An Efficient Soft Computing Based Method for Calibration of Vehicular Microscopic Simulation Models

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ABSTRACT

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Hamed Shahrokhi Shahraki

In recent years, due to the advances in computation technology, microscopic vehicular traffic simulation has become one of the main tools used by transportation professionals to solve various design and analysis problems (e.g. safety performance evaluation of highways, impact of different design scenarios in units of safety and efficiency, etc.). The effective use of any of the existing simulation models is limited by the calibration of specific parameters that are based on observed real-life conditions. However, because the calibration of the simulation models is a time consuming and resource intensive process, one might resort to using the default parameter values. In this study, a soft computing-based methodology which synergistically combines Artificial Neural Networks and Genetic Algorithm (GA) applications, is proposed as an alternative for calibration methodology that considerably reduces the computation time in comparison to other commonly used methods. First, a Latin Hypercube Sampling method is used to select representative sets of values for VISSIM's main calibration parameters. Second, the effect of each set of parameter values on the simulated traffic stream speed is recorded. Third, a neural-network is trained to determine the relationship between the input parameter values and the output vehicular speed. Finally, a genetic-algorithm uses the trained neural-network in its fitness function to determine the appropriate set of

values for the calibration parameters. The proposed methodology allows for the calibration of microscopic traffic models with fewer computational resources than is commonly used. The feasibility of the method and its applicability to real-world traffic conditions is proved by employing the model using a real-world High Occupancy Vehicle (HOV) lane along a freeway segment. The results of proposed calibration method are compared with those from GA-only based calibration method.. It is concluded that the proposed method performs faster than the GA based calibration method while maintinaing a certain level of accuracy. To highlight the potential benefits of the proposed calibration method, a before-and-after calibration conflict analysis is presented. It is recommended to apply the proposed method to urban environments and to consider other performance measures (travel time, queue length, etc.) to investigate proposed method's generality.

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Besides, I would like to dedicate my thesis to my parents and my two brothers for their immense love and unconditional support, without them this dissertation would not have come to end.

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LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
DOT	Department of Transportation
MTQ	Ministère des Transports du Québec
FHWA	Federal Highway Administration
HOV	High Occupancy Vehicle
GP	General Purpose
GA	Genetic Algorithm
SA	Simulated Annealing
EA	Evolutionary Algorithms
ANN	Artificial Neural Network
ANN-GA	Artificial Neural Network-Genetic Algorithm
NCHRP	National Cooperative Highway Research Program
LHS	Latin Hypercube Sampling
TRB	Transportation Research Board
MSE	Mean Square Error
API	Application Programming Interface
COM	Component Object Model

CHAPTER 1: INTRODUCTION

1.1 Background

Due to advances in computation technology vehicular microscopic simulation models became one of the main tools used by transportation professionals to solve various problems in design and analysis. For example, evaluation of safety performance of different design scenarios, transportation network's effectiveness analysis, signal design, and many more applications. The level of detail of the outputs of these models depend on the need, and it can vary from microscopic (vehicle trajectories, individual travel time, speed, etc.) to macroscopic (average travel time, queue length, average speed, etc.). Some examples of these vehicular microscopic simulation models are as: VISSIM, CORSIM, AIMSUN, etc.

These models use some adjustable parameters to replicate the real life traffic conditions. This process is called calibration of vehicular microscopic simulation models. Henceforth, when the word calibration is used it means calibration of vehicular microscopic simulation models unless it is explicitly explained.

Extensive use of calibration parameters along with the stochastic nature of vehicle interactions, add considerable complexity to the modeling process and its implementation. Because of the intrinsic complexity of the simulation models, practitioners resort to using search-based heuristic algorithms for their calibration. As will be seen in the literature review chapter, there exists extensive use of the search-based heuristic algorithms for calibration of aforementioned simulation models.

