

Calibration and Validation of the VISSIM Parameters - State of the Art

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Abstract- As a stochastic, microscopic, time-step, behavior-based model with capabilities to provide application of programming interface (API) and simulation, VISSIM has become one of the most useful and reliable programs utilized by contemporary engineers and researchers in the processes of evaluation of control operations and strategies of transportation. In this paper are given 'state of the art' calibration and validation techniques of VISSIM parameters that derive from the need to accurately match the simulations results of the models with the observed field data.

In this context, different practices of different traffic control operations that have been done so far in calibration and validation process are overviewed. For each one of them the aim of calibration, developed methodologies, manner in which are identified "best" parameters for calibration, calibration objective functions, criteria, optimization techniques, evaluation of modeling outputs are emphasized. Finally, a prescription of credibility and reliability of calibrated parameters to the related traffic conditions is given.

Keywords- traffic, microscopic simulation, calibration, validation

1. Introduction

In the past, analysis of the simulation models was done relying on values of default parameters which lead to incorrect results and to huge discrepancy of the simulated results and observed field data. In order to overcome such a situation, researches were pushed to do the calibration of the used models. Similar to other microscopic models of traffic simulation, VISSIM encounters the necessity to calibrate its parameters in order to gain reliability and accuracy of its use by bridging a conditional match of the simulated parameter values with observed traffic field data. We are witnessing a numerous efforts done by researchers in the direction of doing successful

calibration and validation processes of VISSIM parameters.

In this paper are depicted the later and the most important ones that give a meaningful presentation of the availability verity of the VISSIM simulation results to resemble the field traffic conditions.

2. Overview of VISSIM calibration and validation studies

Through the perception of the majority of studies done till now, we are able to notice their belongings to either calibration of freeway, arterial or intersection operations. On the other hand, a high attention is given to the optimization methodologies and techniques of the selection of candidate parameters for calibration as well as the calibration process itself. A summary of the differences and similarities of calibration methodologies that comprise approximately the same elements (either of the procedure or the optimization technique and fitness or objective function use or the subjected test bed) is done. By categorizing the different studies of this review on the respective categories, clearly notice their common convergence point, related to the optimization techniques used. Genetic Algorithm is mostly used and enriched as a heuristic optimization methodology for calibration. An observed differentiation is the number of parameters for which the calculated difference as a measure to prescribe the consistency between field and simulated data, which is single parameter calibration method and multi-parameter method. Parametric and nonparametric statistical methods are another differentiation. Since there are different studies reviewed, as it's described above, in this paper is given a systematization based on the optimization methodology-techniques as a major category, but also other divisions are summarized in table (1).

Table 1. Vissim Calibration Parameters -State Of The Art

Table 1. VISSIM CALIBRATION PARAMETERS -STATE OF THE ART	Otpimization Methodology	Measure of Performance (MOP) of Fitness function	Analysis of parameter Consistency	Network type
Development and Evaluation of a Procedure for the Calibration of Simulation Model [4]	GA	Travel Time	F-test	Actuated signalized intersection
Calibration of Micro-simulation Models Using Nonparametric Statistical Techniques [18]	GA	Travel Time Distributions	Non parametric Moses, Wilcoxon Test,	Arterial
Validation Case Study of VISSIM Simulation Model for a Coordinated Actuated Signal System [3]	GA	Travel time , Queue length	T-test	Arterial
Calibrating Freeway Simulation Models in VISSIM [7]	GA	Maximum Flow Rate,	ANOVA	Freeway
Simultaneous Calibration of a Microscopic Traffic Simulation Model and OD Matrix [2]	GA	Travel time distributions, OD Matrix	Non Parametric Test Chi square Test	Arterial and Freeway
Methodology for Calibration of VISSIM in Mixed Traffic [11]	GA	Delay measurement	ANOVA	Intersections
Micro-simulation Calibration Using Speed Flow Relationships [8]	EA	Speed-flow	Pattern Recognition	Freeway
Development of VISSIM model calibration software [9]	Nelder-Mead	Queue Length	ANOVA	Arterial
VISSIM: A multi-parameter sensitivity analysis [6]	SA	Capacity	ANOVA	Freeway
An Efficient Sensitivity Analysis Approach for Computationally Expensive Microscopic Traffic Simulation Models [13]	Quasi -OTEE	Variation of Travel time and Speed	/	Freeway
Calibration and validation of VISSIM microscopic traffic simulation model parameters using Pareto Archived Dynamically Dimensioned Search [14]	PA-DDS Algorithm	Speed, Volume and CPI	RMSPE Weightet	Freeway
A novel Methodology for Evolutionary Calibration of VISSIM by multi-threading [12]	PSO	Error minimization of any simulated and field parameter sets	/	NA
Case Study of VISSIM Simulation Model for a Coordinated Actuated Signal System [5]	Monte Carlo	Travel Time Queue Length	T-Test	Arterial
Calibration of Steady-state Car-following Models using Macroscopic Loop Detector Data [1]	NA	Free low Speed Steady state Conditions	RMSPE	Intersection

2.1. Genetic Algorithm (GA) optimization

Genetic Algorithm (GA) is a heuristic search method that underlies on the principle of best individual survival from the population through many iterations. Due to its flexibility on finding the optimal solutions, the enormous utility of this technique dates very early in the overall processes of different optimization efforts of the process of evolution better results from

the actual generation than in the previous one through processes of selection, crossover and mutation. In an optimization process through a huge number of generations are obtained local or general optimized values. In a string of a selection process number of individual relates to the number of chromosomes and the number of variables relates to the number of genes. In the below sections are reviewed some calibration studies through GA.

2.1.1. Development and Evaluation of a Procedure for the Calibration of Simulation Model (2005)

Park and Qi [4] developed a procedure of calibration of a VISSIM simulation model. An actuated signalized intersection located at the junction of U.S Route 15 and U.S Route 25 in Virginia was proposed as a test site. The main steps of the proposed procedure of this study are: simulation model setup, initial calibration, feasibility test, parameter calibration by use of genetic algorithm (GA) and model evaluation.

In the initial evaluation the average travel time of the left turn movements of one intersection approach is chosen as the performance measure, since the author considered that it directly reflects the level of service. From multiple simulations with *default parameters* mentioned below, the travel times are evaluated.

