Development of a Tool for an Efficient Calibration of CORSIM Models

Final Report

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Augost, 2014

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EXECUTIVE SUMMARY

This project proposes a Memetic Algorithm (MA) for the calibration of microscopic traffic flow simulation models. The proposed MA includes a combination of genetic and simulated annealing algorithms. The genetic algorithm performs the exploration of the search space and identifies a zone were a possible global solution can be located. After this zone has been found the simulated annealing algorithm refines the search and locates an optimal set of parameters within that zone. The design and implementation of this methodology seeks to enable the generalized calibration of microscopic traffic flow models. Two different CORSIM vehicular traffic systems were calibrated. All parameters after the calibration were within reasonable boundaries. The calibration methodology has been developed independently of the characteristics of the traffic flow models. Hence, it is likely to be easily used for the calibration of any other model. The proposed methodology has the capability to calibrate all model parameters considering multiple performance measures and time periods simultaneously. A comparison between the proposed MA and the SPSA algorithm was provided. The results are similar; however, the effort required to fine-tune the MA is considerably small compared to the SPSA. The running time of the MA-based calibration is larger compared to the SPSA. The MA still requires some knowledge of the model in order to set adequate optimization parameters. The perturbation of the parameters during the mutation process must be large enough to create a measurable change in the objective function but not too large to avoid noisy measurements.

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INTRODUCTION

The calibration of traffic flow simulation models continues to be an open area of research. The various frameworks that have been proposed in the literature to address the associated optimization problem *(1)* are not general enough to provide adequate results for the large number of available simulation models and required traffic scenarios. Figure 1 illustrates the general conceptual calibration process where model inputs are adjusted between realistic boundaries until simulation results are reasonable close to field measurements *(2)*. That is, the optimization problem seeks for the values required by the parameters of the simulation model so as to minimize the difference between simulation outputs and the corresponding field measurements.
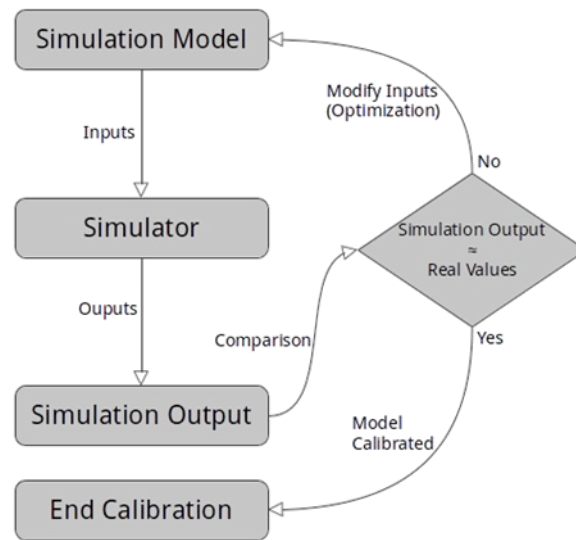
FIGURE 1 Conceptual calibration process

The solution space of the optimization problem is defined by the range of model parameters. A broad number of algorithms have been proposed to solve the optimization problem for a particular traffic flow system and/or simulation model. Some of the proposed algorithms include evolutionary approaches such as genetic algorithms *(3)(4)*. Others claim that metaheuristics can provide better results *(5)*. The sequential simplex algorithm was used to calibrate parameters for car-following, acceleration/deceleration, and lane-changing behavior *(6)*. However, only a subset of parameters was considered. Moreover, the required computational time is considerably high and the solution could be a local optima. Stochastic approximation methodologies were used for the simultaneous calibration of traffic flow model parameters *(7)(8)(9)*. Although the methodology can provide adequate results, a complex fine-tune process of the algorithmic parameters is required for each model *(10)*.

Although the research community has produced a large number of approaches for the calibration of simulation-based traffic flow models, a single automated methodology capable of calibrating various simulation models and traffic scenarios is not yet available in the literature. The primary challenge is the lack of a generalized optimizer algorithm. Clearly, the lack of a generalized optimizer is not a problem exclusive of the calibration of traffic flow models. Many other engineering and designer problems face the same issue. This has motivated the

development of memetic algorithms (MA) which combine global and local research mechanisms. That is, memetic algorithms combine an extensive search of the best zones on the search space (exploration) and a more detailed search is performed on the zones with better possible solutions (exploitation). The equilibrium between exploration and exploitation improves the results *(11)*. Hence, memetic algorithms are particularly convenient for problems involving large search space.

Depending on the mechanisms chosen for global and local search, a memetic algorithm can be implemented and used relatively easy and with little need for fine-tuning of its model parameters. Hence for practical purposes, memetic algorithms can provide better results than other well established approaches such as genetic algorithms, tabu search, and simulated annealing*(12)*.

In this study, a memetic algorithm is proposed to search for the values of the parameters used by the traffic flow simulation model so as to minimize the difference between simulation and the corresponding field measurements. Previous studies have either considered a subset of model parameters, a single performance measure was used, or fine-tune was required for the parameters used by the optimization algorithm. The proposed methodology implements a MA to determine an adequate set of all model parameters. To the best knowledge of the authors MAs have not been used for the calibration of traffic flow models. The proposed algorithm seeks to minimize user intervention during the calibration process. The parameters used by the proposed MA are relatively simple to fine-tune and independent of the characteristics of the traffic flow simulation model *(13)(14)*. During the experiments, various simulation models and scenarios were calibrated with a memetic algorithm using the same values for its parameters. Optimization algorithms in the existing literature involve an extensive sensitivity analysis of the algorithm parameters. In addition, most methodologies require pre-calibrated model parameters and/or demand patterns to achieve adequate results *(15)(16)*.

SECTION 1: METHODOLOGY

Formulation of the Calibration Problem

The calibration of the simulation model parameters, θ, is formulated using mathematical programing approach. The analysis period is divided into a number T of discrete time periods. The objective function, normalized root mean square ($NRMS$), is provided by Equation (1). The NRMS is the sum over all calibration time-periods of the weighted average of the sum over all links N of the root square of the square of the normalized differences between actual and simulated performance measurements. The normalization enables the consideration of multiple performance measures simultaneously. The calibration problem using vehicle counts and speeds as performance measures is formulated as follows:

$$\text{Minimize } NRMS = \frac{1}{\sqrt{N}} * \sum_{t=1}^{T}\left(W * \sqrt{\sum_{i=1}^{N}\left(\frac{V_{i,t}-\tilde{V}(\theta)_{i,t}}{V_{i,t}}\right)^2} + (1-W) * \sqrt{\sum_{i=1}^{N}\left(\frac{S_{i,t}-\tilde{S}(\theta)_{i,t}}{S_{i,t}}\right)^2} \right) \quad (1)$$

Subject to:

Lower bound $\leq \theta \leq$ Upper bound

where:

$V_{i,t}$ = actual link counts for link i and time t,

$\tilde{V}(\theta)_{i,t}$ = simulated link counts for link i and time t

$S_{i,t}$ = actual speeds for link i and time t

$\tilde{S}(\theta)_{i,t}$ = simulated speeds for link i and time t

N = total number of links in the model,
T = total number of time periods t, and
W = weight used to assign more or less value to counts and speeds.

Calibration criteria

The guidelines provided by the Federal Highway Administration for CORSIM models were used in this study. The difference between actual and simulated link counts should be less than 5% for all links; and, the GEH statistic (17) should be less than 5 for at least 85% of the links. The GEH statistic is calculated as follows:

$$GEH = \sqrt{\frac{2(V_i - \tilde{V}(\theta)_i)^2}{V_i + \tilde{V}(\theta)_i}} \quad (2)$$

V_i = actual link counts for link i, and

$\tilde{V}(\theta)_i$ = simulated link counts for link i.

Memetic algorithms

Concepts from evolutionary optimizations such as population and individuals are used in the formulation. An individual θ represents a vector of parameters containing a solution of the optimization problem. Each individual has a measure of effectiveness, functional adaptation. The algorithm seeks to create a population through the generation and conservation of appropriate individuals (exploration). The best individuals are used to generate new populations through the iterative steps of the algorithm. Additionally, after the best individuals are selected the exploitation process refines the search in order to obtain better solutions *(11)*.