1.2 Problem Statement

Many studies show that the current techniques used for calibration of vehicular microscopic simulation models are considered time consuming and computation intensive approaches. Because calibration is time consuming and computation intensive process, one might resort to using un-calibrated model while it rarely leads to reliable results. There have been very few studies that attempted to improve the calibration procedure in terms of optimization speed. Also, there have been no studies that attempted to compare the achieved accuracy of different calibration methods. Therefore, the shortcomings in the current state of practice in calibration based on the reviewed literature can be summarized as following:

- The current commonly search-based methods used for calibration processes are time consuming and one might resort to using un-calibrated model which seldom leads to accurate and reliable results.
- There are very few studies trying to improve the calibration procedure in terms of processing time specifically to improve the optimization speed.
- The accuracy of the calibrated parameters using different methods have not been investigated, based on the reviewed literature.

1.3 Research Objectives

With respect to the aforementioned problems, the major objective of this research is to develop a soft computing search based method that is attributed with less computation time while maintaining an acceptable level of accuracy. This objective can be reached by completing the following tasks:

- Identifying the current state of practice in calibration of vehicular microscopic simulation models.
- Developing a soft computing based approach that improves the currently used methods in optimization speed while keeping an acceptable accuracy.
- Verifying the feasibility and applicability of the proposed methodology for real case(s) of study.
- Establishing a comparison of optimization speed and accuracy to highlight the advantages of the proposed methodology.
- Highlighting the importance of calibration by employing a before-and-after calibration conflict analysis.

1.4 Thesis Organization

The thesis consists of seven chapters. Chapter 1 is the introduction section of the thesis and includes problem statement, research objectives, summary of the research methodology, and thesis organization. Chapter 2 presents an elaborated literature review on previous studies in calibration, surrogate safety measures, and an introduction to High Occupancy Vehicle (HOV) lanes and in Chapter 3, a comprehensive description of the proposed methodology is provided. Chapter 4 presents the data collection and analysis. Chapter 5 presents the application of the proposed methodology to real-world cases of study. The developed method is compared to Genetic Algorithm-based calibration, which is widely used in the calibration practices, in units of optimization speed and closeness of the results to the real filed measures. To highlight the importance of the proposed calibration method, a before-and-after calibration conflict analysis is presented in that chapter. Chapter 6 summarizes the conclusion and highlights of the results and lists the immediate recommendations and concepts for future research.

1.5 Limitations of the Study

The limitations encountered through this study can be stated as followings:

- Due to availability of the simulation platform, the proposed methodology is applied only to VISSIM as simulation platform. Upon the availability of the simulation platform, it is recommended to apply the proposed calibration method to test its generality.
- The proposed method is compared only to GA, while it is worth including other search-based optimization methods commonly used in the literature (e.g. Simulated Annealing (SA)). This will be possible by replacing the optimization method as SA rather than GA in minimizing the differences between simulated and field measures of network performance(s).

CHAPTER 2: LITERATURE REVIEW

2.1 Microscopic Vehicular Simulation Model

Most vehicular simulation models are computer implemented numerical models that simulate the transportation system by capturing the vehicle interactions at different levels of details (microscopic, mesoscopic, or macroscopic) to help with the planning, design, and analysis of transportation networks. Traffic simulation models can be useful when analytical methods could not be employed because of network complexity. Also, simulation models are useful when different scenarios have to be evaluated and analyzed, prior to real life deployment. Traffic simulation models can be classified based on the level of simulated details into microscopic, mesoscopic, and macroscopic. Within microscopic model, the network's interactions are captured at the vehicle level (e.g. CORSIM, VISSIM). Macroscopic models focus on the aggregate characteristics of traffic stream such as average speed and density of traffic flow (e.g. TransModeler, SYNCHRO). Mesocopic models are a combination of the previous two types, by considering the interaction between the platoons of vehicles for network analysis (e.g. DynusT).

A typical traffic simulation model consists of several sub-models developed to emulate different components of the simulation process. Examples of frequently-used simulation models are VISSIM, PARAMICS, CORSIM, and AIMSUN. VISSIM is used as the simulation platform in this thesis, and a brief description is presented here.

VISSIM is a stochastic, behavior-based microscopic simulation software which is developed based on psycho-physical driving behavior theory of Wiedemann (PTV

(2011)). The modeling approach assumes that the deceleration and acceleration are based on driver's perception of speed and spacing between themselves and the vehicles in front. Stochastic distributions of vehicles speed and spacing replicates the individual driving behavior.