1. Similar resolution,
2. Number of observed preceding vehicles,
3. Average standstill distance
4. Additive part of desired safety distance, and
5. Multiple part of desired safety distance (both have impact on saturation flow rate),
6. Priority rules for minimum headway,
7. Priority rules for minimum gap time and
8. Desired speed distribution.

Similarly to the first review study, the Latin Hypercube test is used to reduce the huge number of scenarios of parameter combinations, which has led to an overall number of 200 scenarios each with 5 seeded simulations with a total of 1000 runs. Through

the use of the Analysis of Variance (ANOVA) it was found that the minimum gap and the desired speed distribution were two parameters important to the results. The travel time became higher when the minimum gap increased or the mean desired speed decreased, or both. ANOVA *F*-test, measured the mean difference between groups, and the sum of squares (SSR) between groups. A small *P*-value and a large SSR indicate that the null hypothesis is rejected and that this parameter is important for the result. The group pairs were listed if the mean difference was significant at either the 0.5 or the 0.05 level.

Therefore, additional tools like the HCM procedure and field data were used to check and help clarify the ranges of some parameters, such as the saturation flow on the southbound approach and the field speed within the intersection. The saturation flow rate was calculated by examining the queue discharge headway from field and the average headway of the third vehicle and the *n*th vehicle. Based on these two parameters, the ranges of the desired safety distance and multiple part of safety distance were modified. So, before implementing genetic algorithm (GA) for calibration, the ranges of the parameter values: desired speed distribution and safety distance were modified.

2.1.2. Calibration of Micro-simulation Models Using Nonparametric Statistical Techniques (2005)

Unlike the above reviewed paper, Kim J. and Rilett L. [18], in this study examine a method for calibrating traffic micro simulation models so that simulation results, such as travel time represent observed distributions obtained from the field and not

the mean or central tendency mean of the parameters. The experiments are done on an arterial section of Bellaire Boulevard in the southwest part of Huston, Texas which is 1.1 km long and comprises of four intersections, i.e. three signalized intersections and one two-way stop-controlled intersection. Calibration

process is done through genetic algorithm (GA), which uses the nonparametric statistical testing methods. Authors of this paper emphasize that the use of Mean Absolute Error Ratio (MAER) values of the measurement parameter is not practical in cases when the distributions for the simulated and observed parameters are not identical. To avoid this situation the authors propose a statistically based approach, i.e. on a more disaggregate form of the observed travel time. Specifically, the “closeness” of the observed travel time distribution to that of the simulated travel time distribution is chosen as the objective function. Two nonparametric tests used to test the difference between two populations are: **Moses' Distribution free Rank-Like and Wilcoxon Rank-Sum Test**. The **Kolmogorov–Smirnov (K-S) test** is used to test the hypothesis that two populations have the same distribution.

The driver behavior parameters that have been considered by authors are: 1. The number of vehicles (located ahead of the current vehicle) that a driver will consider when making a decision, 2. Look ahead distance, 3. Average standstill distance, and 4. Desired safety distance: additional parameter and a multiplicative parameter, and 5. Lane change distance. The minimum and maximum values were based on the engineering judgment of the authors.

The analysis of the calibration results showed that the one with the lowest MAER might be selected because it would represent the parameter set that provides the closest measure of central tendency while still providing a statistically valid distribution. Alternatively, the parameter with the highest *p* value could be selected as the one that most closely represents the observed distribution. To validate the calibrated parameter sets, the saturation flow rate for the accepted parameter sets were compared with that from the *Highway Capacity Manual* (HCM). In the end it is shown that simple metrics such as MAER are not robust enough to identify parameter sets that mimic the actual travel time distribution. Also authors propose that the model should be applied on other networks and other network types (i.e., freeway) to determine whether the results identified in this paper hold in other situations as well.[4]

2.1.3. A case Study of Coordinated Actuated Signal System (2006)

Before performing this study, Park and Schneeberg, did the simple one with Monte Carlo method instead of GA employment to calibration on [5]. The test bed is on a larger network of 12 intersections with coordinated, actuated signals in the U.S route 50 in Fairfax, Virginia. While the travel time data was used for calibration and queue length for validation, the calibration issue does not stand the same. Beside the use of GA in calibration process, five more parameters were added. Parameters used are:

1. Emergency stopping distance,
2. Lane change distance,
3. Desired speed distribution,
4. Number of observed preceding vehicles,
5. Average standstill distance,
6. Waiting time before diffusion,
7. Maximum headway,
8. Waiting time before diffusion,
9. Minimum headway,
10. Maximum deceleration,
11. Reduction rate,
12. Accepted deceleration.

The flow chart of the Calibration and Validation procedure is given in Figure 1.

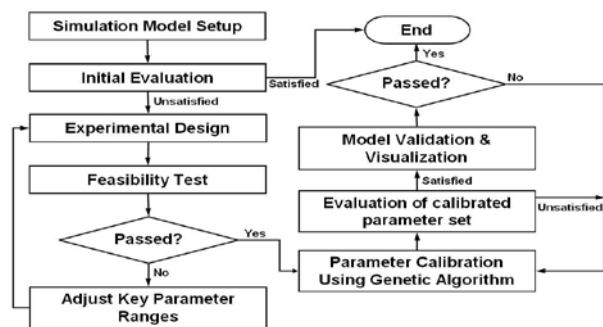


Figure 1. Calibration and Validation procedure (A case Study of Coordinated Actuated Signal System [3])

When 14 calibration parameters with 5 possible values for each parameter are considered, the total number of possible combinations is 5^{14} (i.e., 6,103,515,625). This is almost impossible to evaluate within a reasonable amount of time. Latin Hypercube sampling was used to produce 200 parameters sets with five random seeds for each for a total of 1000 runs. The genetic algorithm was then run for these parameters and ranges and converged to a solution in 10 generations. The GA parameters used in this study included maximum number of generations of 10, population size of 10, crossover rate of 0.8, and

mutation rate of 0.05. The GA program converged within 10 generations. A few multiple GA runs showed similar convergences.

