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Swarm Intelligence in Transportation Engineering

Original Scientific Paper

Submitted: 22 Oct. 2018

Accepted: 12 June 2019

# AN AUTOMATIC CALIBRATION PROCEDURE OF DRIVING BEHAVIOUR PARAMETERS IN THE PRESENCE OF HIGH BUS VOLUME

## ABSTRACT

Most of the microscopic traffic simulation programs used today incorporate car-following and lane-change models to simulate driving behaviour across a given area. The main goal of this study has been to develop an automatic calibration process for the parameters of driving behaviour models using metaheuristic algorithms. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and a combination of GA and PSO (i.e. hybrid GAPSO and hybrid PSOGA) were used during the optimization stage. In order to verify our proposed methodology, a suitable study area with high bus volume on-ramp from the O-1 Highway in Istanbul has been modelled in VISSIM. Traffic data have been gathered through detectors. The calibration procedure has been coded using MATLAB and implemented via the VISSIM-MATLAB COM interface. Using the proposed methodology, the results of the calibrated model showed that hybrid GAPSO and hybrid PSOGA techniques outperformed the GA-only and PSO-only techniques during the calibration process. Thus, both are recommended for use in the calibration of microsimulation traffic models, rather than GA-only and PSO-only techniques.

## KEY WORDS

traffic simulation models; calibration; driving behaviour; Genetic Algorithm; Particle Swarm Optimization; VISSIM;

## 1. INTRODUCTION

In recent years, advances in computing hardware technology and new traffic engineering applications have led to greater use of traffic simulations in the

analysis of complex interactions between various traffic components [1]. Microscopic traffic models are those based on the principle of the movement of each individual vehicle or pedestrian included in the traffic, taking account of actions and decisions such as acceleration, deceleration, and lane/trajectory changes in response to the surrounding conditions [2]. A wide variety of traffic simulation software is either commercially or freely available on the market. Some examples of this microsimulation software include VISSIM, AIMSUN, CORSIM, PARAMICS, MITSimLab, FRESIM, DRACULA, and SUMO. Although a wealth of microscopic traffic simulation software is available, traffic simulation studies still lack a unified perspective in terms of mimicking the real-world conditions. Having a fine-tuned and best-matched simulation model which represents the real-life behaviour of drivers, is of pivotal importance to traffic engineers. Thus, before any analysis can take place, models need to be calibrated to be able to represent real-life conditions. The calibration process has the objective of finding the statistically significant values of model parameters based on data collected from the field [3]. From these samples, the performance of a traffic model can be determined by employing statistical analysis with respect to various measures [4, 5].

The validity of the model can be done simply in terms of the probability that the difference between the observed and simulated output is of less than a

delineated tolerable difference [2]. Various optimization methods have been employed to minimize the difference between the observed and simulated outputs. These include GA [6–8], SPSSA [9], PSO [10], OQMS [4], and a combination/comparison of various of these [5, 11]. The aforementioned studies show that GA is the optimization method most favoured by researchers because of its ease-of-implementation. However, no information exchange is taking place between individuals during the GA process. For instance, in the selection stage, the members of the initial population have no direct competition to being selected and neither do parents in the crossover stage experience any information exchange with each other or that of the offspring created by them. On the other hand, when a mutation occurs, this mutant lacks the right direction. These are the reasons for lower performance of GA compared to other techniques.

This study outlines an automatic calibration process for driving behaviour model parameters using metaheuristic algorithms. The Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and a combination of GA and PSO (i.e. hybrid GA and hybrid PSO) were utilized for optimization purposes. A case study of an urban highway section is presented within the microsimulation environment of VISSIM [12]. The main contribution provided by the proposed methodology is a hybrid method for overcoming the limitation of single optimization algorithms in order to yield better results in a fully automatic way. Four optimization algorithms – namely, GA, PSO, GAPSO, and PSOGA – were coded in MATLAB and the results compared in order to find the most suitable to be used in the VISSIM calibration process. The Component Object Model (COM) ability of VISSIM was employed to provide a bridge for the exchange of information between MATLAB and VISSIM and an automated calibration process. Although hybrid PSO and hybrid GA are used in other fields of study [13–16], this study is the first that implemented a combination for the calibration of traffic microsimulation parameters.

Other sections of the study deal with a brief literature review of the driving behaviour models, parameters, and optimization algorithms. The proposed calibration methodology is described in Section 3. This is followed by a real-world application of the proposed calibration methodology as tested on an urban

highway in Istanbul, Turkey. Section 5 discusses the results of the calibration and optimization process in detail, followed by our conclusion and suggestions for future research.

## 2. BACKGROUND

In this section, VISSIM driver behaviour models including car-following, lane-change, their parameters' description, and optimization methods are discussed briefly.

### 2.1 VISSIM Car-following and Lane-change models description

Many studies opt to use default car-following and lane-changing parameters. However, the traffic composition, network geometry, vehicle ages, engine size, and (most of all) driver behaviour vary significantly in different parts of the world. Thus, the default parameters of the simulation software should be carefully examined in order to obtain reliable results. As an example, it has been noted that lane-changing is a highly strong characteristic of Istanbul traffic and drivers are frequent and aggressive in cutting and overtaking, taking every opportunity to change lanes at the slightest opening [17]. As explained in [12], the two models of driving behaviour parameters are Wiedemann 74 (W74) and Wiedemann 99 (W99). The W74 model, generally, has been used for urban arterials and merging areas. The W99 has been utilized in modelling freeways and diverging areas. *Tables 1-4* outline the general parameters, lane-changing, W74, and W99 models parameters respectively. The first column contains the ID of each parameter used by VISSIM during COM interface, along with the parameter description, their range, and default values in other columns.