VISSIM utilizes several models to control the different driving behaviors (e.g. car following, lane changing, lateral behaviour, amber behaviour, etc.). Each of these models is controlled by some adjustable parameters. For example the car following model considers that the driver can be in one of the four following states:

- Free driving: no influence from the observable preceding vehicles. In this mode, the driver will drive at its desired speed not constant but oscillating around that.
- Approaching: in this state, the driver adapts his own speed to the lower speed of the preceding vehicle by decelerating. The speed differentials of the two will be zero while the follower keeps its safety distance.
- Following: the driver tries to keep the safety distance as constant as possible regardless of the acceleration/deceleration values. In this state also the speed differential of the vehicles oscillates around zero.
- Braking: in this situation the safety distance of the follower falls below the safety distance and the follower vehicle applies braking to avoid collision until it reaches the minimum safety distance.

The simulation model can model and analyze transportation systems under some specific constraints such as geometric configuration, type of users, traffic signals, etc.

The performance measures generated by VISSIM can range from individual vehicle assessment to overall network performance; some examples of outputs are: individual and aggregated speed, vehicles' trajectories, travel time, queue length, emissions, node assessment and more.

The links as the basic modeling component in VISSIM represent the physical transportation infrastructure. Vehicles can be routed throughout the network, from one link to another via the link connectors. VISSIM network can include additional attributes and characteristics such as types of users, desired destinations and route choice, traffic signals, and data collection points, etc.

As previously mentioned, the microscopic vehicular simulation models use some adjustable parameters to replicate the real life traffic conditions. The process of adjusting the parameters is called calibration of vehicular microscopic simulation models. In the following chapter, a summary of the previous studies in the area are presented.

2.2 Calibration Methods

There are many studies that investigated the calibration of vehicular microscopic simulation models. This section presents a summary of the reviewed relevant studies in the area.

Kim and Rilett (2007) proposed a sequential simplex-based method to calibrate vehicular microscopic simulation models. The proposed methodology was applied to TRANSIM and CORSIM models of an interstate highway in Texas to replicate traffic volumes at the link level given the origin-destination (O-D) matrix. Different traffic behavior parameters (e.g. lane changing, acceleration and deceleration rate, car following sensitivity parameters, etc.) were considered for calibrating CORSIM. For TRANSYM the following parameters were used in the proposed calibration procedure: the deceleration probability, the lane-change probability, and the plan look-ahead distance. The authors concluded that the model calibrated with the proposed method leads to better results when compared to the usual manual calibration or to using the default parameters. The authors concluded that with the decrease of congestion, the performance of the proposed method is decreased when compared to default parameters and manual calibration method.

Yu et al. (2006) proposed a GA-based approach for calibration of driving behavior of a VISSIM model developed for a case study of a corridor equipped with Bus Rapid Transit (BRT) in China. The authors used GPS collected speed data as a validation performance measure. The calibrated parameters were the waiting time before diffusion, the minimum headway (front/rear), the maximum deceleration, the accepted deceleration, the maximum look ahead distance, the average standstill distance, the additive part of desired safety distance, the multiple part of desired safety distance, and the distance of standing. The resulted set of parameters was validated by being exposed to VISSIM model of an intersection to replicate the traffic volumes. MATLAB GA toolbox was used to implement the GA algorithm. Based on the results it was concluded that the proposed approach can be used for practical purposes. To verify the versatility of the proposed method, the authors suggested the inclusion of more performance measures (e.g. delay, queue length, etc.) in the objective function as well as applying the method to other networks.

Zhizhou and Jian (2005) also used GA-based optimization to calibrate driving behavior parameters of VISSIM for an expressway model in Shanghai. The authors used a sensitivity analysis to determine that the following driving behavior parameters significantly affect speed and volume of the network: the desired speed in reduced speed area, the desired lane-change distance (DLCD), the average desired distance between stopped cars (CC0), the headway time (in second) that a driver wants to maintain at a certain speed (CC1), and the safety distance a driver allows before he intentionally moves closer to the car in front (CC2). GA optimization is implemented with the objective to minimize the root mean square error (RMSE) between the simulated and real values of speed and volume. The method was found to lead to more accurate results in comparison with the default set of parameters.