Then 100 random seed runs were done for this solution parameter set. This first solution produced travel times that matched the field data, but not the queue lengths so an additional solution was created using the genetic algorithm. The second solution's results from 100 random seeded runs matched both the field travel times and queue lengths. In the runs for both parameter sets no unusual visualizations were observed. For both sets of runs the 2 most influential parameters were the additive part of safety distance, α , and the desired speed distribution.

The author concludes that since only one field collected data point was used during each of calibration and validation tests it is more desirable to collect multiple data points, collected over time, of field data to account for the day-to-day variability.

The effectiveness of the accuracy of the field and simulated results stands on using GA rather than the conventional method used on the previous paper [5] of the author.

Since this reviewed studies cover the case of actuated coordinated, in sense the procedure does not seem to address the conceptual issue of impact of traffic control parameters incorporation (i.e. controller settings parameters, ring barrier design RBC, which are available on VISSIM interface module) in calibration.

2.1.4. Calibrating Freeway Simulation Models in VISSIM (2006)

Woody [7] performed a research due to the calibration and validation of freeway simulation models in VISSIM. According to this study, the model calibration is divided into two categories: 1) system calibration and 2) operational calibration when each described and reasoned with its steps and the choice of related parameters. Sensitivity analysis was conducted by creating different appropriate parts of freeway models in which the effect or impact of the respective calibration parameter were tested.

System calibration stage is the highest level of calibration where the goal is to verify all model operations based on the assumptions of the system. The main task of system calibration includes

checking of assumptions of all inputs associated with the model. System level calibration parameters include assumptions on vehicle route choice, traffic demand inputs, traffic composition, study area boundaries, seeding period, and temporal distribution of demand and routing[10].

Operational calibration is the process of modifying model parameters that affect the overall traffic operations of the study network. Operational calibration consists of modifying detailed driver behavior parameters that affect the overall capacity of the transportation facilities, aggressiveness of drivers, and locations for lane changing. The operational calibration step is essential for modeling freeway bottlenecks and local driving behavior that can affect overall traffic flow, speeds, facility capacity, and congestion in a given study area.

Examples of operational calibration parameters include car following characteristics (headway, standstill distance, safety distance), lane changing, accepted deceleration rates, routing lane change distance, and lane selection. The operational calibration requires the most time and resources to complete. [10]

Sensitivity analyses are made to Driver Behavior Parameters, partially on the Car Following Behavior on a lane conceptual model crated in VISSIM.

The following assumptions were made about the test VISSIM network:

- Mean speed = 75 mph, Standard deviation of speed = 5 mph
- 2% trucks in the traffic stream
- Default vehicle characteristics were used
- Simulation time steps of 10 steps/second
- Demand Volume = 3,500 veh/hour

All the Wiedemann parameters (CC0, CC1, CC2, CC3, CC4, CC5, CC6, CC7, CC8 and CC9) were kept by default values and then the maximum flow rate was collected based on simulation runs. A close relationship of the CC1, CC2 and CC8 parameters with the maximum flow rate parameter was withdrawn out.

In the sensitivity analysis of Necessary Lane Changing Behavior the lane changing behavior was tested on a conceptual freeway merge section using VISSIM. Modifications to the maximum deceleration rates for the merging and trailing

vehicles and car following headways were conducted to determine the effect on the mainline and ramp throughput of merge section.

A comprehensive conclusion is that different parameters have impact on the different operational parts of freeways.

Freeway merging sections rely most heavily on necessary lane changing and the Wiedemann 99 car following parameters during the calibration stage [10]. Modifying a combination of the deceleration rates for the merging (own) and trailing vehicles as well as the car following headway parameter (CC1) will enable the designer to give throughput priority to the mainline section or the ramp section.

Freeway diverges are most affected by the necessary lane changing and lane change distance parameters during the calibration stage. The percentage of vehicles routed to the off ramp and the number of lanes of the mainline section can affect the values required for the lane change distance and lane changing parameters.

Author underlines that calibration of freeway weaving sections are more complicated than both merge and diverge facilities and utilize parameters related to both merging and diverging sections. The most important parameters to consider when the calibrating weaving sections are the necessary lane change behavior, lane change distances and the CC1 (car following headway parameter) [10].

2.1.5. Simultaneous Calibration of a Microscopic Traffic Simulation Model and OD Matrix (2006)

In his dissertation Seung-Jun Kim [2] developed a methodology in which the Origin-Destination (OD) matrix is calibrated simultaneously with model behavior parameters using a bi-level calibration framework.

Also, a statistically based calibration objective function is introduced to account for disaggregate form of Intelligent Transportation System (ITS) data in the calibration of microscopic traffic simulation models and, thus, accurately replicate behavior of observed traffic conditions. Specifically, the Kolmogorov-Smirnov (KS) test is used to measure the “consistency” between the observed and simulated travel time distributions.

Experiments are done in two test sites: 1) on an urban arterial and 2) on a freeway in Houston, Texas. The arterial is Bellaire Boulevard located in the southwest of Houston. It is a 1 km long arterial with 4 intersections. The freeway corridor is comprised of a 15.4 km section of eastbound Interstate 10 (I-10) leading to downtown Houston.

The author emphasizes that traffic conditions have large variability, so that aggregated performance measures such as average travel time may not be the most appropriate measure of effectiveness. For example, travel times are likely to deviate from their means in significant ways, especially during peak periods. The best way for alleviating this, is the incorporation of the OD matrix as a function of travel time and vice versa in the process of calibration which provides the basis of the simultaneous calibration on a bi-level approach.

Bi-level calibration approach

Bi-level calibration approach is adapted where the OD matrix and the microscopic traffic simulation parameter set are calibrated in an iterative manner [2].

In the first level the minimization of the difference between observed and simulated traffic conditions, thus adjusting the values of the model parameters is done. To achieve this, a GA algorithm is selected through which the best parameters based on the statistically objective function are identified. The statistically based objective function is used to evaluate the selected performance measure. The bi-level approach procedure is presented in figure (2).