The proposed MA integrates a genetic *(18)* and simulated annealing *(19)* algorithm. The genetic algorithm is used for exploration and the simulated annealing algorithm is used for exploitation. After the stopping criteria are met, the best individual is stored and the population is reset. The generation of new populations helps the algorithm to avoid local optima.
The MA is implemented using the following steps:

Step 0: (Initial *Population*):
Generate an initial population with 128 individuals. This population is randomly generated using constraints to avoid unrealistic values.
Step 1: (*Parents* selection):
Parent selection is performed using "roulette wheel selection" conserving and paring the best 60% individuals.
Step 2: (Crossover):
A crossover process is used to combine parents to generate new individuals (children).
Step 3: (Mutation):
Small perturbations (± 1%) are applied to approximately 30 % (mutation percentage) of the parameters of each child in order to explore nearby solutions.
Step 4: (Population management strategy):
If the new child is better compared to older individuals, the new child will replace the worst individuals.
Step 5: (Exploitation - Simulated Annealing (SA)):
Step A: Create a neighbor around the best mutation. A sub-set (30%) of the parameters is randomly modified by adding +1% or -1% with a probability of 50% each.
Step B: If the neighbor is better than the current best result, the neighbor replaces the best result and the algorithm goes to Step C. If the neighbor is not better, the temperature and the evaluation of the objective function are used to calculate the probability (Pro) of selecting or not the neighbor as the starting point for the next iteration of Simulated Annealing. Equation (3) provides the probability of selecting the neighbor.

$$Pro = e^{\frac{NRMS\_neighbor \ - \ NRMS\_best}{Temperature}} \tag{3}$$

$$Temperature = Temperature - Cooling \ Rate$$

Step C: The stopping criteria is provided below. If stopping criteria is met, go to Step 6 of the GA. Otherwise, go to Step A.

Step 6: If the stopping criteria is met, store the best individual and go to Step 0; otherwise, go to Step 1.

The initial population, selection, crossover, mutation, and replace percentages were assigned following recommendations in literature. *(12)(13) (15)*.

Stopping Criteria

Equation (3) is used as stopping criteria. When this inequality is satisfied or a pre-specified maximum number of iterations is reached, the stopping criteria is met.

$$\frac{\sum_{k-n+1}^{k} \sqrt{(NRMS_{AV} - NRMS_k)^2}}{n} < \rho \tag{3}$$

where,

$NRMS_{AV}$ = average *NRMS* of the last *n* iterations,
$NRMS_k$ = *NRMS* at k iteration,
k = iteration counter,
n = pre-specified integer = 10, and
ρ = pre-specified convergence condition = 0.015.

At least 10 iterations are required before Equation (3) can be used and the stopping criteria can be evaluated. The experiments conducted as part of this research required no more than three population resets.

SECTION 2: EXPERIMENTS AND RESULTS

Micro-simulation Model

The proposed methodology was tested using CORSIM models. CORSIM integrates FRESIM (Freeway simulation) and NETSIM (Arterial simulation) to represent the complete traffic environment *(20)(21)*. The *Traffic Analysis Toolbox Volume IV: Guidelines for Applying CORSIM Micro-simulation Modeling Software (22)* describes a manual procedure for the calibration of CORSIM micro-simulation models. However, these guidelines do not suggest a particular methodology to perform the calibration in an efficient and effective manner. Issues associated with convergence and stability of the solutions during the calibration are not discussed. Nonetheless, alternative studies have proposed and developed practical procedures to accelerate the calibration process, which is typically time consuming *(23)*.

Calibration Parameters for CORSIM Models

CORSIM involves driver behavior and vehicle performance parameters *(20)(21)*. These parameters can be global or local (individual links). In addition, they are defined for arterial, freeways, or both simultaneously. Table 1 shows the different parameters that can be used for the calibration of CORSIM models *(24)*. Several studies have conducted sensitivity analysis for the calibration of CORSIM models *(25)*. The calibration parameters have different effects for specific networks and conditions. The interaction between these parameters is very complex and varies from model to model. As a starting point, the proposed methodology uses a randomly generated set of CORSIM values for the parameters listed in Table 1. These values are generated within realistic bounds. A random generation of these values decreases the human effort during the calibration setup. During calibration, the value of the selected parameters is adjusted while constraining their boundaries.

Experimental Setup and Results

Two experiments are used to test the proposed methodology. The first experiment uses a model for a portion of the Pyramid Highway in Reno, NV. The second experiment uses a hypothetical network provided by McTrans. A software tool was developed to implement the proposed calibration methodology. The tool uses a basic layered architecture were each layer handles a group of related functions. The entire software was developed in Java and it includes more than 5086 lines of code. Java was chosen due to its capability to handle complex data structures and implementing complex mathematical functions. The specifications of the equipment used to perform the calibrations are mentioned below.

System specifications
Operative System: Windows Server, Standard Edition, 2007, Service Pack 2 64Bit
System: Intel Xeon CPU E7450 2.4GHz (4 processors)
Ram memory: 32 GB

The parameters used in the experiments are as follows:
Exploration and exploitation algorithmic parameters:
Genetic Algorithm:
    Initial population = 128
    Selection Percentage = 60

Crossover Percentage = 50/50
Mutation Percentage = 30
Change Percentage = 1%

Simulated Annealing:
Initial Temperature = 0.045
Final Temperature = 0
Cooling Rate = 0.000135

TABLE 1 Calibration Parameters for NETSIM and FRESIM Models

NETSIM Model – Surface streets		
Driver Behavior	**Vehicle Performance**	**Demand Patterns**
• Queue discharge headway • Start-up lost time • Distribution of free-flow speed by driver type • Mean duration of parking maneuvers • Lane change parameters • Maximum left and right turning speeds • Probability of joining spillback • Probability of left turn jumpers and laggers • Gap acceptance at stop signs • Gap acceptance for left and right turns • Pedestrian delays • Driver familiarity with their path	• Speed and acceleration characteristics • Fleet distribution and passenger occupancy	• Surface street turn movements
FRESIM Model – Freeways		
Driver Behavior	**Vehicle Performance**	**Demand Patterns**
• Mean start-up delay at ramp meters • Distribution of free flow speed by driver type • Incident rubbernecking factor • Car-following sensitivity factor • Lane change gap acceptance parameters • Parameters that affect the number of discretionary lane changes	• Speed and acceleration characteristics • Fleet distribution and passenger occupancy • Maximum deceleration	• Freeway turn movements

First Experiment: Pyramid Highway in Reno, NV

In the first experiment, a CORSIM model of the pyramid Highway in Reno, NV was calibrated. The calibration was performed using vehicle counts and speeds as field measurements. This model includes a total of 126 arterial links. Data was available for 45 of these links. Figure 2 *(a)* shows a Google map screenshot and the *(b)* CORSIM model of the Pyramid highway.