Park (2006) applied the GA-based optimization to calibrate VISSIM model of a work zone parameters that impact the network travel time. The authors seek to minimize the difference between the simulated and real travel time. The following parameters were found to have a significant impact on the travel time: the speed distribution, the simulation time step, the waiting time before diffusion, the minimum headway (front/rear), the maximum deceleration, the reduction rate (meters per 1m/s2), the accepted deceleration (m/s2), and the number of observed preceding vehicles. It was concluded that the calibrated parameters resulted by applying the proposed method can successfully replicate the real life condition.

To validate the proposed GA-based calibration method Park et al. (2006) applied it to a corridor equipped with 12 coordinated actuated signalized intersections in Virginia. CORSIM and VISSIM were used as simulation platforms. The corresponding driving behavior parameters were calibrated using the real travel time values. The authors concluded that the method is applicable to complex traffic conditions. The method specifies the effective ranges of parameters by employing a Latin Hypercube Sampling (LHS) experiment design method.

Cheu et al. (1998) used GA to calibrate the FERSIM model of a 5.8 km section of the Ayer Ranjar expressway in Singapore. The GA-based optimization adjusted the network free flow speed and several driver behavior parameters. The method was validated by successfully minimizing the average absolute error between the simulated and field measured values of volume and speed.

Besides GA-based optimization, other studies used Simulated Annealing (SA) as another search-based algorithm used for calibration of traffic models. For example Sun et al. (2005) employed SA to find an optimal combination of parameters of VISSIM model that affect the studied network. The authors investigated four weaving sections in Shanghai, China. It was found that the calibration parameters are: the desired lane change distance, the waiting time before diffusion (WTBD), Wiedmann99 car-following parameters: the average desired distance between stopped cars (CC0), the headway time that a drivers want to keep at a certain speed (CC1), and the safety distance a driver allows before he intentionally moves closer to the car in front (CC2). The SA attempted to minimize the difference between the simulated and real speed on the weaving sections by searching through the effective parameters. Calibrated model's output values were found to match the speeds collected in the field.

Liu, Yang and Sun (2006) proposed a hybrid method that combines SA and GA for microscopic calibration purposes. The hybrid model combines the two methods to reduce the probability of reaching to a premature optima as a solution and to have a faster converging to the optimal solution. The authors applied this method to an urban roadway segment modeled in VISSIM. The following parameters were found sensitive to calibration process: the emergency stop distance, the lane change distance, the waiting time before diffusion, the minimum headway, the number of observed vehicle, the average standstill distance, the additive part of safety distance, and the multipliable part of safety distance. The calibrated parameters set were validated when the model could accurately replicate the observed real time traffic volume. In this study, the authors did not investigate how much faster the proposed method is when compared to using GA or SA solely.

Yang and Ozbay (2011) proposed a numerical optimization approach to calibrate traffic simulation model for safety analysis purposes. The goal of the study was to calibrate a PARAMICS model of a highway to accurately replicate rear-end traffic conflict risk. The validation measure was the root mean square percentage error of traffic conflict, lane changing, traffic count and speed. The highway of study was located near Los Angeles and Next Generation Simulation (NGSIM) data was used. The authors used a stochastic gradient approximation algorithm that search for an optimal set of modeling parameters. Considering the traffic conflict, lane changing, traffic count and speed as the network's overall performance, some parameters controlling lane changing, gap acceptance and car following behavior were found effective. The calibrated set was found to be more accurate when the results are compared to best guessed and default set of parameters.