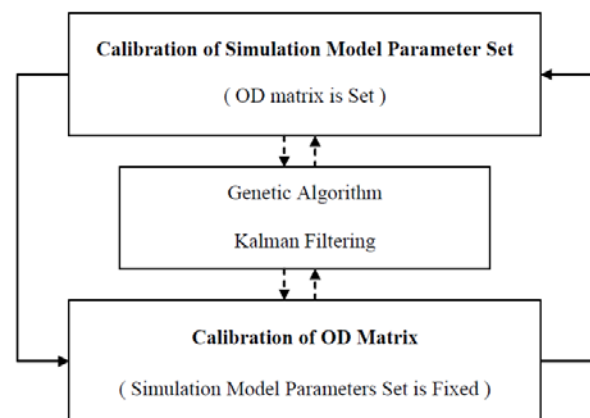


Figure 2. Bi-level approach calibration procedure (Simultaneous Calibration of a Microscopic Traffic Simulation Model and OD Matrix[2])

In the above snapshot of the bi-level calibration approach the prescription of the first step of this level where a set of parameters that need to be calibrated and to translate the selected parameters into binary values is given. The second step involves running the VISSIM simulation with the identified parameters to generate the simulation results. These results are compared against observed data using a statistically based objective function. Genetic Algorithm (GA) is used for optimization of parameters through an iterative process.

On the second level the steps for OD matrix calibration are included. Simulation data of travel time with calibrated parameters (with GA process of the first level) are incorporated in the OD estimator through the Kalman Filter technique [15]. The process of calibration is then repeated for OD matrix and so forth the process is iterative.

Calibration objective function based on non-parametric statistical test

The need for calibration objective function based on non-parametric statistical test is justified by the author from the fact that traffic outputs such as average travel times or traffic volumes do not address sufficiently certain aspects of observed field conditions. Travel time in the form of a distribution is the key decision criteria in contrast to many statistics which rely on a measure of central tendency such as the mean. Moreover, the objective function of calibration is the 'closeness' of the observed and simulated travel time distributions.

Since the distributions of travel times did not result to be normal, the non-parametric tests are used as statistical tests in this approach. Using this kind of techniques there is no need to give an a priori assumption about the distribution of travel times. Kolmogorov-Smirnov (KS) test is used to compare the distributions of the observed and simulated travel time distributions. The other distinguished element of this approach is that instead of only a simple metrics MAER as others researches used, here the p-value is taken also.

Simultaneous calibration of a traffic simulation model and matrix

From the point view of the authors the conventional calibration procedures used calibration methodologies in which the driver behavior and the OD Matrix was always considered as a fix element which was never involved in this process.

Parameters are calibrated simultaneously and presented using a bi-level approach. To formulate the relationship between travel time data and the OD matrix, the observed travel times are incorporated into a Kalman Filter (KF) OD estimator respectively. The Extended Kalman Filter (EKF) is developed to incorporate the travel time information in the OD estimator and to identify the relationship between OD split proportions and travel times. KF algorithms are known as "prediction-correction" techniques which are based on the criterion of the last square unbiased estimation of the state and measurement vectors [15]. Process of KF can be understood by finding the Kalman gain $K(t)$ represents the relative importance of the error which in this case is the difference of OD matrix and estimator OD matrix with respect to the prior state of traffic volumes in our example.

The mathematical model of the EKF is given below:

$$\begin{bmatrix} v(t) \\ TT(t) \end{bmatrix} = \begin{bmatrix} H_v(t) \\ H_{TT}(t) \end{bmatrix} b(t) + \begin{bmatrix} H_v(t-1) \\ H_{TT}(t-1) \end{bmatrix} b(t-1) + \begin{bmatrix} \varepsilon_v(t) \\ \varepsilon_{TT}(t) \end{bmatrix} \tag{8}$$

$$b(t) = b^-(t) + K(t) \left(\begin{bmatrix} v(t) \\ TT(t) \end{bmatrix} - \begin{bmatrix} H_v(t) \\ H_{TT}(t) \end{bmatrix} b^-(t) - \begin{bmatrix} H_v(t-1) \\ H_{TT}(t-1) \end{bmatrix} b^{obs}(t-1) \right) \tag{9}$$

The definitions of the variables used in formulating the EKF OD estimator are shown as follows:

- $b(t)$ = column vector whose elements are b_{ij} , OD split proportions entering the network from origin i to destination j during interval t ;
- $v(t)$ = column vector whose elements are v_i , number of link traffic volumes passing link l during time interval t ;

H_v = linear link volume connection matrix which is the product of the link choice proportion matrix $L(t)$ and diagonal matrix $O(t)$

$TT(t)$ = column vector whose elements are travel time obtained from AVI data during interval t ;

H_{TT} = travel time connection matrix; and

K_{TT} = Kalman gain matrix for travel time measurements for time interval t

ε = error matrix of link volumes $v(t)$.

Results of this research have demonstrated that the marked improvement can be achieved by calibrating the OD matrix and driver behavior parameters simultaneously. Specifically, both models (EKF_LTT and EKF_ODTT 170 algorithms) provided the average AVI section travel times and the average OD travel times nearly identical to the observed data after several iterations. Even though it was not possible to replicate statistically valid travel time distributions for entire AVI sections, there were also noticeable improvements in travel time distributions [2]. In the analysis of the bi-level calibration effects the simulated outputs were compared to the observed data:

- 1) Average travel time for the AVI section;
- 2) Average travel time for each OD pair;
- 3) Initial and calibrated OD matrix; and
- 4) Individual travel time distribution.

Kolmogorov-Smirnov test is used for travel time distributions comparison and the closeness test is used for the calibrated OD matrix and initial OD matrix.

Closeness measure for the time interval t is given with the expression:

$$CM = \frac{1}{n} \sum_{i=1}^n \frac{v_{kt} |od_{it}^{ini} - od_{it}^{cal}|}{Tv_t} \quad (10)$$

where:

n = number of OD pairs;

v_{kt} = number of vehicles entering from AVI station k at time interval t (veh);

Tv_t = total number of vehicles entering system at time t (veh);

od_{it}^{ini} = initial OD split proportion of OD pair i at time interval t ; and

od_{it}^{cal} = calibrated OD split proportion of OD pair i at time interval t .