### 2.2 Evolutionary Algorithms

Generally, all EAs consist of a number of common steps, including initialization, variables/parameters definition, objective function definition, iteration steps, stopping criteria. There is a small difference in the procedure required for various types of EA. The two most frequently used EA algorithms are GA and PSO.

Table 1 – General Parameters

IDrivingBehavior	Parameter description	Range	Default
LookBackDistMax	Max. look back distance [m]	50 ~ 200	150
LookAheadDistMax	Max. look ahead distance [m]	100 ~ 300	250
ObsrvdVehs	No. of observed preceding vehicles [veh]	1.00 ~ 5.00	2.00
StandDist	Standstill distance in front of static obstacles [m]	0.00 ~ 3.00	0.50

Table 2 – Lane-changing model parameters

IDrivingBehavior	Parameter description	Range	Default
DecelRedDistOwn	Reduction rate for leading (own) vehicle [m]	100 ~ 200	200
AccDecelOwn	Accepted deceleration for leading (own) vehicle [m/s <sup>2</sup> ]	-3.00 ~ 0.50	-1.00
MinHdwy	Min. spacing (headway) [m]	0.50 ~ 3.50	0.50
SafDistFactLnChg	Safety distance reduction factor	0.10 ~ 0.60	0.60
CoopDecel	Max. deceleration for cooperative lane-change/braking [m/s <sup>2</sup> ]	-6.00 ~ 3.00	-3.00
CoopLnChgSpeedDiff	Max. speed difference for cooperative lane-change/braking [m/s]	5.00 ~ 20.00	10.80
MaxDecelOwn	Max. deceleration for leading (own) vehicle [m/s <sup>2</sup> ]	N.A	-4.00
MaxDecelTrail	Max. deceleration for following (trailing) vehicle [m/s <sup>2</sup> ]	N.A	-3.00
DecelRedDistTrail	Reduction rate for following (trailing) vehicle [m]	N.A	200
AccDecelTrail	Accepted deceleration for following (trailing) vehicle [m/s <sup>2</sup> ]	N.A	-0.50

Table 3 – Wiedemann 74 car-following model parameters

IDrivingBehavior	Parameter description	Range	Default
W74ax	Average standstill distance	0.50 ~ 2.50	2.00
W74bxAdd	Additive factor for security distance	0.70 ~ 4.70	2.00
W74bxMult	Multiplicative factor for security distance	1.00 ~ 8.00	3.00

Table 4 – Wiedemann 99 car-following model parameters

IDrivingBehavior	Parameter description	Range	Default
W99CC0	Desired distance between lead and following vehicle [m]	0.60 ~ 3.05	1.50
W99CC1DISTR	Headway Time [s] Desired time between lead and following vehicle	0.50 ~ 1.50	0.90
W99CC2	Following Variation [m] Additional distance over safety distance that a vehicle requires	1.52 ~ 6.10	4.00
W99CC3	Threshold for Entering 'Following' State [s] Time in seconds before a vehicle starts to decelerate to reach safety distance (negative)	-15.00 ~ -4.00	-8.00
W99CC4	Negative "Following Threshold" [m/s] Specifies variation in speed between lead and following vehicle	-0.61 ~ 0.03	-0.35
W99CC5	Positive "Following Threshold" [m/s] Specifies variation in speed between lead and following vehicle	0.03 ~ 0.61	0.35
W99CC6	Speed dependency of oscillation [1/ms]	7.00 ~ 15.00	11.44
W99CC7	Oscillation Acceleration: Acceleration during the oscillation process [m/s <sup>2</sup> ]	0.15 ~ 0.46	0.25
W99CC8	Standstill Acceleration [m/s <sup>2</sup> ]	2.50 ~ 5.00	3.50
W99CC9	Acceleration with 80 km/h [m/s <sup>2</sup> ]	0.50 ~ 2.50	1.50

Evolutionary algorithms differ from a classical, derivative-based, optimization algorithm in two main ways, as summarized in Table 5.

#### Genetic Algorithm

GA [18] is one of the best-known population-based (biological) example among EAs. It has been used for both binary and continuous forms in single and multi-objective optimization processes. All GA forms generally possess common rules including selection, crossover, and mutation, at each step creating new chromosomes (generation) from the existing ones. At

each stage, GA selects initial population (generation) randomly, selects parents from among the current population, and combines selected parents to produce offspring (children) for the next generation during the crossover process using various methods such as single-, double-point crossover, or uniform crossover. There are several tuning elements which are involved in GA, including the number of initial population, maximum iteration number, crossover percentage, mutation percentage, mutation rate, etc. Detailed information concerning how sensitivity analysis of tuning elements influences the GA is described in Section 5

Table 5 – Classical and evolutionary algorithm differences

Classical algorithm	Evolutionary algorithm
Generates a single point at each iteration. The sequence of points approaches an optimal solution.	Generates a population of points at each iteration. The best point in the population approaches an optimal solution.
Selects the next point in the sequence by a deterministic computation.	Selects the next population by computation which uses random number generators.

of [19]. We use uniform random selection for initial population, an arithmetic crossover (a kind of uniform crossover), create and add noise (random number) using Normal Distribution (with mean=0 and variance=sigma) for improving selected offspring during the mutation stage, and following settings for the GA elements given in Table 6.