<div align="center">(a)   (b)</div>
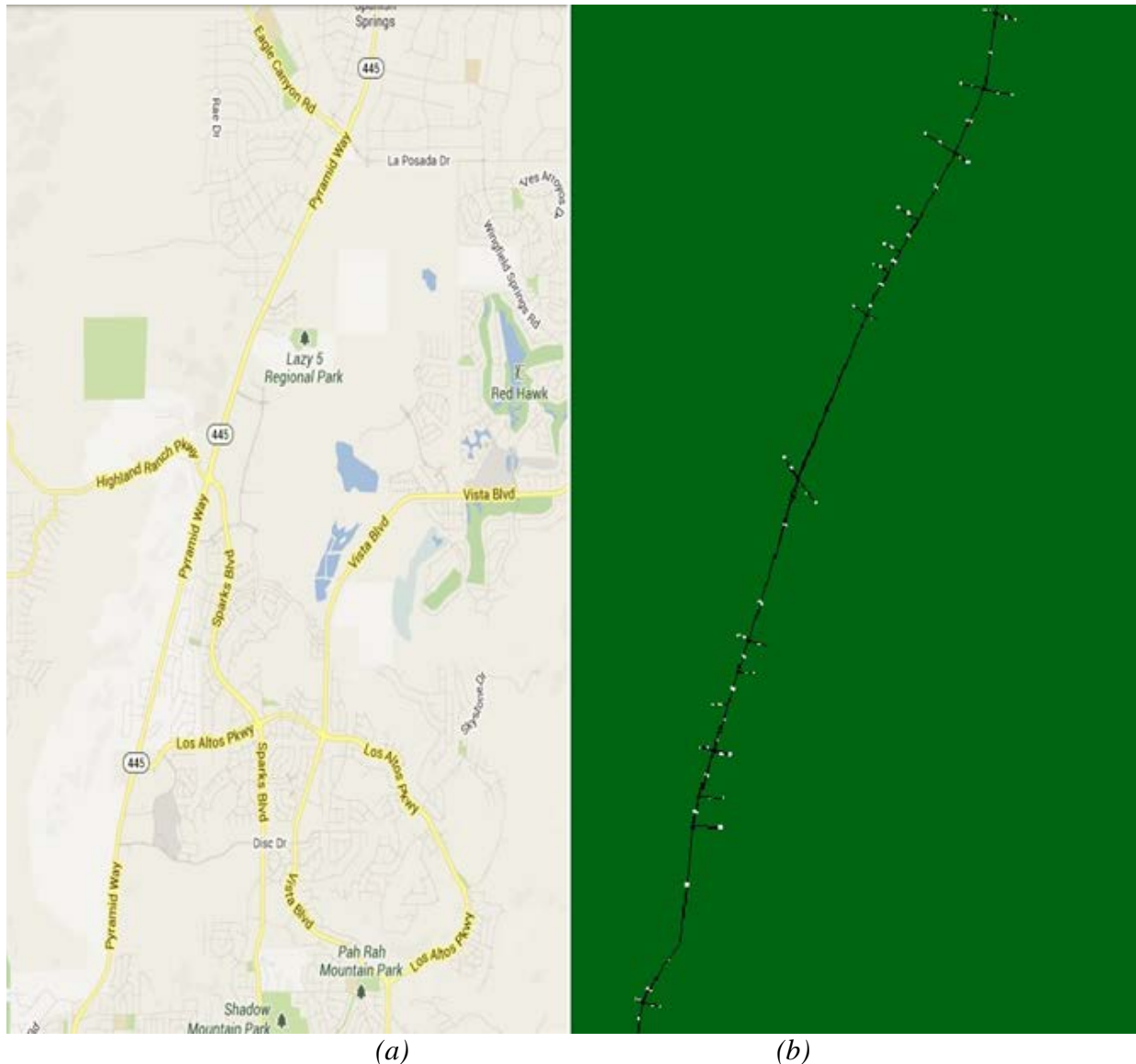
FIGURE 2 Pyramid Highway, Reno, NV, (a) Google Map, (b) CORSIM Model.

Figure 3 shows the improvement of the objective function during the calibration process. The concept of improvement rather than iteration is used here to illustrate the results. An improvement is achieved every time that the objective function provides a smaller NRMS compare to the existing best result. This removes all the noise associated with the random component of the search process. The initial value of the objective function was 0.42. After 77 improvement steps, the NRMS decreased to 0.10.
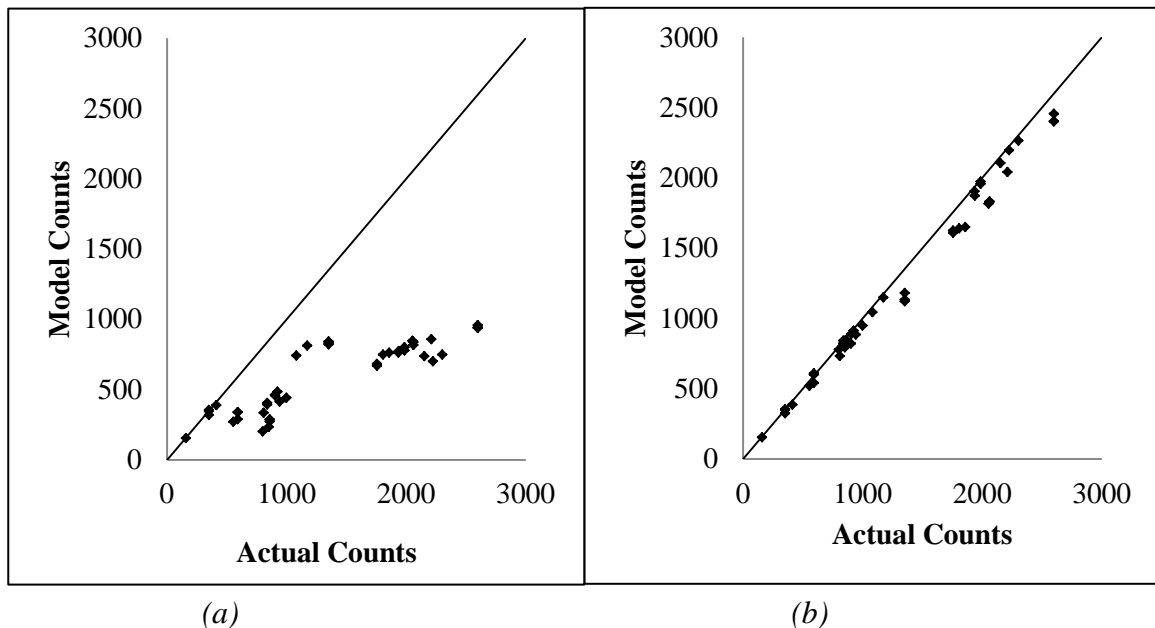
Figure 4 represents vehicle counts before and after calibration. The 45 degree line represents the state where model counts and field measurements perfectly match for each link. The initial values are far from the 45 degree line especially for higher counts. After the calibration, the counts were improved for all the links and the model represents field counts more accurately.

Similarly to Figure 4, Figure 5 shows the speed values before and after calibration for the 45 links with data available. The speed vales were improved specially for the lower values in

Figure 5 (a). The proposed MA algorithm was able to modify the more biased values at higher rates than values closer to the 45 degree line. This capability is important for the calibration of networks with zones under congested conditions.
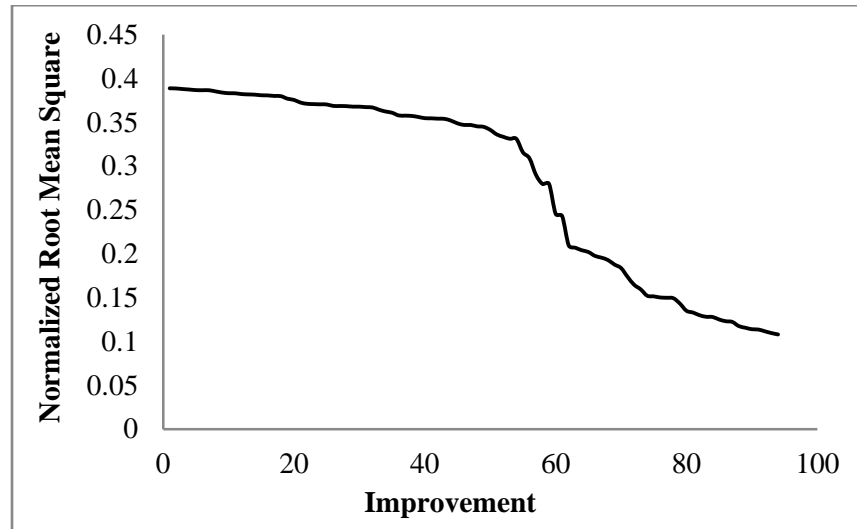

FIGURE 3 Objective function improvement.

(a)   *(b)*

FIGURE 4 Vehicle counts before *(a)* and after *(b)* calibration.

Figure 6 illustrates the GEH statistic for the model before and after the calibration process. The dotted line represents the initial condition of the model for the 45 links. The initial GEH value was less than 5 for approximately 11% of the links. The solid line represents the model condition after the calibration. The GEH was improved considerably, it got smaller than 5 for 89% of the links.