2.1.6. Methodology for Calibration of VISSIM in Mixed Traffic (2012)

Unlike the above reviewed researches when almost in all of them the vehicle traffic is homogeneous and with less complexity in the process of calibration, the authors PruthviManjunatha and Peter Vortich[11] addressed some specific aspects of mixed (heterogeneous) traffic in which the complexities are evidential. The complexity of the traffic is attributed to the diversity of some static (lane, width, etc.) as well as dynamic (acceleration, deceleration, speed etc.) properties of vehicles and geometric representation.

Additional elements of such traffic are the absence of lane marking and lane discipline resulting in complex movement of vehicles especially at intersections [11]. In the methodology of calibration of mixed traffic, the simulation runs are done with default parameters as one of the major steps where the discrepancy of the field and simulated parameters are evaluated. In this process, characteristics in terms of length, width, acceleration, deceleration, speed ranges, even to axle configuration and turning radius are set for every single type of composed vehicle. Regarding geometric representation, particular importance is given to the number of approaches, to the width of each approach, and turning space, to the space occupied by each turning movement in the intersection. One other aspect is the representation of the signal control system.

By implementing this methodology through Vissim software for two signalized intersections in Mumbai car following parameters and apart lateral distance and speed- acceleration profiles were defined for each individual vehicle type. Parameter ranges as lower and upper bound are analyzed due to the delay measurement through GA optimization technique. Input parameters for each individual type of vehicles to Vissim that are involved in the process of calibration are: vehicle length, the vehicle width, the minimum lateral distance for two ranges of speed (0 km/hr and 50 km/hr), the desired speed and the traffic composition.

Parameters with significant effect of this study were found to be CC0, CC1, CC2, CC7 and CC8 among all of them starting from CC0 to CC9 were examined.

2.1.7. Micro-simulation Calibration Using Speed Flow Relationships (2007)

Menneni, Sun and Vortisch[8] proposed a calibration procedure based on speed-flow graphs. They developed a method of pattern recognition which serves as a method to study the match of the speed-flow graphs from simulations and fields. The prescribed motivation of the authors is the fact of resulted loss information due to the usage of single parameters such as capacity or maximum flows. The amount of information available in an objective function is of utmost importance; therefore, speed-flow graphs could perform better since they contain more information.

A modified pattern recognition method as a fitness measure is presented in the objective function prescription. A fitness function for measuring closeness of simulated and field speed-flow graphs is needed. In addition, the fitness function should be automated and consistent across multiple evaluations. A generic objective function based on minimizing the dissimilarity between speed-flow graphs was developed. An important part of a speed-flow graph is its shape. Shape can be described in terms of area. The dissimilarity of two graphs can be measured by calculating the amount of area that is not covered by the other. Since speed and flow measurements are represented as point sets, discretization to convert point information to area is necessary. The objective function Z for the calibration process of the field is as follows:

Min. $Z = \text{Sum of all the speed-flow area in the field data that is not covered by the simulated data.}$

The proposed methodology is developed in two modeled networks. For calibration procedure, the following driver behavior parameters are used: CC1, CC2, CC3, CC4, CC5. The Evolutionary Algorithm (EA) is used for optimization. EA is one of the many algorithms based on principles of survival of the best individuals among in population as the GA does. For each scenario, 5 runs were performed, each run being 3 simulation-hours. Five minute speed and flow data

were collected from the mainline detectors. The data from multiple runs were aggregated and the speed-flow graphs were produced. The three objective functions consisted of comparisons between the field and simulated data for:

1. Maximum five minute flows (Maximum Flow)
2. Maximum five minute flows sustained over 15 minutes (Sustained Flow)
3. Matching speed-flow graphs (Speed-Flow)

Speed-flow graphs are given for three objective functions. The comparison is done due to the visual inspection that the speed-flow objective resulted in the best match between field and simulated data.

Although, there were been largely used in the past, pattern recognition methods did not seem to have much important attention due to the lack of mathematical background as there were more ranged as quality observed methods rather than quantity.

In this reviewed paper, the issue differs because consistency is calculated through mathematical formulation for finding the minimal value of sum of all the speed-flow area in the field data that is not covered by the simulated data through EA which is the advantage. The darkness side of pattern recognition of speed -flow diagram is the lack of taking into consideration the time parameter.

2.3. Nelder-Mead (NMA) Optimization Algorithm

Intentionally listed after GA algorithm since it constitutes a classical heuristic algorithm as the Evolutionary Algorithm, whose usefulness seems to be if it is combined with GA. Saying so, we must understand that NMA is an search optimization algorithm of local optimal based. After finding the optimum global solutions through GA , the competence exceeds to NMA to further seek the local solution of the search space.

The disadvantage of using directly NMA may result in blocking any local solution but not seeking the best global solution, thus obtaining weak consistency on the parameters of fitness function and finally unrealistic simulation results.

2.3.1. Development of VISSIM model calibration software (2008)

In his research, Denis Zenkov[9] proposed and developed a slightly different procedure for calibration of micro simulation models. He developed a calibration software in Visual Studio 2008 exploiting C#. Instead of using the GA lonely, he proposed one of the most lately known methods of optimization wherein the GA is combined with another local optimization method, thus producing improving calibrated model credibility. Local optimization comes into action on the very later iterations of the GA, sophisticating the approximate solutions of it.

Nelder -Mead (NMA) or known as Simplex Method for local optimization algorithm is used in this work. It is one of iterative simplex method algorithms. NMA works with three points simultaneously (apexes of the non-degenerate triangle) where in each iteration worst of them is replaced via heuristic search[9].

2.4. Sensitivity Analysis Method

Through reviewing the Vissim calibration methodologies, realized important attention is paid to the sensitivity analysis of the parameters that need to be calibrate. Their consistency (or discrepancy) in the relation to the measure of performance plays an important role on the incorporation to calibration process. Lately are being more efforts on finding sensitivity analysis methods on evaluating the error between different parameters than on error of one parameter. Listed are two reviewed studies for multi-parameters sensitivity analysis. Combination of parameters is done in paper [6] in order to measure the impact of each one on the measure of performance. A novel approach toward this purpose is done in a paper [13] for quasi-Optimized Trajectories based Elementary Effect (OTEE) method, which implies the generation of some trajectories by choosing the ranges of any parameter sets that give the best results of sensitivity between input and output parameters.