*Particle Swarm Optimization*

PSO, firstly introduced by [20], is also a population-based algorithm but it uses particle swarms of intelligence ability; for instance, the behaviour of fish when they are confronted with a shark. PSO is an algorithm for continuous variables, but with some modification it can be used in discontinuous optimization problems, too [21]. PSO begins with a determination of the position and velocity of each individual (particle) and proceeds with a calculation of the objective function based on that particle's location. Then, the objective function values are to be compared with global objective function values, with the better one assigned as a global objective value. The new velocity and position of the particles are calculated based on the best particle information. The main advantage of PSO is that an information flow exists between all particles at each moment. This means that all particles use other information to find the best solutions. This capacity of PSO is used for solving GA limitation issues, particularly during the selection, crossover, and mutation stages.

There are several stopping criteria for both GA and PSO, including Max Stall Iterations, Function Tolerance, Max Iterations, OutputFcn or PlotFcn, Objective Limit, and Max Stall Time. However, we use only Max Number of Iterations (MaxIt) as stopping criteria for the proposed method because we wanted to let all the methods perform a similar number of function evaluations.

**3. PROPOSED CALIBRATION METHODOLOGY**

There exist two types of methods for Driving Behaviour Parameters (DBP) calibration; (1) calibration of DBP using trajectory data (lane-changing, acceleration, deceleration, etc.) extracted from video files using image-processing techniques [22–24]; (2) calibration of DBP using traffic flow measurement data (volume, speed, etc.) collected by detectors [6, 25, 26]. As we do not possess the capabilities for automatic image processing, we used the latter approach. Figure 1 illustrates the whole picture of the proposed methodology. Each part of the flowchart is described in detail in the following sections. As noted in Section 2.2, all EAs consist of a number of common steps (top of the optimization flow) while each algorithm has its own operator (bottom of the optimization flow).

**3.1 Objective (i.e. error) function definition**

As noted in the background, there are many single and multi-objective functions used to minimize

Table 6 – GA operator settings for the current proposed methodology

<pre> MaxIt=40; nPop=10; pCrossover=0.8; nCrossover=round(pCrossover*nPop/2)*2; pMutation=0.3; nMutation=round(pMutation*nPop); Mu=0.1;                     </pre>	<p>Maximum Number of Generation (stopping criteria)</p> <p>Population Size</p> <p>Crossover Percentage</p> <p>Number of Parents (Offspring)</p> <p>Mutation Percentage</p> <p>Number of Mutants</p> <p>Mutation rate</p>
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Table 7 – PSO operator settings for the current proposed methodology

<pre> MaxIt=40; nPop=10; phi1=2.05; phi2=2.05; phi=phi1+phi2; chi=2/(phi-2+sqrt(phi^2-4*phi)); w=chi; c1=chi*phi1; c2=chi*phi2                     </pre>	<p>Maximum Number of Iterations</p> <p>Swarm (Population) Size</p> <p>Definition of Constriction Coefficients</p> <p>Inertia Weight</p> <p>Personal Learning Coefficient</p> <p>Global Learning Coefficient</p>
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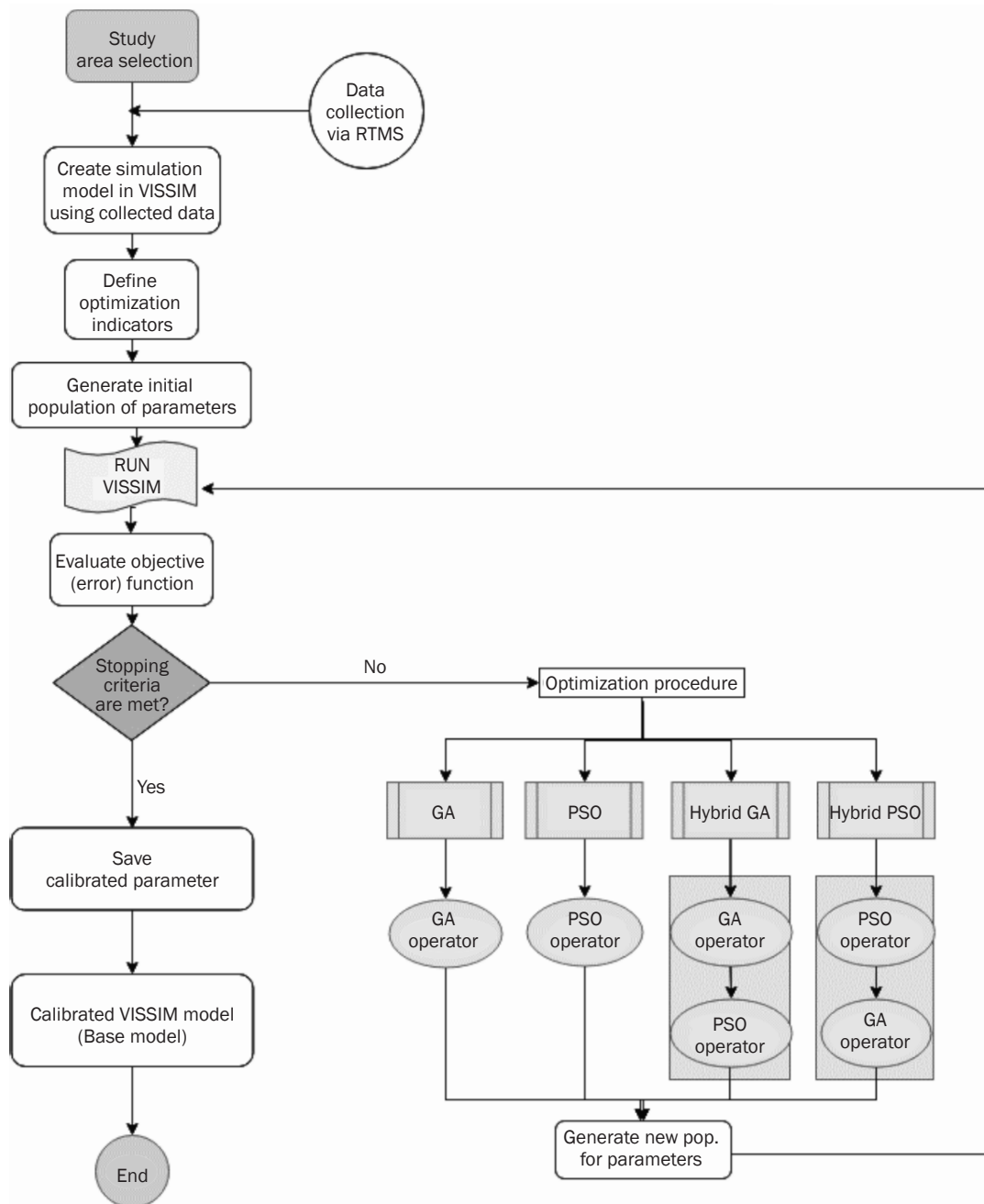


