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Calibrating Traffic Microscopic Simulation Model Parameters Using an Evolutionary Approach

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Abstract

Traffic management solutions are often evaluated by microscopic simulation models. From this strategy it is possible to test and analyze the impacts of strategies without demanding new constructions or costly investments. In order to reproduce, as close as possible, the real condition of the traffic network to be analyzed in the simulation model, it is necessary to calibrate the model. In the calibration process, vehicle performance and driver behavior parameters need to be adjusted so that the model outputs are similar to observed data. Therefore, this paper presents a genetic algorithm-based microscopic simulation model to calibrate the parameters of Aimsun simulator to a network of intersections in Belo Horizonte city, Brazil. Genetic algorithm (GA) is used to find an optimum set of theses control parameters that minimize the mean absolute normalized error (MANE) between the Akcelik delay time estimation model used by GA and the field observed delay time data. Results obtained showed that calibration process is essential in the use of microscopic simulation models to define and predict traffic managements strategies. The application of the best solution found by the GA in the traffic model provided a MANE value 73% lower than when using the default values of the parameters.

Keywords: calibrating traffic parameters, traffic microscopic simulation; intelligent transportation systems; evolutionary algorithms.

1. Introduction

According to Costa, Almeida and Caldeira (2011), microscopic simulation, accompanied by the use of computational intelligence techniques, such as evolutionary algorithms, can help the work of traffic engineers, providing greater efficiency, safety and agility in the strategic decision-making of traffic control. In this context, efficient traffic programming leaves vehicle flow more stable, minimizing congestion and delays.

Traffic microsimulation models are used to analyze the performance of transport systems and include a range of parameters that must be calibrated before the model can be used in a network of intersections (Hollander and Liu, 2008). In the calibration process, vehicle performance and driver behavior parameters need to be adjusted so that the model outputs are similar to observed data. It leads to a traffic simulation model, as close as possible, to the reality of the traffic network to be analyzed, so, this simulation model can be used to define and predict traffic managements strategies.

Optimization of traffic microsimulation model performance involves the selection of the best set of values for the traffic parameters (Ma and Abdulhai, 2002). This set can be obtained using genetic algorithms (GAs), which achieve the combinatorial optimization of the parameters of microsimulation by minimizing an objective function.

Many studies on optimization of traffic control models using evolutionary algorithms can be found in the literature. Genetic algorithms have been widely used in traffic control systems to optimize the traffic conditions (Teklu *et al*., 2006; Leal *et al*., 2016; Leal *et al*., 2017). In the paper by Kwasnicka and Stanek (2006), the authors present a traffic control system based on simulation and optimization using the genetic algorithm. Turky, Ahmad, and Yusoff (2009) use GA in the traffic control and pedestrian crossing system to provide intelligent responses from intervals to green times using dynamic traffic loads. (Bielli *et al*., 2002; Lam *et al*., 2016; Wren and Wren, 1995) use genetic algorithms in public transport management problems and (Novae *et al*., 2011; Shimamoto *et al.,* 1993) use it in routing problems.

GA has also been used to calibrate traffic simulation models, a problem considered complex due to the large number of parameters to be calibrated and the fact that direct measurement of these parameters is very difficult, either because many of them represent subtle features that are hard to isolate or because it requires extensive data collection. In the work of Cunha *et al*., (2009), a GA is used to search for optimum calibration parameter values for the vehicle performance models used by CORSIM and Integration simulation models. Bessa Jr. *et al*., (2017) performs the calibration and validation of behavioral submodel parameters of the TransModeler simulator using GA.

A limitation of most of these related works is that the use of the simulator to evaluate the solutions of GA may leave the process of convergence slow, totally dependent of the simulation and difficult to adapt and use in the real world.

Given this, the general objective of this paper is to present a calibrating traffic microscopic simulation parameters model, independent of simulation to evaluate the solutions, which results in greater practical ability and ease of adaptation to the real world. From the construction of this model, using the genetic algorithm (GA) in the optimization process, it is intended to establish the best set of vehicles performance and drivers behavior' parameters to realize an efficient traffic control, satisfying the objective of minimize the mean absolute normalized error (MANE) function, which is the absolute value of the difference between the real delay time of the network observed in field and the Akcelik delay time estimation obtained by the optimization of these parameters values.