Kang et al. (2009) used the orthogonal experiment method to calibrate the parameters of VISSIM models of some intersections. The methodology has been devised in three steps: first the calibration target is determined, second the parameters to be modified were selected and, third the orthogonal experiment method was employed to adjust the ranges of parameters and to search for optimal set of parameters that best replicate the case of study. It was found that the following parameters affect the network in relation to through vehicles delays: the look ahead distance, the observed vehicle, the minimum headway, the maximum deceleration, the average standstill distance, the additive part of desired safety distance, and the multiple part of desired safety distance. The method was found effective and practical by successfully calibrating the VISSIM model.

By use of Latin orthogonal square experiment method, Jinggue et al. (2009) calibrated driving behavior parameters of VISSIM. The investigated case study was a weaving section in Shanghai, China. The effect of the parameters on network travel time were evaluated and the following parameters were found to be effective: the standstill distance, the headway time, the following variation, the desired lane change, and the maximum deceleration for cooperative braking. The methodology comprises of two steps: first the parameters that lead to accurate volumes are selected and next, among those, the sets that best replicate the real speed are chosen as the optimal solution. Based on the results of this study, it was concluded that the calibrated VISSIM environment is suitable for capturing complex interactions between real-world vehicles.

Wang and Liu (2010) also implicitly utilized the orthogonal experiment for calibration purposes. The authors employed linear regression method using MATLAB toolbox for calibration of VISSIM driving behavior parameters when the travel time of the network was affected by that parameter. The model was set up and calibrated using the following collected data: geometry of the case study, signal timing, traffic flow, and entrance road delays as well as speed for three peak 15 minutes in morning, noon and afternoon. The following parameters were found effective in relation to the travel time of the network: the observed distance from the front, the observed number of vehicles from the front, the average stopping distance, the safe distance from the additive factor, the safe distance from the multiplication factor, the temporarily unconscious, the minimum headway (front/read), the maximum deceleration. The author measured the actual value of these three parameters: the observed distance from the front, the temporarily unconscious, and the maximum deceleration. To reduce the number of combinations of parameters, the authors employed the orthogonal experiment design. The authors concluded that the calibrated model using the proposed method can replicate accurately the condition on real life. To verify the versatility of the proposed method, the authors suggested to apply the method to variety of facilities.

Zhou et al. (2010) calibrated the parameters of a VISSIM model using a two-stage experimental optimization method for safety analysis purposes. The model was developed for a network of six intersections in Shanghai, China. For safety analysis, the authors used the Surrogate Safety Assessment Model (SSAM) software that takes the vehicles' trajectories as input and returns the conflict indices calculated based on the trajectories. The number of conflicts, velocity of conflicting vehicles and network delay were considered as measures of effectiveness. The following parameters were found to have impact on the network performance measures: the observed vehicle, the average standstill distance, the additive part of safety distance, the multiple part of safety distance, the waiting time before diffusion, minimum headway, the safety distance reduction factor, the maximum deceleration for cooperation braking, the reduction factor close to stop line, the end downstream of stop line, the own acceleration of necessary lane change, and the trailing vehicle acceleration of necessary lane change. The authors investigated three different types of conflicts in their study: rear-end, lane changing, and crossing conflict. It was concluded that the proposed approach is feasible and valid to be used in future research. The authors also concluded that the proposed method is theoretically suitable for mixed traffic, but additional study is required in order to include the conflicts between motorcycles and pedestrians/bicyclists.

Dowling et al. (2004) developed a three step top-down framework for calibration of microscopic vehicular simulation model. First, the capacity of the bottlenecks of the network is calibrated, next the flows at the non-bottlenecks are calibrated; in this step the route choice parameters are calibrated and finally the network's overall performance (e.g. travel time, delay, etc.) is calibrated to replicate the real life condition. At each step, global parameters are calibrated prior to link-level parameters. For capacity calibration the authors considered headway (mean headway for freeway and mean queue discharge headway for freeway) as a calibration effective factor. The calibration parameters used in the second level of the procedure are route choice parameters to better replicate the traffic volume on link level. For system performance calibration, delay, travel time and speed were considered as network's overall performance. The proposed method was successfully applied to a study area of an urban arterials consisting of some intersections with known travel time, delay, queue and speed values.