(a)   *(b)*
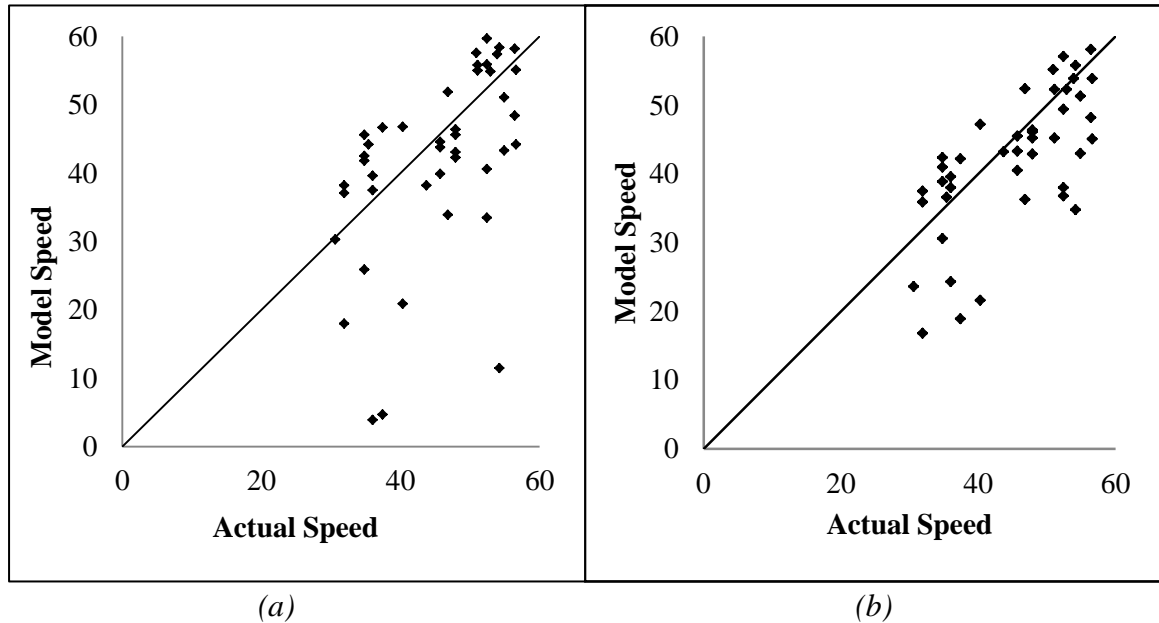
FIGURE 5 Speed values before *(a)* and after *(b)* calibration.
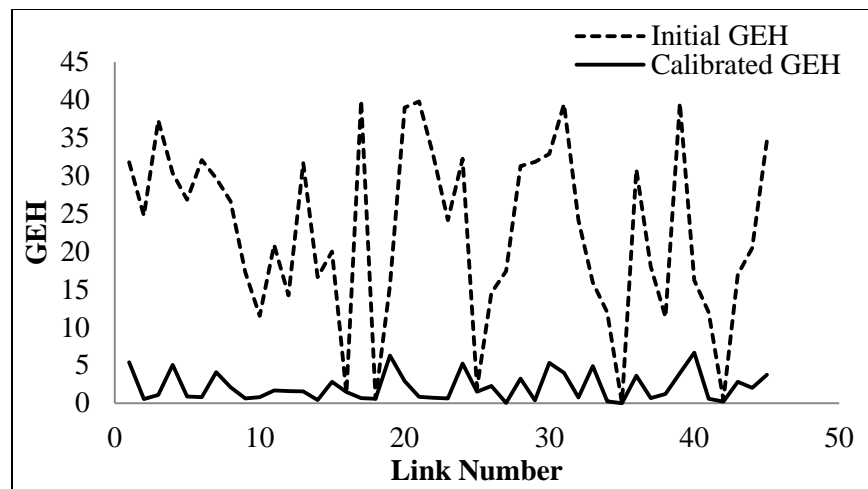

FIGURE 6 GEH Statistics.

Table 2 provides the summary of the calibration results. The NRMS and the GEH statistic were improved considerably. In addition, the total link counts are closer to the actual values after the calibration. The calibration criteria were met for this model.

TABLE 2 Summary of results for the first experiment

|	NRMS	Total link counts	GEH
Before calibration	0.42	45,359	< 5 for 11% of the cases
After calibration	0.10	55,956	< 5 for 89% of the cases
Actual		59,610	

Second Experiment: Example from McTrans data files

A network provided the McTrans was calibrated. The default parameters for this model were taken as the calibrated condition. The outputs from this default model were assigned as the field data for the experiment. Subsequently, all the calibration parameters were randomly modified. This modified model was used as a starting point for the calibration. This model includes a total of 20 arterial links. Vehicle counts and speed were simultaneously used to perform the calibration. Figure 7 shows the model used in this experiment.
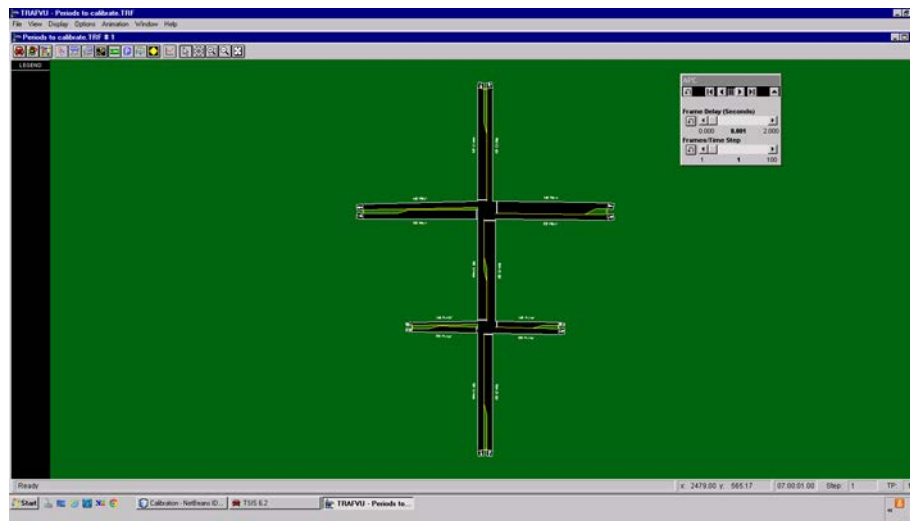
**FIGURE 7 McTrans data files CORSIM model.**

Figure 8 shows the improvement in the evaluation of the objective function during the calibration process for the second experiment. The initial value of the objective function was 0.36. After 94 improvement steps, the NRMS decreased to 0.05.
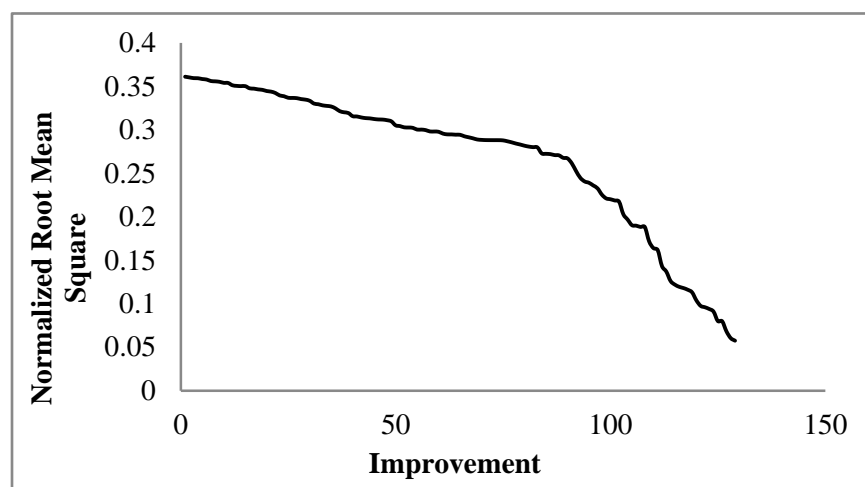
**FIGURE 8 Objective function improvement.**

Vehicle counts before and after calibration are shown in Figure 9. Even though the initial condition of the model was close to meet the calibration criteria, the proposed methodology improved the results for all the links in the network.