The development of this paper is justified by the importance of finding a set of values for these parameters which ensures that simulation model accurately reflect the local driving environment so that further strategic decisions on traffic management for the network analyzed made on the basis of these results will not be misinformed decisions.

For the study case, the microscopic simulation parameters of AIMSUN simulator will be calibrated to a network of intersections in Belo Horizonte city, Brazil. The demand generated in the simulation is based on real data collected by the Transport and Traffic Company of Belo Horizonte (BHTrans) and it will be used for the study case. The experiment will be analyzed and discussed in order to find if these parameters affect the simulation model results.

The paper is organized as follows: Section 2 describes the calibrating traffic microscopic simulation parameters process. In section 3, some concepts about genetic algorithms, the objective function, the variables and the computational representation adopted are presented. Section 4 shows the data collection process and the traffic network modeling. Section 5 describes the experiments realized and discuss the results. Finally, Section 6 summarizes the main conclusions and remarks of the study.

2. Related work

Many methodologies for calibrating traffic microscopic simulation models has been proposed in the literature. In the work of Kim, Kyu-Ok and Rilett (2001), an automatic calibration approach for microscopic simulation model that is based on a genetic algorithm is presented. The author's approach found that the GA identified better parameter sets for TRANSIMS and CORSIM simulators when compared to the default parameter sets. Ma and Abdulhai (2002) use a genetic optimizer for traffic micro-simulation models called GENOSIM to search for an optimal set of traffic control parameters. Hourdakis *et al.,* (2003) presented a three-stage general and systematic methodology for calibrating microscopic traffic simulators. In that paper, the results suggested that the automated calibration technique does not rely on very good initial parameter estimates, which further simplifies the calibration task and it also indicates the existence of multiple solutions, all acceptable for that study case. Ma *et al.*, (2007) apply three heuristic methods, including GA, in the calibration of a microsimulation model of northern California network. The results found by that work revealed that some model parameters affect the simulation results more significantly than others.

Thus, this brief study of art shows the importance of calibrating traffic simulator's parameters before using the model as a tool for prediction and analysis of traffic strategies.

3. Calibrating Traffic Microscopic Simulation Parameters

The general scheme of the process for calibrating traffic microscopic simulation parameters proposed in this paper, can be described in Fig 1.

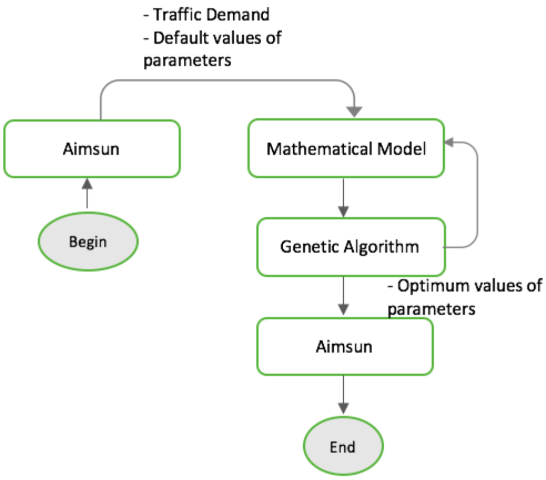

Fig 1. Calibrating traffic microscopic simulation parameters model.

This schema works as follow:

1. **Begin**: Initialization of the calibrating parameters process;
2. **Aimsun**: The traffic network drawn in Aimsun will generate traffic demand for the model and provide the default parameters calibrating values for the network in study.
3. **Mathematical Model:** These data are used by a mathematical model to estimate the mean absolute normalized error (MANE) function, which is the difference between the real delay time of the network observed in field and the Akcelik delay time estimation obtained by the optimization of the traffic microscopic simulation parameters values by GA.
4. **Genetic Algorithm:** In the initialization of GA, it receives the default values of parameters used in the traffic network drawn in Aimsun and set them as part of the initial population of the algorithm. Then, GA starts the evolution process in which it uses the MANE estimation calculated by the mathematical model to find the optimum set of the microscopic simulation parameters for the traffic network.
5. **Aimsun**: The optimized configuration of parameters from GA is loaded into the simulator for observing its behaviour.
6. **End**: Finalization of the calibrating process;

4. Genetic Algorithm

According to Gaspar-Cunha et al. (2013), the genetic algorithm (GA) is a technique to find the optimal solution of a problem whose operators (selection, crossover and mutation) are inspired by simplified models of natural evolution. GA process an initial set of possible solutions of a problem (initial population). This set is transformed and evolved over successive generations. The fittest members of a generation are selected (evaluated by a fitness function) to serve as progenitors of the solutions that will appear in the next generation. The crossover and mutation operator act on the elements generating new solutions while try to ensure that the process will maintain an adequate level of diversity.