Fellendorf and Vortisch (2001) illustrated several methods to calibrate microscopic traffic simulation models. The authors calibrated the models by using car-following and lane-changing driving behavior, speed distribution, and speed-flow diagrams. The authors showed that the calibrated microscopic model can reasonably replicate the observed interactions by applying the speed-flow diagram to American and German highway facilities. The authors concluded that a smaller time step would lead to more accurate simulations by extracting vehicle trajectories using different time resolutions.

There exist three main criticisms against use of simulation models and the calibration in few studies of the reviewed literature:

- Simulation models are rarely validated while un-calibrated models would rarely leads to reliable results (Hourdakis (2003)).
- Calibration of microscopic simulation models is a time consuming and computation intensive process (Burghout (2004), Ge (2012), Zhang (2008), and Wu (2002)).
- There is no generic standard procedure that has been developed for calibration of microscopic vehicular simulation models (Ge (2012), Zhang (2008)).

Calibration of traffic simulation models was also identified by Park & Qi (2005) as a computation time intensive process and exhaustive search for optimal solution is oftentimes impossible and not an option to tackle calibration issue. This argument is also present in Zhang (2008), a study in which traffic volumes on link level of a PARAMICS model were calibrated given the Origin-Destination (OD) matrix. Burghout (2004) in his studies mentioned the current state of practice in calibration as processing time and resource intensive approaches. Ge (2012) mentioned that calibration of vehicular simulation models is very time consuming especially when large-scale networks are to be calibrated. Calibration is considered as the most time and computation intensive part in a simulation project in study of Zhang (2008). Wu (2002) believed that evaluating all proposed solution is the time consuming part of calibration process. In studies of Hourdakis (2003), an automatic calibration technique is introduced that can improve the optimization speed when compared to manual calibration.

Use of un-calibrated models in analysis which rarely leads to reliable results, is another criticism against traffic simulation models applications (Hourdakis (2003)). Also lack of standards by which the level of calibration, validation or verification of a model can be measured, is another issue mentioned by Hellinga (1998) and Burghout (2004).

The following issues are the major problems identified from the reviewed literature, and based on them the rest of the thesis was developed:

- One of the criticisms against the use of vehicular simulation models is that they are oftentimes used without prior calibration. This rarely leads to reliable results.
- Because of the complexity that is associated with calibration of vehicular microscopic simulation models, search-based techniques are frequently used for calibration purposes. GA, a search-based optimization algorithm, is the one that has been used most frequently. Conflicting objectives and modifying calibration parameters simultaneously are the main causes of complexity in the calibration procedure.
- Calibration of vehicular microscopic simulation models is considered as the most time consuming and computation intensive part of simulation projects. This issue has been mentioned in several studies as one of the concerns, but there are few studies that attempted to quantitatively compare optimization speed between different methods and tried to improve it. As was mentioned, evaluating proposed set of calibrated parameters is considered as the part that consumes time the most.
- Based on the reviewed literature, there seems to be no study that attempted to assess the level of accuracy of the simulation results when different calibration methods are compared.

2.3 Surrogate Safety Measures

This section presents a review of the existing studies related to one of the emerging safety analysis methods - surrogate safety measures analysis.

The new advances in computation technology along with the drawbacks in traditional crash-based method, resulted in shifting to surrogate safety measures analysis known as conflict analysis. The review of the following studies: Gettman & Head (2003), Saunier (2012), Gousios, et al. (2009), Ozbay, et al. (2008), Huang, et al. (2011), Chan (2006), Hyden (1977), and St-Aubin (2011) identified several limitations associated with crash data and the analysis. A complete definition of surrogate safety measures is presented in Table 1.

- Crash-based analysis is a retroactive method to help with identifying possible countermeasure while the proactive methods are thought to be more efficient.
- The crash events are rare and consequently, the collection of crash data is time consuming task and good data accuracy is often times difficult to achieve.
- There exist high costs associated with field data collection.
- The subjectivity that comes with the interpretation of field data, make them somehow unreliable because not all individuals perceive the safety conditions the same way.
- It is oftentimes difficult to attribute a single cause to a collision event and that makes the analysis more complex.
- Police and ambulance reports are oftentimes biased toward the responsibilities rather than causes of accident. Also the reports have different levels of details.