(a)   *(b)*
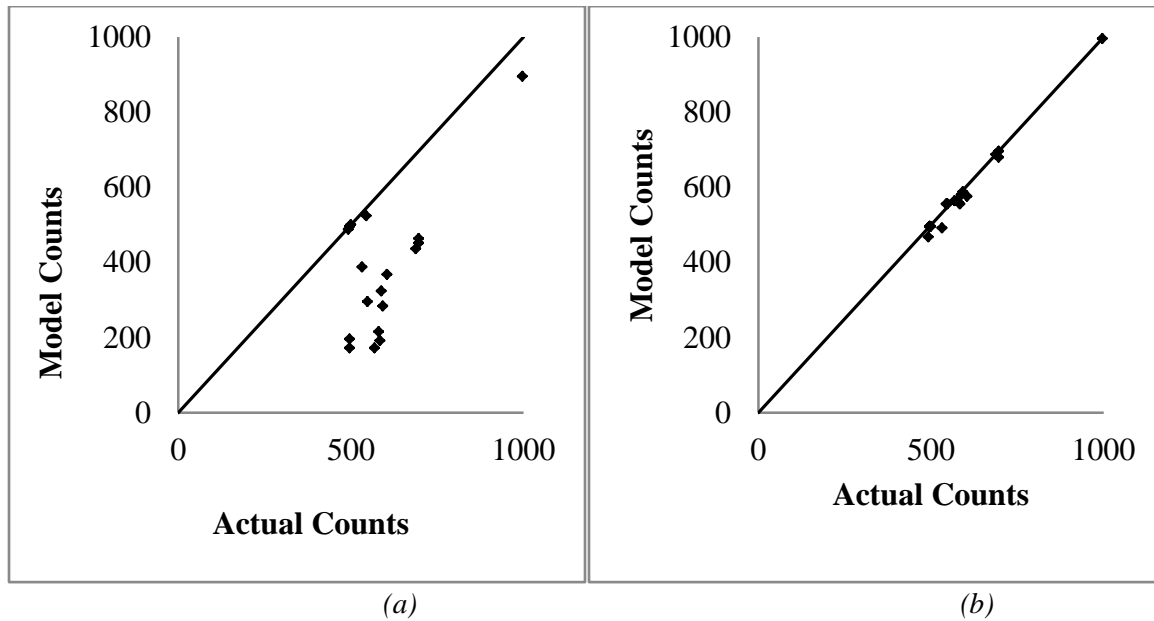
FIGURE 9 Vehicle counts before *(a)* and after *(b)* calibration.

For the second experiment the speed values were considerably improved compared to the results from the first experiment. Figure 10 shows the speeds for the before and after calibration conditions of the model. This improvement is due the accuracy of the model used.

(a)   *(b)*
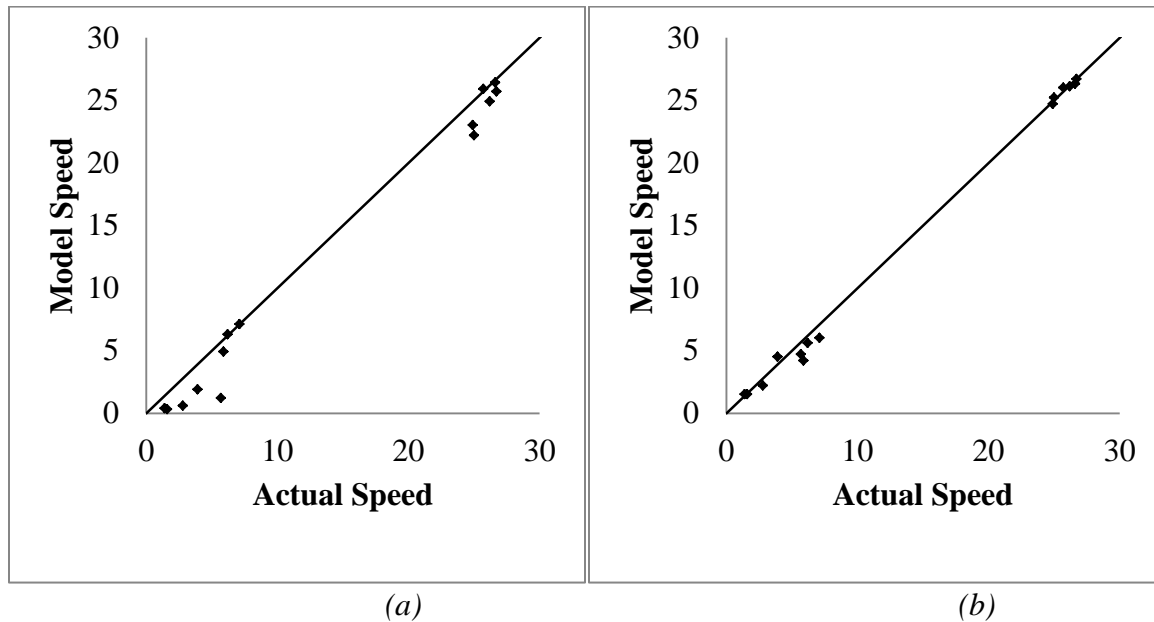
FIGURE 10 Speed values before *(a)* and after *(b)* calibration.

Figure 11 illustrates the GEH statistic for the model before and after the calibration process. The dotted line represents the initial condition of the model for the 20 links. The initial GEH value was less than 5 for 30% of the links. The solid line represents the model condition after the calibration. The GEH was improved considerably. It was lower than 5 for 100% of the links.
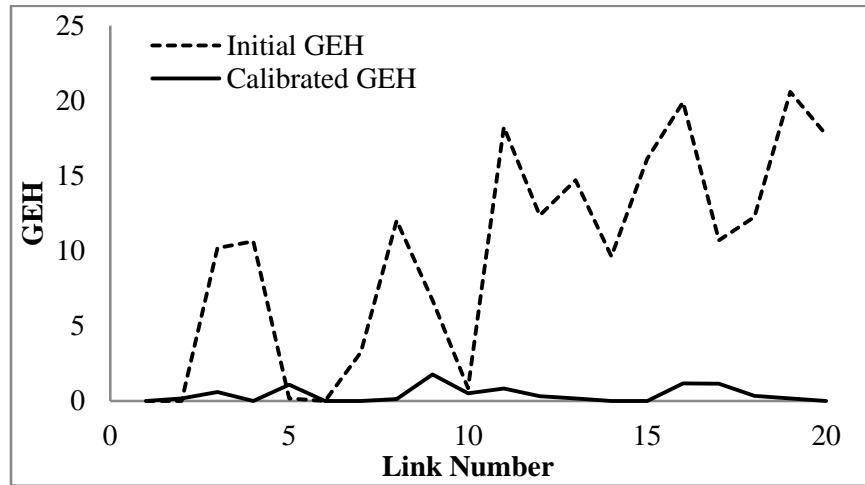
FIGURE 11 GEH Statistics.

Table 3 illustrates the summary of the calibration results for the second experiment. The NRMS and the GEH statistic were improved. In addition, the total link counts are closer to the actual values after the calibration. The calibration criteria were met for this model.

TABLE 3 Summary of results for the second experiment

	NRMS	Total link counts	GEH
Before calibration	0.361231	8,040	< 5 for 30% of the cases
After calibration	0.057464	12,072	< 5 for 100% of the cases
Actual		12,224	

.

SECTION 3: COMPARISON BETWEEN MA AND SPSA ALGORITHMS

In order to illustrated the advantages of the proposed MA, a comparison with the Stochastic Perturbation Simultaneous Approximation (SPSA) *(26)* algorithm is provided. That is, the performance of the two algorithms for the calibration of microsimulation traffic flow models is compared. The running time, efforts during both algorithms fine-tune process, and overall results are compared. A clear pattern to fine-tune the optimization parameters was not found for the SPSA. Hence, empirical methods were used to find a set of proper parameters. On the other hand, the selection of parameters for the MA is considerable simpler. Knowledge from previous studies was used to select proper parameters. In addition, it is highly likely that the parameters founded for the MA can be used for any other CORSIM model because they were determine without using any information about the simulation and the same parameters worked well for the two tested models. The results in terms of GEH and NRMS are slightly better for the SPSA algorithm. Running time is larger for the MA. However, the effort required to fine-tune the MA was considerably small compared to the SPSA algorithm. Considering that analyst time is very valuable, the MA appears to be superior for this particular application because its fine-tuning process is very short compared to the fine-tuning for the SPSA. Table 4 provides a summary of the approximate time and results for both algorithms.