2.4.1. VISSIM: A multi-parameter sensitivity analysis (2006)

Lowenes and Machemehl[6] analyzed the effect of some different parameters from the previous studies to another measurement of performance. It is intended to underline the importance of the capacity in the process of calibration, since it is considered of higher-level measurement and as a function of lower-level defined parameters. The basic guidelines for the capacity calibration are taken from the strategy by FHWA. The test of this study is a stretch of freeway in Dallas, Texas metropolitan area. More detailed, the selected bottleneck location for simulation is the interchange of US 75 NB and SH190 near the cities of Plano and Richardson, Texas.

Parameters of Wiedemann 99 car following model was chosen for calibration:

- 1.CC0 – Stopped Condition Distance, 2.CC1 – Headway Time, 3.CC2 – ‘Following’ Variation, 4. CC4 & CC5 – ‘Following’ Thresholds, 5.CC8 – Stopped Condition Acceleration,

From these parameters, six parameter combinations were made. Each parameter was analyzed in five levels, resulting in 25 new pairs of combination in total..[6]

The parameter combinations are: CC0 and CC8, CC1 and CC4/CC5, CC2 and CC4/CC5, CC7 and CC2, CC7 and CC4/CC5, CC7 and CC8.

As seen from the combinations, CC7 parameter is mutual for the last three combinations. The reason of involving this parameter in this combination is described by emphasizing its individual lower significant influence on the capacity while having more influence on the impact of other parameters in capacity.

Analysis of Variance (ANOVA) is used for each of the parameter combinations with an α -level of 0.05. The results for each combination were shown in an interaction plot displaying the mean capacity for each pair of values. In two of six combinations, interaction between parameters was discovered. These combinations were CC0 and CC8 / CC1 and CC4/CC5. The impact on capacity of CC8 and CC4/CC5 was dependent on the twenty five respective values of CC0 and CC1. It was concluded that this was true because CC0 and CC1 are the two

factors used in the calculation of the parameter minimum headway in VISSIM [6].

2.4.2. An Efficient Sensitivity Analysis Approach for Computationally Expensive Microscopic Traffic Simulation Models (2014)

QiaoGe and Monica Mendez [13] developed the quasi-Optimized Trajectories based Elementary Effect (OTEE) method based on Sensitivity Analysis method for finding the candidate calibration parameters whose variations have distinct effect on travel time.

Through Elementary Effect (EE) method which is a qualitative and stochastic approach for screening the influential parameters from a complex model first developed by Morris [13], the effect of every single function parameter is defined. Afterwards, the mean μ , standard deviations σ and the absolute mean μ^* of these effects present the Sensitivity Indexes (SI).

Quasi - OTEE is an improved method of the EE method through a combinatorial optimization in order to reduce the number of trajectories in the input space for reducing the computational time and costs. The total number of trajectories' sets is decreased by finding through iterative manner the longest trajectory set distance.

Experimental work that was done on a network in Zurich with complex urban layout with narrow

streets, hills, mixed transportation modes, a large amount of pedestrians, when the SA is employed into the examination of impact of 14 parameters through 600 simulation runs.

The first and important step of this method is generation of a certain number of trajectories form parameter sets and their ranges.

Subjected parameters are:

1. Average standstill distance,
 2. Additive part of desired safety distance,
 3. Multiplicative part of desired safety distance,
 4. Maximum deceleration,
 5. Accepted deceleration,
 6. -1 m/s^2 per distance,
 7. Maximum Deceleration,.
 8. Accepted Deceleration,
 9. -1m/s^2 ,
 10. Minimum headway,
 11. Safety distance reduction factor,
 12. Maximum deceleration for cooperative braking,
 13. Lane changing distance and
 14. Emergency stop distance,
- from which the SA drawn parameters 1, 2, 3, 4 13 and 14 as the most effective on travel time which is measured on 20 sections of the network. Analogically, the measures of the mean and variance of every parameter and its impact on the travel time is presented through the figure (3). According to estimation that the parameter with the highest value of mean and variation is concluded that parameter 2 is more prone than 1 and 3 to be considered in the process of calibration.

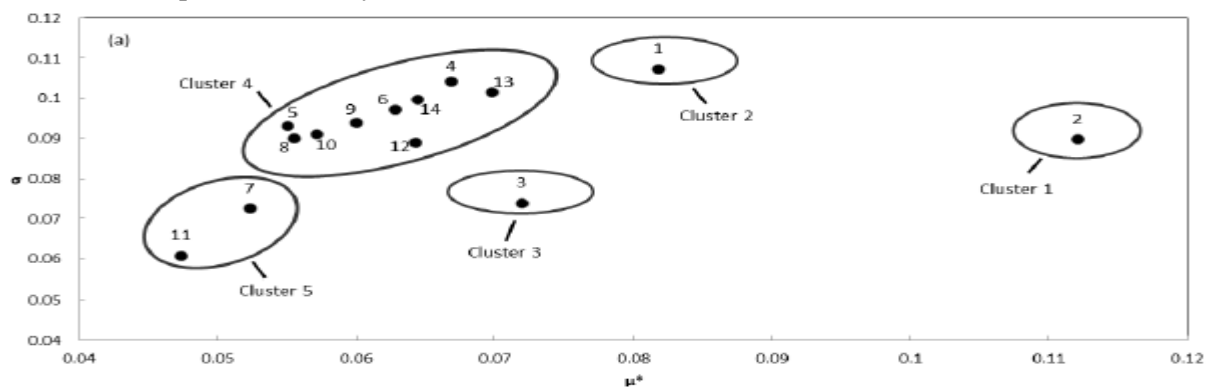


Figure 3. Plots of μ^* versus σ of the EE with Respect to travel time for the 14 Parameters (An Efficient Sensitivity Analysis Approach for Computationally Expensive Microscopic Traffic Simulation Models [13])

Authors underline that the proposed procedure does not guarantee the shortening of computational time rather than efficiency on obtaining the sensitivity results.

Those with the least effect are parameters 7 and 11, but at this point is raised the question of the inter

relationship of parameters that belong to cluster 4 which is standing for the doubtful promising of this sensitivity analysis which in fact is qualitative.