Figure 1 – Flowchart of the proposed methodology

the error of simulated and observed data. The Root Mean Square Error (RMSE) [5, 27, 28] and the Mean Absolute Normalized Error (MANE) [4, 11, 29, 30] fall among several multi-objective functions used in previous studies for the calibration of VISSIM simulation model parameters and are widely used around the world. The developed code, here, can perform the optimization process based on both single (e.g. speed-only, volume-only, and occupancy rate) and multi-objective functions. In this study, we tried to minimize the error between simulated and observed data utilizing MANE and RMSE objective functions formula:

$$\text{Minimize } Z(\text{MANE}) = \frac{1}{N} \sum_{j=1}^N \left( \frac{|V_{obsj} - V_{simj}|}{V_{obsj}} + \frac{|S_{obsj} - S_{simj}|}{S_{obsj}} \right) \quad (1)$$

$$\text{Minimize } Z(\text{RMSE}) = \sqrt{\frac{1}{N} \sum_{j=1}^N (S_{obsj} - S_{simj})^2} \quad (2)$$

w.r.t the constraints:  $Lb_{X_i} \leq X_i \leq Ub_{X_i}$

where:

$Z$  – general form of objective function (here based on speed and traffic volume);

$X_i$  –vector of continues parameters (e.g. W74 or W99 Car-following models + Lane-change model parameters);  
 $Lb_{X_i}, Ub_{X_i}$  –lower and upper value of parameter  $X_i$  (e.g. CC1:  $Lb_{cc1} = 0.5$  and  $Ub_{cc1} = 1.5$  s);  
 $V_{obsj}, S_{obsj}$  –observed traffic volume and speed collected by detectors;  
 $V_{simj}, S_{simj}$  –simulated traffic volume and speed by VISSIM;  
 $N$  –total number of data collection intervals (e.g. for one hour observation (3,600 sec) with two minutes intervals (120 sec), it is equal:  $N=3,600/120=30$ ).

### 3.2 Programming of the optimization process

Implementation of the iteration step of the proposed flowchart in *Figure 1* needs to be programmed using the aforementioned required information on GA and PSO algorithms. MATLAB was used to develop a code for the fully-automatic calibration procedure. To this end, the COM interface features between VISSIM and MATLAB are studied to integrate the code written in MATLAB with microscopic model simulated in VISSIM. For the optimization process, during the calibration procedure, one of GA, PSO, or a combination of both can be used. We coded our own algorithm structures for GA, PSO, and hybrid without utilizing the optimization toolbox of MATLAB. This increased the flexibility of our proposed methodology and gave us the opportunity to extend/improve the code for further studies noted in the conclusion part. Possible options for the optimization process in the proposed methodology were as follows: GA-only, PSO-only, PSOGA (called hybrid PSO), GAPSO (called hybrid GA).

There are several possible combinations of GA and PSO for the hybrid method used in other fields of studies [14, 31, 32]. All try to use the advantages of local search capability of GA and social thinking ability of PSO as both algorithms have strengths and weaknesses. They concluded that the combination of standard PSO and standard GA resulted in better performance compared to the use of single algorithms. Some of them used only one or more operators of GA such as using crossover and mutation operators in the PSO for improving and balancing PSO's exploration and exploitation ability [14]. Others use the ability of PSO in saving and updating the personal and global best in GA [33]. In the proposed methodology, as seen in the optimization process flow of *Figure 1*, the initial population of PSO is created and assigned by the GA operator. The total numbers of iterations are equally shared by GA and PSO, if MaxSubItGA and MaxSubItPSO are set to 1. In other words, in every iteration, the code runs one GA and one PSO operator. A user can also modify the share of using the GA and PSO operators in every iteration by increasing

or decreasing the number of MaxSubItGA and MaxSubItPSO. The order of the operation of the GA operator and the PSO operator is related to the hybrid type used for the calibration. As seen below for instance, in hybrid GA-PSO, initial position and velocity of particles (here driving behaviour parameters) are determined randomly over the search space. Then, the crossover and mutation operators of GA are applied for each particle in swarm separately to improve the diversity of the population and find better sets of parameters. The information (position, velocity) of each particle was calculated and compared with their previous information and also with the global best. If new information is better than the previous personal best and global bests both of them were updated based on new information. The solutions obtained by the GA operator are given as initial population of the PSO; PSO operator starts to search within the search space around the best particle by introducing swarm intelligence as explained in Section 2.2. It attracts the particles toward the actual best position while maintaining the parameters diversity to gain the new best in every iteration compared to the previous iteration. The proposed Pseudo code of GAPSO algorithm for VISSIM calibration is presented below.