TABLE 4 Comparison between MA and SPSA

| Experiment/Criteria	MA		SPSA	
	Reno Network	**McTrans**	**Reno Network**	**McTrans**
Running Time	20.76 hours	13.3 hours	25.5 minutes	10 minutes
Root Mean Square	0.108	0.057	0.10	0.09
GEH	< 5 for 89% cases	< 5 for 100% cases	< 5 for 100% cases	< 5 for 100% cases
Time required for fine-tuning parameters	1 hour		20 hours	

SECTION 5: CALIBRATION TOOL USER'S GUIDE

CORSIM categorizes all inputs into sets named, record types. Geometry, traffic flow, and calibration parameters are grouped in different record types. Inputs are stored in text files with extension .trf. A calibration tool was developed to implement the proposed calibration methodology to update all parameters in the .trf file. A graphical user interface (GUI) is used to facilitate the calibration process, which involves five steps as depicted below.
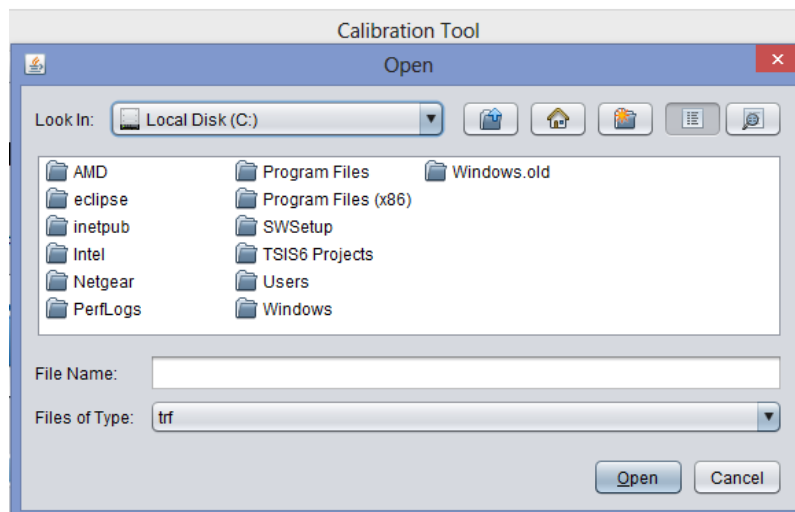
Step 1: Network Selection
The first step requires locating the .trf file with the corresponding CORSIM model. From the main menu, click on 'Select a .trf File' and browse to the location of the file in the disk.
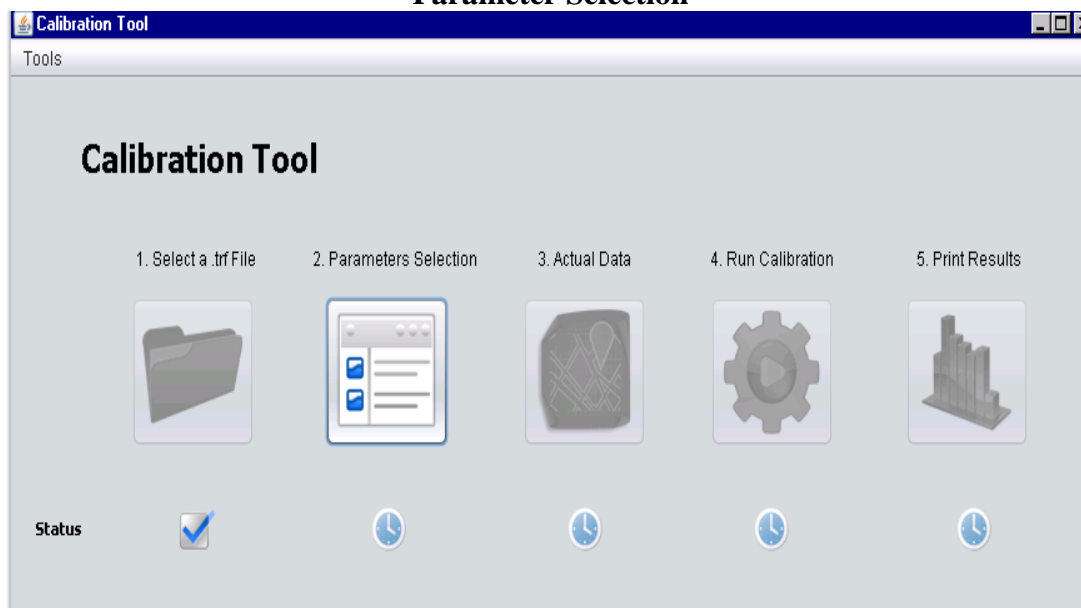
**Step 1: GUI - Calibration Tool -Main Menu**
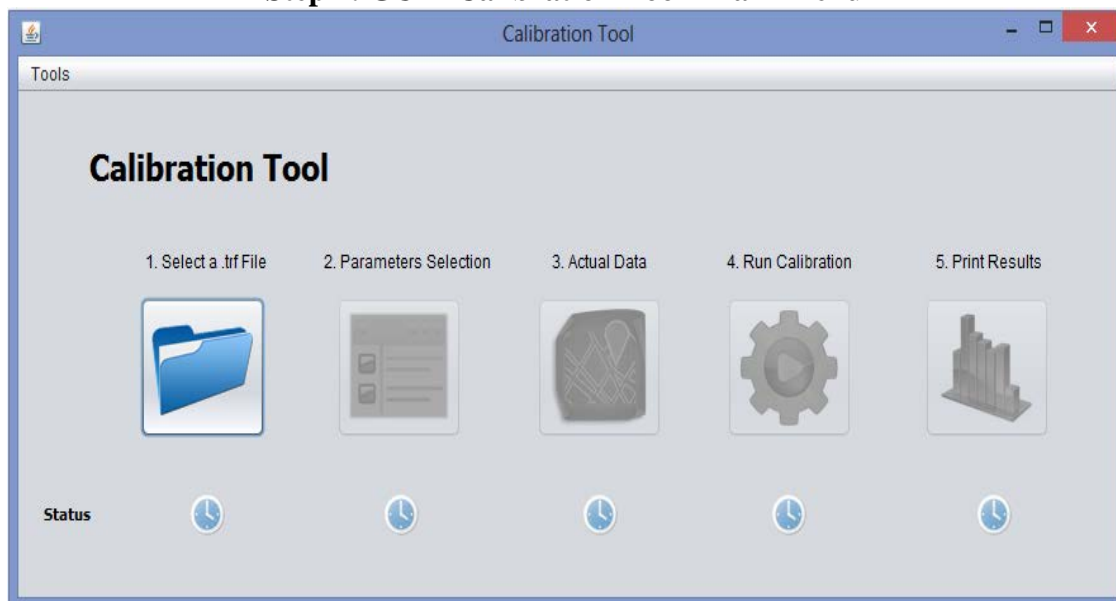
Browser