Thus, as the number of generations increases gradually, GA converges to regions of the search space where the promising solutions are. The optimization ends when a criteria termination is reached (Pacheco, 2007).

The termination criteria used in this paper is the maximum number of generations equals to 1000 and the population size is of 50 individuals. These values were chosen because it showed good results when compared to other sets of values for this GA's parameters.

GA was chosen because of its usage in the literature in solving intelligence transportation systems' problems, as can be shown by the related work here shown. However, the optimized calibration method used here is general and allows employment of any optimization technique one wishes to use.

4.1.1. Genetic Operators

Genetic operators are used by GA to find the optimal solution of the problem. They are:

1. **Selection**: In the selection process the fittest individuals are most likely to be selected to give birth to the new generations. In this work, it will be used the selection by tournament method (Mitchell, 1998), in which a number of individuals is chosen randomly to form a temporary sub-population. From this group, the selected individual will depend on a defined probability.
2. **Crossover**: According to Pacheco (2007), in the crossover process, pairs of parents are chosen randomly from the population and new individuals are raised from the exchange of genetic material. The probability of applying the crossover is a GA parameter, its value is usually high (typical values between 0.7 and 1.0). In this paper, the chosen crossover probability is 0.8. The single-point crossover method used in this study was proposed by Holland (1992). It is performed on two parent strings; each parent is cut at a random point along the chromosomes and recombined with one piece of the other to form the descendants
3. **Mutation**: The mutation aims to maintain an adequate level of diversity in the population. In this work, the mutation rate is 0.4 and the mutation method used is the Gaussian, where the new value for the Gi gene is obtained by the following expression:

$$Gi \leftarrow Gi + N\,(pi, \alpha), \tag{1}$$

in which $N\,(pi, \alpha)$ is a normal distribution with mean pi and standard deviation α.

4.1.2. Decision Variable

The decision variable corresponds of a vector containing the set of parameters from Table 1. For this paper, the real representation was adopted in which each individual corresponds directly to the value of a decision variable.

Table 1. Calibrating parameters

Parameter	Default Value	Search Space of GA Minimum - Maximum
Reaction Time	0.75	0.5 – 2.0
Reaction Time at Stop	1.35	0.70 – 3.0
Reaction Time at Traffic Light	1.35	0.70 – 3.0
Vehicles' Maximum Desired Speed	110km/h	50 – 180
Vehicles' Maximum Deceleration	6.0m/s^2	4.0 – 7.0
Vehicles' Speed Acceptance	1.10	0.5 – 2.0
Vehicles' Minimum Distance	1.0m	0.5 – 2.0

This set of parameters, default values and search space were chosen to calibrate the parameters of AIMSUN simulator to the traffic network of study based on previous research (Akishino, 2018; Figueiredo *et al.*, 2014; Giuffrè *et al.*, 2015).

4.1.3. Objective Function

The objective (fitness) function is the mean absolute normalized error (MANE) function (Equation 2), which is the difference between the observed delay time of the network and the delay time obtained by the optimization of these parameters values.

$$MANE = \frac{1}{N}\sum_{1}^{N}\frac{x_i - y_i}{y_i}, \tag{2}$$

in which N is the number of measurements; y_i = i-th average delay time obtained by the calibrating model and x_i = i-th observed average delay time.

The MANE objective function was chosen because it indicates an average error in absolute terms, without considering whether there are systematic deviations, being constantly applied in calibration studies of traffic simulators (Hollander and Liu, 2008).