2.5. Heuristic Optimization Search Algorithms (Pso, Pa-Dds)

In the framework of multi dimensionality (of parameter) calibration methodologies lately are ranked new optimization methodologies. Pareto Archived Dynamically Dimensioned Search (PA-DDS) and Particle Swarm optimization (PSO) as global optimization method are finding a huge utility on the optimization problems, and particularly on the calibration efforts of microscopic simulation models.

2.5.1. Calibration and validation of VISSIM microscopic traffic simulation model parameters using Pareto Archived Dynamically Dimensioned Search (2011)

The aim of the research by David Duong [14] was to argue the inability of single criterion calibration approach on recognizing the multidimensionality attribute of traffic as well as to guarantee the accuracy of not just one attribute (for example travel time) but the others too. The Pareto Archived Dynamically Dimensioned Search Algorithm (PA-DDS) is used on improvement of Multi-Objective Genetic Algorithm (MOGA). The PA-DDS is a modification of the original Dynamically Dimensioned Search (DDS) algorithm [19], which first was introduced also by the author of this reviewed research.

A comparative analysis is done between the single criterion measures of performances (MOPs) of: i) single root-mean-squared-percentage-error (RMSPE) of *speed*, ii) RMSPE of *volume*, and iii) RMSPE *Crash Potential Index* (a surrogate safety performance metric) and multi criterion (weighted summation) of (RMSPE speed + RMSPE volume + RMSPE CPI) on data of FHWA NG-SIM Interstate Highway 101.

Parameters included into calibration process are driver behavior parameters: 1. Look ahead distance, 2. CC0, 3. CC3, 4. CC5, 5. Accepted deceleration of trailing vehicle for lane change, and 6. Safety distance reduction factor. Through algorithm it is aimed to minimize the objective function (multi criterion weighted summation) of RSMPE of each

MOP: speed, volume and CPI. Sets of parameters which resulted on the lowest values of RSMPE of each mentioned one are the selected, but on the other hand a special care is given to assessment of increased values of RSMPE of other parameters, in order to do a good compromise.

PA-DDS algorithm employs the calculation of the non-dominated and dominated solutions. The mathematical definitions for non-dominance and dominance are as follows [14]:

Definition 1 (inferiority or dominated)

A vector $\mathbf{j} = (j_1, \dots, j_n)$ is said to be inferior to (or dominated by) $\mathbf{k} = (k_1, \dots, k_n)$ if \mathbf{k} is partially less than \mathbf{j} ($\mathbf{k} \prec \mathbf{j}$), i.e., $\forall i = 1, \dots, n; k_i \leq j_i \wedge \exists i = 1, \dots, n : k_i < j_i$

Definition 2 (superiority)

A vector $\mathbf{j} = (j_1, \dots, j_n)$ is said to be superior to $\mathbf{k} = (k_1, \dots, k_n)$ if \mathbf{k} is inferior to

Definition 3 (non-inferiority or non-dominated)

Vectors $\mathbf{j} = (j_1, \dots, j_n)$ and $\mathbf{k} = (k_1, \dots, k_n)$ are said to be non-inferior (non-dominated) by one another if \mathbf{k} is neither inferior nor superior to \mathbf{j} . vector $\mathbf{j} = (j_1, \dots, j_n)$ is said to be superior to $\mathbf{k} = (k_1, \dots, k_n)$ if \mathbf{k} is inferior to \mathbf{j} . The crowding distance procedure was introduced by Deb et al [14] in order to introduce 'elitism' to their algorithm called the NSGA (e.g. we discriminate against solutions on more crowded regions of the solution space). For each point on the same non-dominated set a cuboids is established with respect to its two neighboring points and a crowding distance, I_{di} is estimated in terms of the average of the cuboids lengths.

The definitions of non-dominated sets and crowd distance calculations are presented in Figure (4).

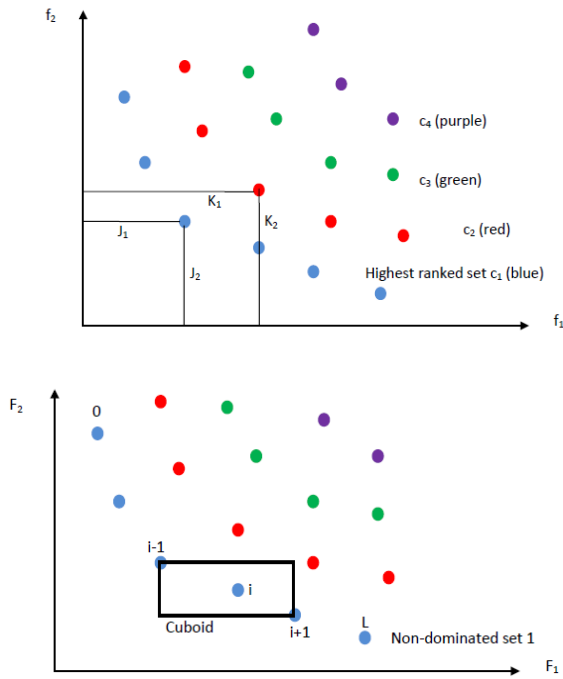


Figure 4. Graphical presentation of a) non-dominated sets and b) crowd distance calculations (Calibration and validation of VISSIM microscopic traffic simulation model parameters using Pareto Archived Dynamically Dimensioned Search [14])

The dark side of this methodology seems to be the cause of disproportional weights of different parameters of MOPs, through which process some of them obtain the worst ones and some have the good benefit.

2.5.2. A novel Methodology for Evolutionary Calibration of VISSIM by multi-threading(2013)

KayvanAghabayk[12] provided a novel methodology to auto-tuning calibration of VISSIM where the Particle Swarm Optimization (PSO) is used to solve the optimization problem and tune the VISSIM parameters automatically, although there is not presented any numerical example for calibration. Moreover, the proposed steps of this methodology are described much more in a general framework rather than traffic parameters calibration.

PSO was first introduced by Kennedy and Eberhart (1995, 2001) [12]. The idea of PSO algorithm is derived from nature occurrences, i.e. from the collective motion of a flock of particles: the particle swarm. In a n-dimensional function, each particle is presented as a n-dimensional vector representing a single point in the search space.