**Initialization loop**

**For i = 1: nPop**

    Initialize position and velocity of particles randomly  
 Calculate cost (objective function evaluation) of particles  
 Update Personal Bests (position, cost)  
 Update Global Best

**End**

**Main loop**

**For it = 1: MaxIt**

**% GA Operator**

**For GAit = 1: MaxSubItGA**

**For i = 1: nPop**

                Selection  
 Crossover (Popc)  
 Mutation (Popm)  
 Merge Population (Popi, Popc, Popm)  
 Sort Population  
 Delete Extra Individuals (Truncation)  
 Generate new population  
 Update Personal Best  
 Update Global Best

**End**

**End**

**% PSO Operator**

**For PSOit = 1: MaSubItPSO**

**For i = 1: nPop**

                Update particles velocity  
 Apply Velocity Bounds  
 Velocity Reflection  
 Apply Position Bounds  
 Function (objective function evaluation) Evaluation  
 Update Personal Best  
 Update Global Best

**End**

**End**

**End**

#### 4. REAL-WORLD APPLICATION

In order to test the proposed calibration method, a case study area was selected and the proposed methodology implemented on the simulated highway stretch. For this purpose, one segment of the O-1 Highway in Istanbul, Turkey, specifically the Yıldız junction, was selected. A bottleneck area is formed at Yıldız junction through one mixed traffic lane and a spatial bus priority lane merging into three-lane mainline [34]. The driving and lane-changing behaviour in this specific section are observed to be peculiar due to its distinct geometry and traffic composition, as shown in Figure 2.

##### Data collection procedure

As shown in Figure 2, the Yıldız merging area of the O-1 highway consists of three lanes with mixed traffic flow per direction. Due to the distribution of residential and business districts in Istanbul, the majority of Bosphorus crossings go from the Asian side to the European side in the morning hours, with the opposite flow appearing in the evening hours [35, 36]. This study

just considered the flows in the European to Asian-side direction. There are two Remote Traffic Microwave Sensor (RTMS) devices installed in the upstream (No. 303) and downstream (No. 60) of the bottleneck area which provide presence indication and accurate measurements of volume, occupancy, and speed with a detection range (increment) of 0.4 m (1.3 ft) for each two-minute time interval in 7/24 duration. The one-week data (07.05.18 - 14.05.18) of RTMS detectors from 6:00 AM to 10:00 PM provided by Istanbul Metropolitan Municipality, Traffic Control Center (IMM-TCC) was analysed in order to select the start and end time-point of the capacity drop phenomena during the morning and evening peak hours. In this study, traffic conditions between 14:30-15:30 are modelled including an un-congested flow, transition condition, and congested flow conditions.

##### Simulation of the study area using VISSIM

The well-known microsimulation software, VISSIM version 10 [12] was used to create a microscopic model of the Yıldız merging area. In the base model, we use the default values of parameters for driving behaviour

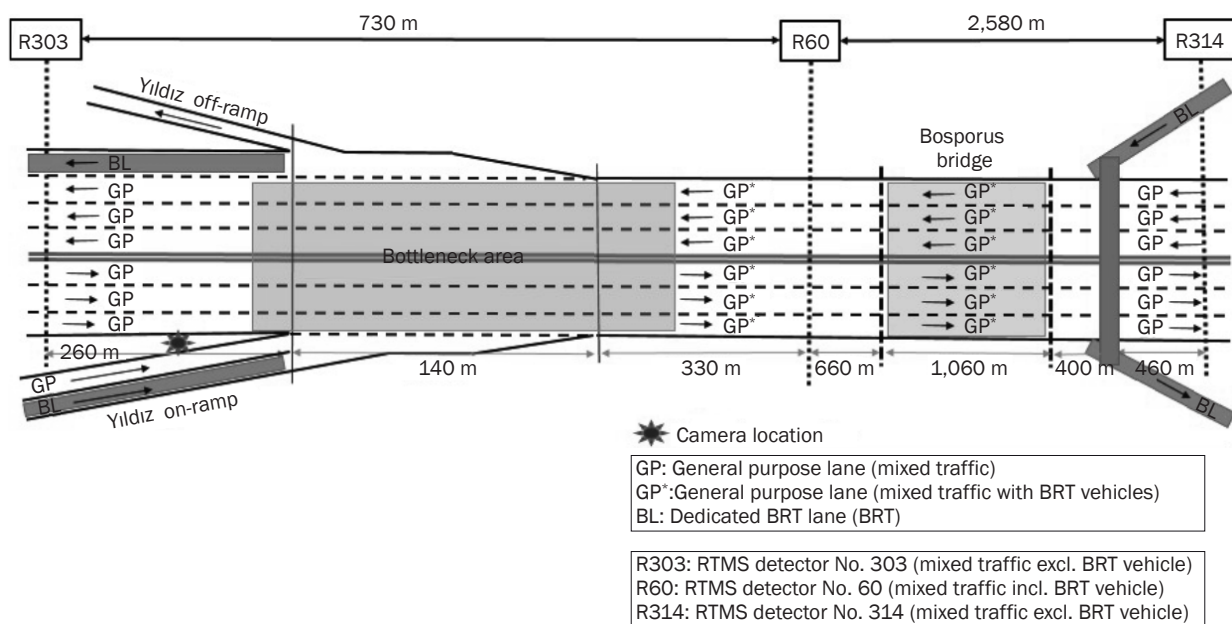


Figure 2 – A schematic view of Yıldız merging area in O-1 Highway in Istanbul



Figure 3 – Modelled study area by VISSIM (left) vs. Bird's eye view of study area (right); Source: Google Earth