Step 2: Parameter Selection

In this step, the parameters for calibration are selected along with their initial values. Default values are available through 'Use Default Parameters'. However, these parameters can be edited as desired or required by using the editor menu, as shown below.
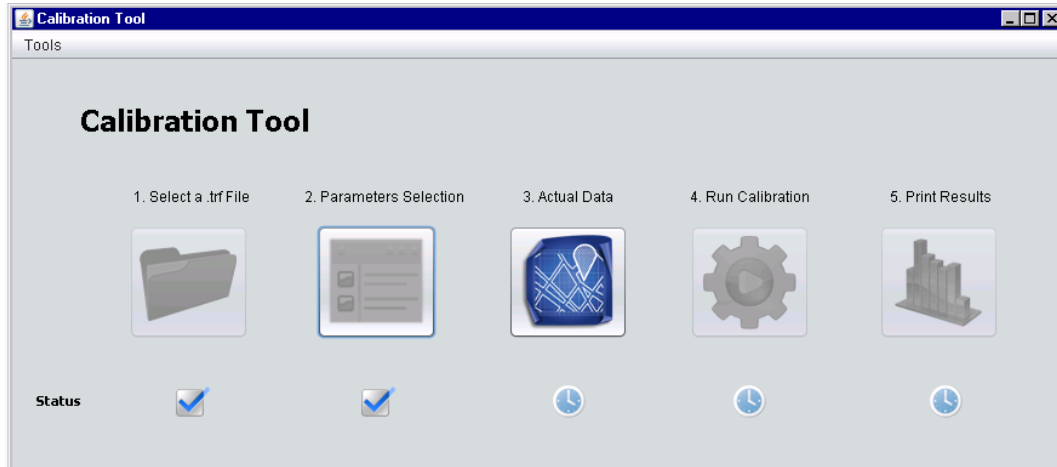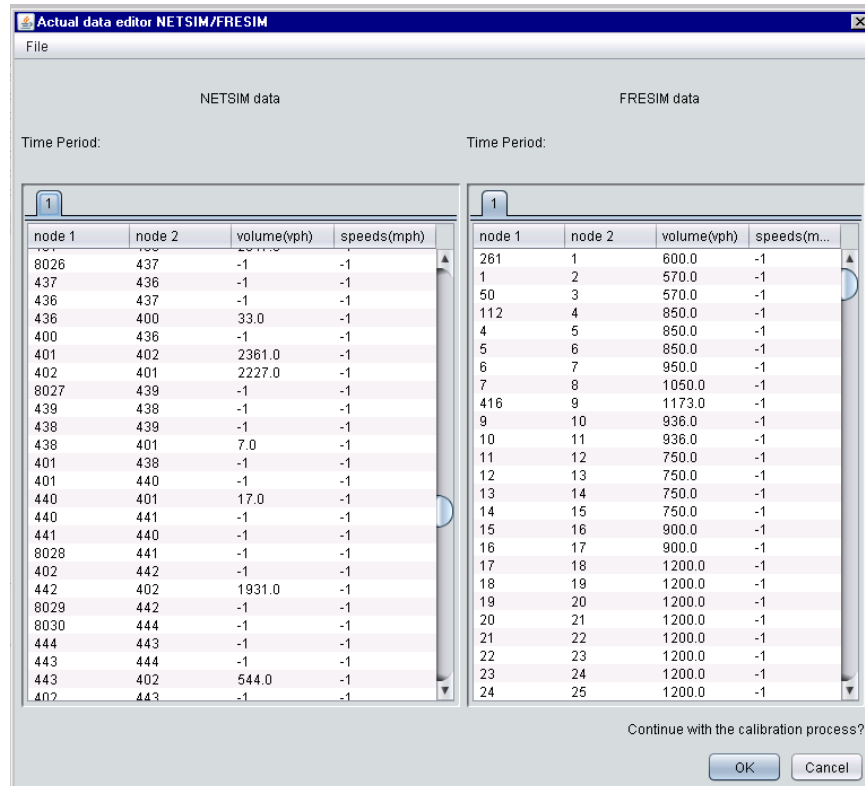
Parameter Selection

Parameters Editor
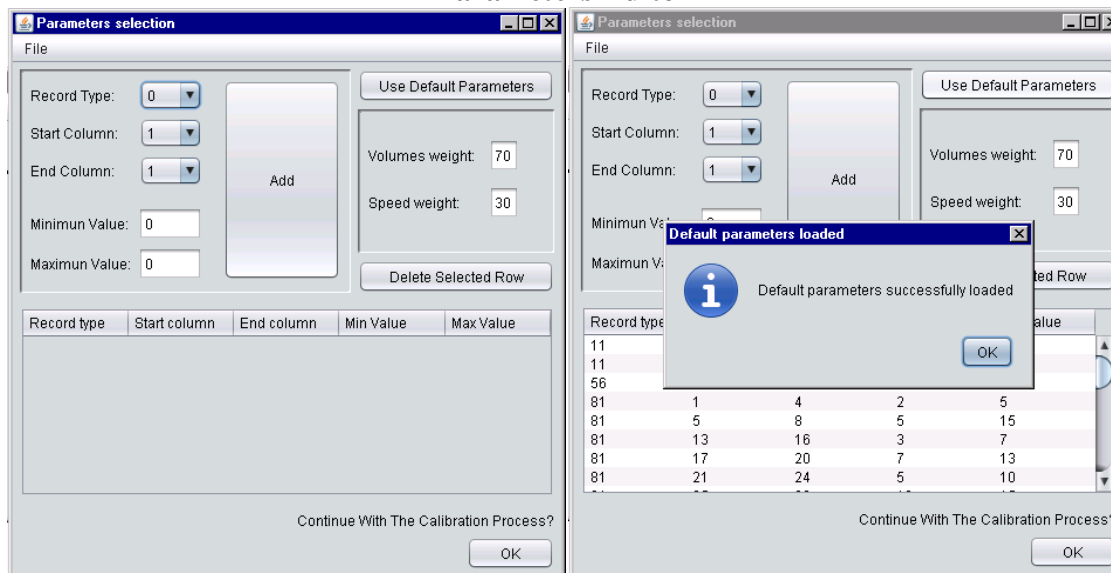
Step 3: Loading of Actual Data

This step involves loading the actual vehicle counts and/or speeds for calibration. An editable table is provided for the user to enter manually the available data. This table allows saving and modifying values at any time.
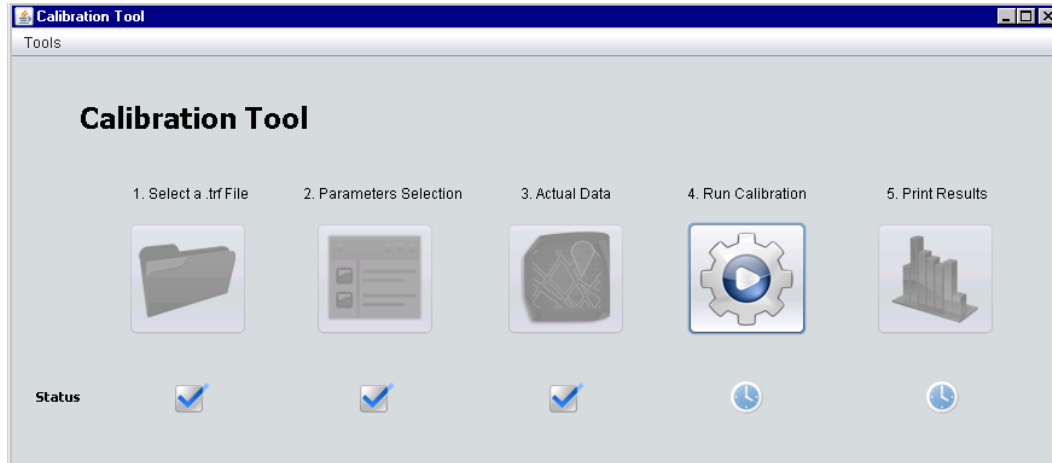
Actual Data

