factors which were calculated from field traffic data. According to Roess, Prassas, and McShane (2004), the criterion based on the average headways, namely calculating the ratio of the average headways between pairs of vehicles (passenger cars, heavy vehicles, passenger cars-heavy vehicles, heavy vehicles-passenger cars) to the average headways between pairs of passenger cars only was used.

Since there is the relation $Q = D \cdot S$, the estimation of one of three relations, $Q = Q(D)$, $S = S(D)$, $S = S(Q)$, involves the specification of the remaining two others. For this purpose, different models were examined (Edie, 1963; Greenberg, 1959; Greenshields, Channing, Miller et al., 1935; Underwood, 1961); the single-regime model proposed by May (1990) seemed to fit the data a lot better than the other models, especially the values of the maximum densities in congested traffic conditions. According to the May model, the relation between speed and density, $S = S(D)$ is expressed by Eq. (1) as a function of the free flow speed ($S_{FF}$) and the critical density ($D_c$), or the density to which the reaching of the capacity $C$ is associated:

$$S = S_{FF} \cdot \exp\left[-0.5\left(\frac{D}{D_c}\right)^2\right] \qquad (1)$$