models. After simulation, we compared simulated traffic volumes and speeds at detectors for every two-minute interval with the measured values. A comparison between the modelled data and observed data reveals that there is a significant difference between these two sets of data. It justifies the need for formulating a calibrated model based on actual traffic condition before making a scenario analysis. The results of the optimization process and the driving behaviour model parameters using the proposed calibration method are discussed in detail in Section 5.

*VISSIM simulation and evaluation settings*

The following values for the simulation and evaluation attributes were set. As noted below, the total simulation time (period time) was calculated as 300 + 3,600 = 3,900 sec. We assumed 300 seconds as a warm-up time at the beginning of the simulation period. Data collection was done in just 60-minute simulation period with a two-minute time interval (120 sec) excluding warm-up periods. In order to decrease the simulation time as well, 'QuickMode' and 'UseMaxSimSpeed' attributes were activated. In order to eliminate the stochastic discrepancy, in each scenario, five independent runs with the same initial condition and different speeds were made and an average of the total time was recorded. To this end, the simulation settings used in VISSIM were as follows: initial random speed = 40, speed increment = 3, number of runs = 5, step time (resolution) = 5, simulation time=3,900 with max speed for Simulation ('UseMaxSimSpeed', true and 'QuickMode', 1).

**5. RESULTS AND DISCUSSION**

In our study, eleven parameters to be optimized using the proposed methodology were selected. They were selected from the general parameters ("LookBackDistMax", "LookAheadDistMax", "StandDist",

"ObsrVdVehs"), W74, and lane-change model parameters. Table 8 presents the obtained MANE and RMSE values. As shown in Table 8, the simulation with default values of the driving behaviour and lane-change parameters yielded worse MANE and RMSE values compared to simulations with calibrated parameters using any of the metaheuristic methods examined. It can also be seen that GAPSO, PSOGA algorithms have the best MANE values of 0.353 and 0.366 as well as the best RMSE values of 9.080 and 9.466, respectively.

Table 9 presents the optimized parameters obtained using GA, hybrid GA, PSO, hybrid PSO, and default parameters. For example, the value of "DecelRedDistOwn" and "AccDecelOwn" which is calibrated by GAPSO is 137 m and -1.62 m/s<sup>2</sup>, in comparison to default values of 200 m and - 1.00 m/s<sup>2</sup>, respectively.

Figure 4 shows the best MANE values obtained by GA, hybrid GA, PSO, and hybrid PSO algorithms with respect to the Number of Function Evaluations (NFE). The value of objective function MANE was calculated by using Equation 1. The x-axis denotes the number of function evaluations and y-axis represents the minimum objective function (MANE) value up to every NFE.

Figure 5 shows the best RMSE values obtained by GA, hybrid GA, PSO, and hybrid PSO algorithms with respect to NFE. The value of objective function RMSE was calculated using Equation 2. The x-axis denotes the number of function evaluations and y-axis represents the minimum objective function (RMSE) value up to every NFE.

Table 8 – Summary of different objective function values for the optimization problem

Method	Default	GA	PSO	GAPSO	PSOGA
MANE	1.280	0.436	0.433	0.353	0.366
RMSE	34.508	11.611	11.721	9.080	9.466

Table 9 – Selected driving behaviour parameter values before and after calibration

Parameters	Range	Default	GA	PSO	GAPSO	PSOGA
W74ax	0.50 ~ 2.50	2.00	1.03	0.98	1.83	1.25
W74bxAdd	0.70 ~ 4.70	2.00	2.88	2.42	3.18	3.03
W74bxMult	1.00 ~ 8.00	3.00	4.55	5.89	3.90	4.52
LookBackDistMax	50 ~ 200	150	112	128	135	127
LookAheadDistMax	100 ~ 300	250	262	191	195	170
StandDist	0.00 ~ 3.00	0.50	1.50	1.93	0.76	1.08
ObsrVdVehs	1.00 ~ 5.00	2.00	2.88	3.03	2.75	3.40
DecelRedDistOwn	100 ~ 200	200	175	156	137	152
AccDecelOwn	-3.00 ~ 0.50	-1.00	-1.60	-2.03	-1.62	-2.27
MinHdwy	0.50 ~ 3.50	0.50	2.37	2.47	2.01	1.92
SafDistFactLnChg	0.10 ~ 0.60	0.60	0.32	0.38	0.40	0.33