The delay function used was the time-dependent expressions for delay by Akcelik (1980) and Akcelik (1981) is:

$$D = \frac{\left(C.(1-p(X))^2\right)}{(2.(1-p(X).s))} + 900 * T * \left((degreeOfSat - 1) + \sqrt{r} \right), \tag{3}$$

in which $\boldsymbol{C}$ is the cycle time (seconds); $\boldsymbol{p}$ is the fraction of green (the relationship between effective green time $\boldsymbol{x}$ (Equation 4) and cycle time $\boldsymbol{C}$); $\boldsymbol{s}$ is the degree of saturation (the relationship between demand and capacity); $\boldsymbol{T}$ is the time; ***degreeOfSat*** is the degree of saturation and $\boldsymbol{r}$ is calculated by Equation 6. All parameters are calculated from data obtained by sensors in the infrastructure (in the experiments undertaken here, they are provided by AIMSUN micro simulator). This function was used because of its relevance in the literature and for showing good estimation rates for delay time in previous traffic management studies.

$$x = g + y - l, \tag{4}$$

in which $\boldsymbol{g}$ is the normal green time (for the experiments, it's used the default set of green times provided by BHTrans); $\boldsymbol{y}$ is the yellow time and $\boldsymbol{l}$ is the lost time (delay in driver's perception and reaction time). Yellow time $\boldsymbol{y}$ is calculated by:

$$y = l + \frac{v}{2a}, \tag{5}$$

in which v is the speed and a is vehicles' maximum deceleration.

$$r = (degreeOfSat - 1) ** 2 + 12 * ((degreeOfSat - x0)/(capacity * T)), \tag{6}$$

in which capacity is the capacity of the road and x0 is the relation between capacity and the cycle time.

5. Data collection and the traffic network modeling

The traffic network reproduced inside AIMSUN (see Figure 2) is a region of Floresta neighborhood, near to the center of Belo Horizonte, in Brazil, a capital city with about 4M inhabitants and a huge fleet of more than 1.2M private vehicles. Traffic congestion is a huge problem in this region of study, since it is surrounded by commerce, schools, banks, bars and it's also a residential area.

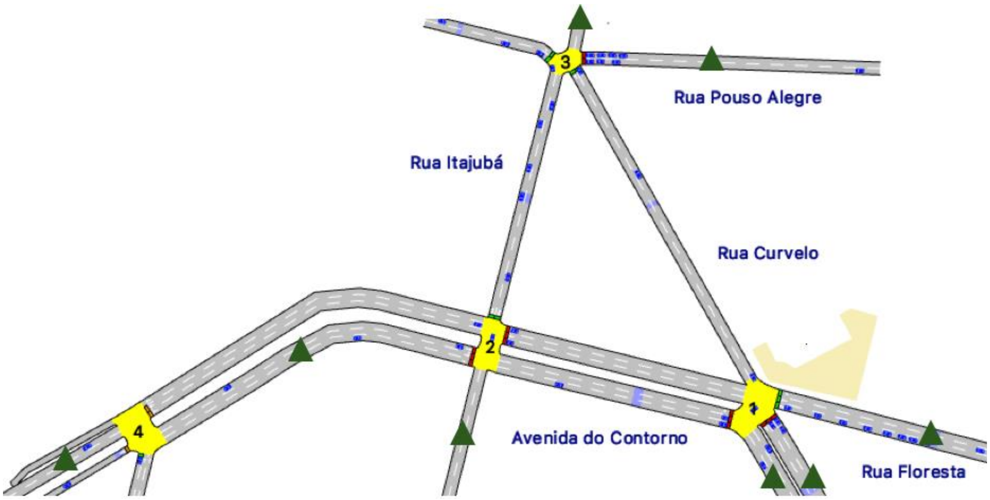

Figure 2. Traffic network of Belo Horizonte, Brazil, reproduced inside AIMSUN.

In figure 2, the green triangles represent the points of measurement in field and also represent where data detectors of the Aimsun network are placed.

Vehicles flow data of the four intersections at the region uploaded in the simulator is based on data collected by BHTrans from 08:00am to 10:00am, for a period of one month (July). Although the experiments reported here were undertaken by means of simulation, the proposed technique is easy to implement in a real-world network, by substituting AIMSUN for real-time data collected by sensors installed at the traffic infrastructure, e.g. loop detectors, video cameras or similar equipment capable of measuring the input variables to the mathematical model.

Field data was collected in the region of study in the same period as the data collected from BHTrans. For this data collection, the Plate Method was used, which, as mentioned in the Traffic Studies Manual (DNIT, 2006), consists of the annotation, at the entrance and exit of the section analyzed, of the plate and the time of passage of the vehicles. Subsequently, the plates recorded in the entries and exits of the segments are compared, obtaining delay measurement of vehicles, per direction.