In calibration each particle is associated with a set of parameters related to model chosen for calibration.

Through PSO algorithm it is attempted to find the best personal and global position of particle (parameter sets) based on the objective function settled which in this case [12] is proposed to be the minimization of the difference of the values of simulated traffic measurements and the observed traffic measurements and so-called error.

The position of the i^{th} particle (x_i) can be presented as:

$$\vec{x}_i = (x_{i1}, x_{i2}, x_{i3} \dots x_{in}) \tag{14}$$

Each particle memorizes the position vector and velocity vector as well as the best individual (personal) point which has produced the minimum value of the cost function. This point is

$$\vec{p}_i^{best} = (p_{i,1}^{best}, p_{i,2}^{best}, p_{i,3}^{best} \dots p_{i,n}^{best}) \tag{15}$$

The best experience of the swarm is the point which has produced the minimum value of the cost function within the whole population. This point is called global best (Gbest).

The basic concept of the PSO algorithm lies in updating the position of each particle towards its pbest and gbest points at each iteration by adding an increment vector called velocity. The velocity and position of the i^{th} particle at the $(k+1)^{th}$ iteration can be determined by:

$$\vec{v}_i(k+1) = w \cdot \vec{v}_i(k) + c_1 \cdot \vec{r}_1(k)[p_1^{best}(k) - \vec{x}_i(k)] + c_2 \cdot \vec{r}_2(k)[g_1^{best}(k) - \vec{x}_i(k)] \tag{16}$$

$$\vec{x}_i(k+1) = \vec{x}_i(k) + \vec{v}_i(k+1) \tag{17}$$

where w, c_1 and c_2 and are positive constants; \vec{r}_1 and \vec{r}_2 are vectors of random numbers from $U(0,1)$ in the $(k)^{th}$ iteration.

The research provides detailed explanations about the PSO algorithm, parallelization and their implementation for auto calibration of VISSIM. Geometrical illustration of PSO is given in the figure (5) [16]

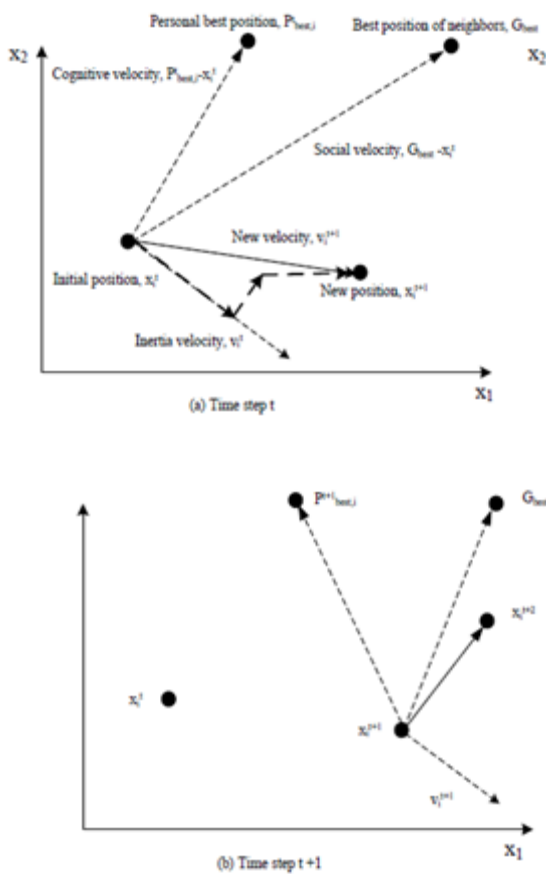


Figure 5. Velocity and position update for a particle in a two-dimensional search space (Mathematical Modelling and Applications of Particle Swarm Optimization[16])

3. Conclusion

Several efforts of researchers for developing different methodologies for Vissim calibration have been done over the time. In this paper are reviewed the most prominent ones which have developed innovative methods and which are also used in other micro-simulation models. All of the mentioned papers possess their similarities and differences in terms of the proposed methodology for calibration, parameter identification, optimization techniques and objective functions.

The earliest methodologies emphasize the issue of parameter incorporation into calibration process rather than seeking and developing a proper optimization technique as the latest ones do [8],[12],[13],[14]. From literature review we may find that the identification of candidate parameters is done from the level of the scientific judgment underlying [1] and [9] to the examination through

statistically based objective functions as majority studies do.

By categorizing the different studies of this review on the respective categories, clearly notice their common convergence point, related to the optimization techniques used. Genetic Algorithm is mostly used and enriched as a heuristic optimization methodology for calibration. An observed differentiation is the number of parameters as a measure to evaluate the consistency between field and simulated data, that is single parameter calibration method and multi-parameter method. Parametric and nonparametric statistical methods are another differentiation.

Due to the addressing of importance of inter-relationships between O-D matrices, and driver behavior parameters in the process calibration, is performed a methodology of be-level approach where the OD matrix and driver behavior are calibrated simultaneously.[2] The essential issue of this procedure is the calibration of the OD matrix with the incorporation of calibrated parameters performed on the first level.

Application, exploiting, modification and sophistication of the optimization algorithms seem to be a co-mutual effort that pursue the nowadays researching frameworks from classical algorithms as NMA to heuristic optimization techniques such as GA, PSO, PA-DDS, except of SPSA [1],[12],[14] and [17] respectively.

Due to its flexibility on finding the optimal solutions, enormous utility of GA dates very early in the overall processes of different optimization efforts as well as on the microscopic model calibration issues. Results from the reviewed paper which employed GA showed improved results on the calibration comparatively to the older methods as Monte-Carlo or trial-error methods.

Because of their possibilities and affectivity for multi-criterion calibration, an important attention should be given to lately developed heuristic and meta-heuristic methodologies as PSO, PA-DDS and OTEE.

SPSA is a stochastic approximation method which can be applied in both stochastic gradient and gradient-free settings and also can be applied to solve optimization problems that have a large number of variables.

Acknowledgements

*I am grateful for the support and assistance provided during the work of this paper to bright professor **Kristi Bombol!***

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