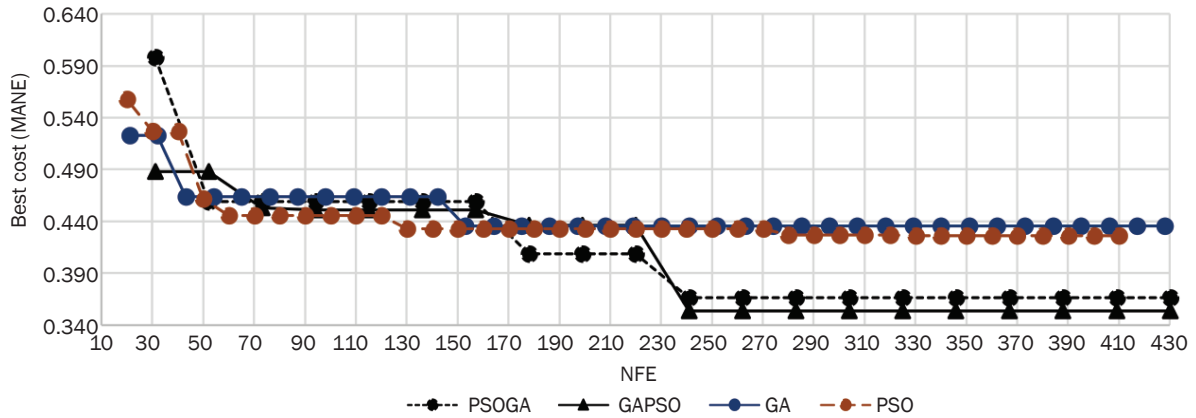


Figure 4 – The best MANE values obtained by hybrid and single optimization algorithms

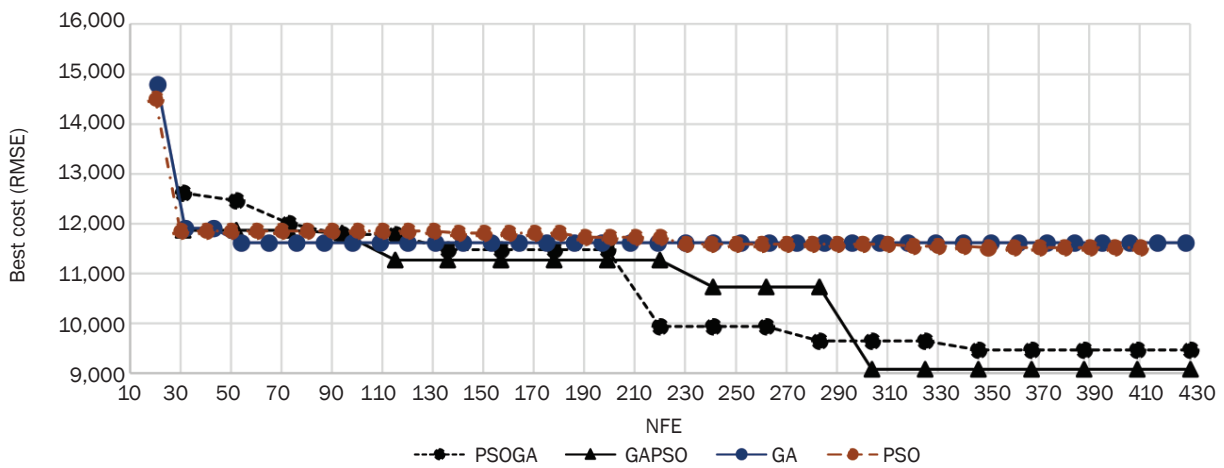


Figure 5 – The best RMSE values obtained by hybrid and single optimization algorithms

One can clearly see that the hybrid algorithms outperform the single algorithms and that the lowest values of both MANE and RMSE are achieved with the hybrid GA algorithm. It is possible to compare the performance of the four algorithms with respect to the percent change from the initial MANE and RMSE scores (1.28 and 34.50) calculated using default values for the selected parameters. Initially, PSO and PSOGA start with the higher MANE values – just above 0.55, whereas GAPSO registers a better value. After around 240 NFEs, good improvement of MANE values

at PSOGA and PSO algorithms could be noticed. Finally, at the end of optimization iterations, hybrid and single algorithms manage to reduce the MANE and RMSE values by 72%, and 66%, respectively, when compared with the initial values.

Figure 6 presents speed profile over selected time period including uncongested flow condition (14:30-15:00), transition condition (15:00-15:00), and congested flow condition (>15:20). As shown, the simulated data with calibrated parameters value are in an acceptable fit status, while simulated data with default

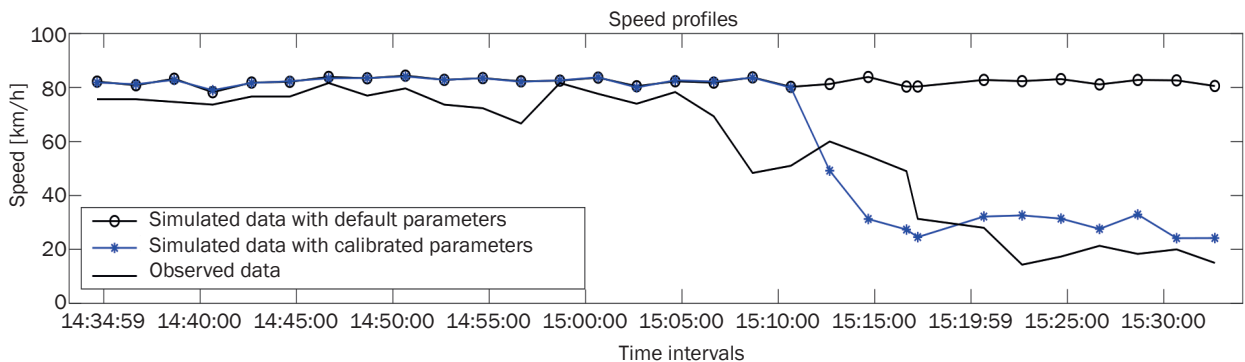


Figure 6 – Speed profiles using default and calibrated parameter values

parameters value has big difference with the observed data, in particular in transition and congested traffic conditions. As conclusion for our case study, in uncongested flow condition, the simulated models with VISSIM default parameters outputs acceptable results and can be reliable; however, calibrated parameters provide better and well-fit results with the observed data for transition and congested flow condition.