Data Editor

Step 4: Search of Parameters

Once the actual data is uploaded, 'Run Calibration' is used to execute the proposed calibration approach to find the set of parameters that minimizes the difference between actual and simulated network states.
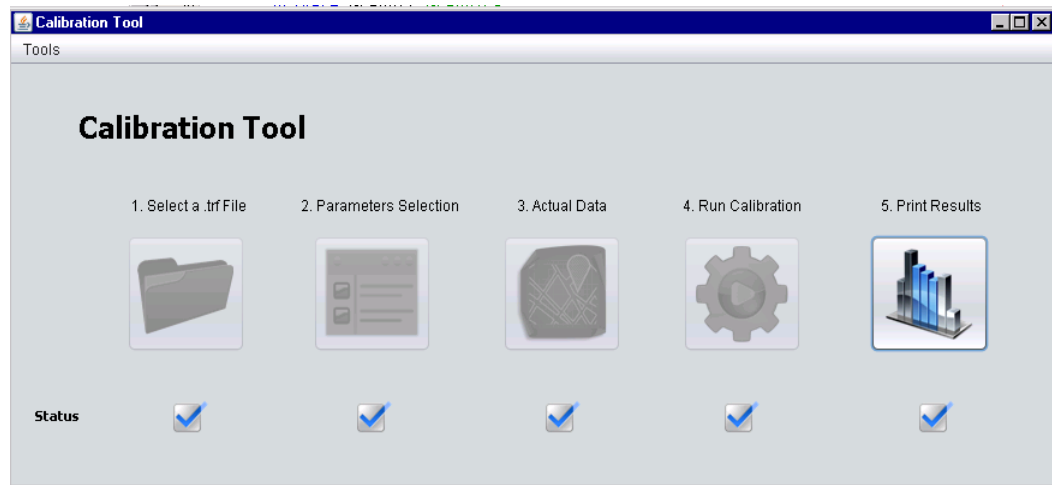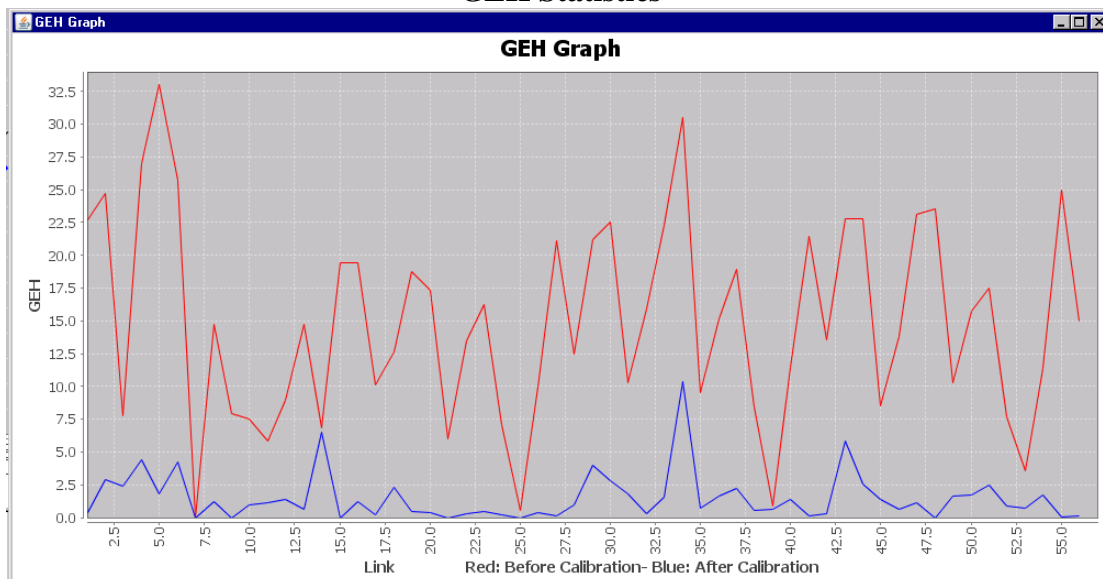
Run Calibration

Step 5: Visualization of Results

Once the search process has determined the desired set of parameters, charts are generated to illustrate the quality of calibrated model relative to the actual data. Three sets of graphs are generated, including the GEH statistics, the 'before' and 'after' counts, and the speeds before and after the calibration. The calibrated .trf file replaces the original file.
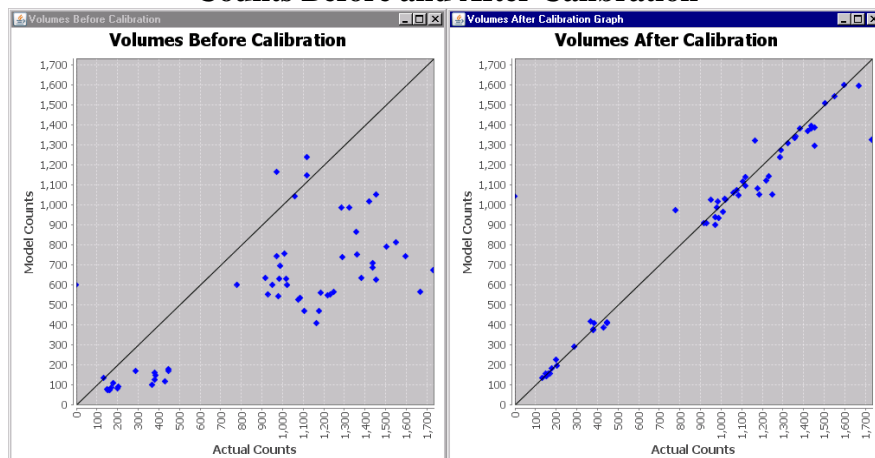
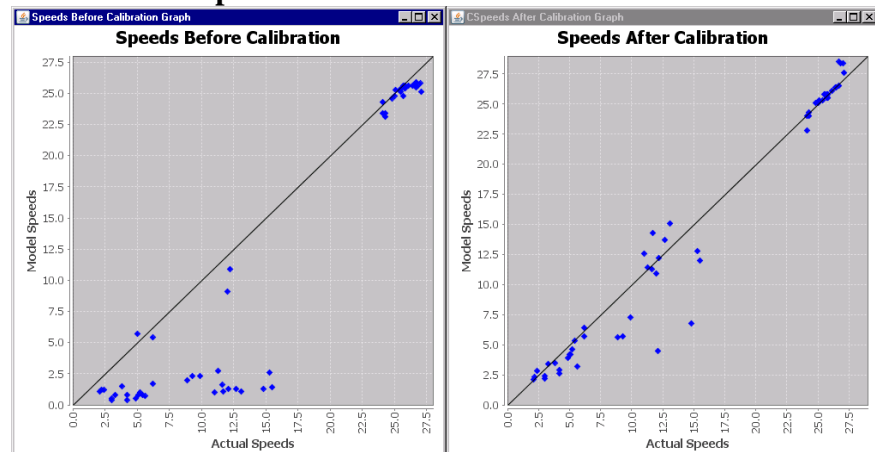**Visualization of Results**

GEH Statistics

Counts Before and After Calibration

Speeds Before and After Calibration

Conclusions

This study proposes a Memetic Algorithm (MA) for the calibration of traffic flow models. The proposed MA is composed mainly by a genetic and a simulated annealing algorithm. The genetic algorithm performs the exploration of the search space and identifies a zone were a possible global solution can be located. After this zone has been found the simulated annealing algorithm refines the search and locates an optimal set of parameters into that zone, this process is called exploitation. The design and implementation of this methodology seeks to enable the generalized calibration of microscopic traffic flow models. Two different CORSIM vehicular traffic systems were calibrated and all parameters after the calibration were within reasonable boundaries. The first model is a network from the Pyramid highway in Reno, Nevada. Vehicle counts and speeds were available for 45 from the 216 links on it. The second network was a model from the McTrans data files. However, the calibration methodology has been developed independently of the characteristics of the traffic flow model and can be implemented for any other models. The proposed methodology has the capability to calibrate all the model parameters considering multiple performance measures and time periods simultaneously.

A comparison between the proposed MA and the SPSA algorithm is presented. The results are similar however the effort required to fine-tune the Memetic algorithm (MA) is considerably small compared to the SPSA algorithm. The running time of the MA-based calibration process is larger than the one sing the SPSA algorithm. However, user intervention has been minimized. The experiments for the MA were set from an arbitrary set of initial calibration parameters. This decreases the effort and time for the calibration process due the minimization of the user intervention. Moreover, the models do not need pre-calibration or sensitivity analysis of the model parameters.

A limitation of the propose methodology is the need of knowledge of the model in order to assign MA parameters. The perturbation of the parameters during the mutation process must be low enough to create a measurable change in the objective function and not large enough to create noisy measurements of the objective function. This perturbation values affect directly the convergence of the algorithm. However, this fine-tune process is simpler than for other methodologies.

Acknowledgements

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