6. Experimental Results

5.1. Average convergence curve

In this paper, the developed Ga sought to obtain values of the Aimsun's behavioral parameters so that the chosen performance measure, the delay time, will have simulated and observed values very similar (MANE function). The experimental results obtained from the execution of the GA for the problem were represented by the graph of the average convergence curve of Figure 3.

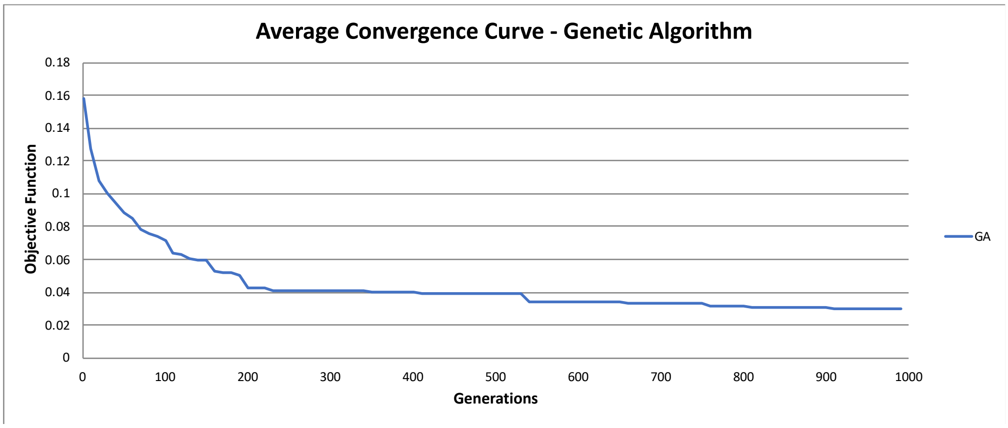

Figure 3. Average Convergence Curve - GA

The convergence curves show the average rating of the best individuals of the populations considering the objective function for every generation, based on 30 executions of the algorithms, to comply with the central theorem limit. Analyzing the experiments, it is worth to note that the curves gradually decrease to smaller and smaller values of the objective function. This fact supports the hypothesis that a genetic algorithm can be used to calibrate microscopic simulation parameters of AIMSUN simulator to a network of intersections. In Figure 3, with 1000 generations, GA reaches a minimum value of MANE around 0.0318, which means that the absolute value of the difference between the real delay time of the network and the delay time obtained by the optimization of these parameters values is of 3%. The best values of parameters found by GA is shown in Table 2.

Table 2. Optimum set of calibrating parameters found by GA.

Parameter	Optimum Value
Reaction Time	0.76
Reaction Time at Stop	2.77
Reaction Time at Traffic Light	2.46
Vehicles' Maximum Desired Speed	115.27km/h
Vehicles' Maximum Deceleration	6.4m/s^2
Vehicles' Speed Acceptance	1.0
Vehicles' Minimum Distance	1.25m

In order to verify if the MANE value found for Aimsun's parameter optimization by GA was good, an experiment was performed using Aimsun's default calibration parameters in the network (default values from Table 1), in which a MANE value of 0.1189 was found. The application of the best solution found by the GA (Table 2) in the traffic microsimulation model provided a MANE value of 0.0318, that is, 73% lower than when using the default values of the parameters.

Notice that the set of best parameters found with 1000 generations of GA shown in Table 2, doesn't indicates global solution, but a better solution for the problem when compared to the default parameters of the simulation model.

7. Conclusion

Within this study, a genetic algorithm-based microscopic simulation model to calibrate parameters of AIMSUN simulator to a network of intersections in Belo Horizonte city was proposed and implemented.

Genetic algorithms found an optimum set of solutions for the problem in the experiments undertaken. The difference between the real delay time of the network observed in field and the Akcelik delay time estimation obtained by the optimization of the traffic microscopic simulation parameters values by GA was low (73% lower than when using the default values of the parameters.), which shows that the model outputs are similar to observed data. Such knowledge is needed to predict—through numerical simulations—the behavior of the vehicles under physical conditions. Reliable predictions allow the engineering requirements to be met at a lower cost.

The application of the best solution found by the GA in the traffic microsimulation model provided a MANE value lower than when using the default values of the parameters, which shows that the calibrating process is essential because it ensures that simulation model accurately reflect the local driving environment so that further strategic decisions on traffic management for the network analyzed made on the basis of these results will not be misinformed decisions.

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