Modelling and calibration processes were done by a personal laptop with the following configuration; CPU: Intel Core™ i5 - 8500@3.00 GHz, RAM: 16 GB, Operation system: Microsoft windows ver. 10 64-bit. This computer needed around 44 hours to complete optimization for each of the methods.

## 6. CONCLUSION

The interaction between each element creates a great complexity in microsimulation traffic models. The driving behaviour and lane-change model parameters have major effect on the level of representativeness. In order to achieve reliable microsimulation models, more efficient calibration optimization methods should be developed and compared. In this study, metaheuristic optimization methods, namely GA, hybrid GA, PSO, and hybrid PSO, have been developed and applied to calibrate microscopic traffic simulation model parameters. The MATLAB and VISSIM microsimulation software are used for the implementation of the proposed optimization methods. The calibration methods have been implemented and tested in a case study by using traffic data collected from a segment of the O-1 Highway in Istanbul, Turkey. The observed traffic parameters have been compared with the results obtained by the simulation runs. The calibration is formulated as a minimization problem in which the objective function values are set to MANE and RMSE. The calibration results of objective functions have been presented in detail. Results show that, hybrid GA, and hybrid PSO methods outperform GA-only and PSO-only methods. Among all the algorithms tested, hybrid GA generated the lowest MANE and RMSE values. Based on the achieved results, the combining metaheuristic algorithms approach is very promising and is therefore highly recommended for calibrating microscopic traffic simulation models.

In terms of the future studies, the application of this methodology could be extended to larger freeway networks or signalized roadways. Improving the optimization and calibration performance of the proposed methodology by developing an auto-tuning process for hybrid GA, hybrid PSO, PSO, and GA parameters including "mutation and crossover rates, phi, w, c1, c2, etc." and also by using different combinations of GA and PSO operators inside the hybrid technique remains an interesting area for investigation. Although the

proposed calibration methodology shows successful computational performance, one might consider using parallel computing techniques to decrease the calibration time of the proposed calibration procedure [37].

## ACKNOWLEDGMENT

This study is a part of Ph.D. thesis of the corresponding author from the Istanbul Technical University, Turkey. We would like to thank Prof. Dr. Tomaž Maher and Assist. Dr. Rok Marsetič from the Traffic Technical Institute of Civil and Geodetic Engineering Faculty, University of Ljubljana, Slovenia, for their kind support, valuable comments, and helpful suggestions. The authors are also thankful to the PTV-AG Karlsruhe Company for their support in providing a thesis-based unlimited version of VISSIM software.

یک روش کالیبراسیون و بهینه سازی اتوماتیک پارامترهای مربوط به رفتار رانندگان در مدل‌های شبیه سازی ترافیک

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امروزه، اکثر برنامه های شبیه سازی ترافیک، برای شبیه سازی رفتار رانندگان از پارامترهای مربوط به مدل‌های تعقیب و تغییر لاین خودروها استفاده می کنند. هدف اصلی این مطالعه، ارائه یک فرایند کالیبراسیون اتوماتیک برای پارامترهای مربوط به مدل‌های رفتار رانندگان با استفاده از الگوریتم های تکاملی (فرانشاختی) است. در این تحقیق، الگوریتم ژنتیک (GA)، الگوریتم ازدحام ذرات (PSO) و ترکیب جدیدی از این الگوریتم ها یعنی GAPS و PSOGA در مرحله بهینه سازی استفاده شده است. همچنین دو تابع هدف شناخته شده یعنی MANE، RMSE جهت کمینه کردن خطای شبیه سازی در فرایند بهینه سازی مورد استفاده قرار گرفته است. برای بررسی عملکرد روش پیشنهادی، یک منطقه مطالعه مناسب با حجم بالای اتوبوس از بزرگراه O-1 در استانبول انتخاب شده و در نرم افزار VISSIM مدل سازی شده است. داده های ترافیکی از قبیل متوسط سرعت، حجم و تراکم خودروها از طریق سنسورهای نصب شده جمع آوری شدند. روش کالیبراسیون پیشنهادی با استفاده از نرم افزار MATLAB برنامه نویسی شده و از طریق رابط VISSIM-MATLAB COM روی مدل شبیه سازی شده مورد آزمایش قرار گرفت. نتایج مدل کالیبره شده (مقادیر خطای بدست آمده) با استفاده از روش پیشنهادی نشان داد که در طی فرایند کالیبراسیون، تکنیک GAPS ترکیبی و PSOGA ترکیبی نسبت به تکنیک های GA تنها و PSO تنها عملکرد قابل قبول تری داشتند. بنابر این، روش پیشنهادی GAPS ترکیبی و PSOGA ترکیبی به جای استفاده تنها از الگوریتم های GA، PSO در کالیبراسیون مدل های ترافیک توصیه می شوند.

کلمات کلیدی: مدل‌های شبیه سازی ترافیک، کالیبراسیون و بهینه سازی، رفتار رانندگان، الگوریتم ژنتیک، الگوریتم ازدحام ذرات، نرم افزار VISSIM

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