- Use of traditional crash data oftentimes lacks considering driver behaviors and the mechanism that causes the crash to occur.

The concept of vehicle conflict was first proposed by Hyden (1977) to be used as an alternative for safety studies that have some benefits over traditional accident-based safety studies. The author proposed the time left to accident occurrence as an indicator of seriousness of the interaction if the vehicles continue at the same speed and direction of their movements. To validate the proposed surrogate safety measure, the correlation between accident data and field detected conflicts was investigated for 115 intersections in Sweden (in Malmo and Stockholm); the conflict data were collected by trained observers for seven hours for each intersection and accident data (only the injury accident data) for those intersections were collected for seven to eight years and a correlation was found between the collected conflicts and the crash data.

The first generation of conflict-based analysis was based on the field observation of conflicts by trained observers. Because of subjectivity problems associated with observer-based conflict detection, the practice in conflict analysis has changed to new generations which are conflict detection based on video data analysis and microscopic simulation models. The following section provides a brief summary of research and studies conducted using this application.

Saunier and Sayed (2006), St-Aubin (2011), and Saunier (2012) developed and employed a new feature-tracking based methodology that analyzes the videos and extracts the vehicle trajectories. These trajectories can be used to extract a variety of information such as speed, surrogate safety measure, types of vehicles, etc. A software package called Traffic Intelligence was developed by the authors to implement the proposed methodology. The following steps are followed in the software: first a coordinate transformation must be performed based on the image coordinates of control points and the corresponding real world coordinates; this process is called camera calibration. Next, the moving features are detected in the video; the detected features are then grouped to form an object based on common attributes; the trajectories for all objects are calculated and saved to a database for each object; further information can be extracted from the objects' database. On the other hand, Gettman and Head (2003) developed a new methodology for calculating the surrogate safety measures from microscopic simulation models. This methodology was developed by the Federal Highway Administration (FHWA) and was validated by applying it to real scenarios. Based on the reviewed literature, the Time To Collision (TTC) has been extensively used for conflict detection. Gousios, Garber, and Liu (2009) applied two different definitions of surrogate safety measures, one is given as output of PARAMICS and the other is based on FHWA's definition. The authors concluded that the FHWA's definition of conflicts leads to a better correlation with the crash data. Conducting a sensitivity analysis, the authors calculated the best value of TTC that makes the highest correlation between the conflicts and collision. Also, the authors created a logarithmic relation between the crashes and conflicts. Ozbay et al. (2008) proposed two surrogate safety measures: 1) conflict severity and 2) conflict consequence severity. These are modified forms of previously defined surrogate measures. PARAMICS is used as the traffic simulation platform in the study. The authors concluded that the modified forms of surrogate measures lead to a better correlation with observed crash data and moreover, the modified surrogate safety measure can capture more conflict situation that would not be possible to capture by use of the traditional one. This was explained by the fact that the method considers the acceleration/deceleration of both follower and leader vehicles in the definition. Huang et al. (2011) investigated the correlation between observed conflicts and simulated conflicts that are extracted by Surrogate Safety Assessment Model (SSAM) providing the vehicles' trajectories of VISSIM. The TTC was used as surrogate safety measure in the study. The authors concluded that the correlation between the simulated and observed conflicts is strong when traffic volumes are relatively high. Chan (2006) developed a new conflict index and validated it by applying it to three intersections in California equipped with driver assistance system for left turning vehicles. The author concluded that the proposed index provides more information regarding the severity of conflicts compared to gap acceptance and TTC measures. The method was validated by use of ranking method that ranks the scenarios considering crashes and conflicts and then investigates the similarities between the two rankings. El-Basyouny and Sayed (2013) also investigated the relationship between collisions and conflicts. A two-step methodology was proposed where the conflicts are predicted in terms of geometric and traffic related parameters and then a relationship is developed that predicts the collisions based on the conflicts. The authors applied the proposed methodology to several intersections in British Columbia and concluded that there is a significant relationship between conflicts and collisions, which allows for conflicts to be used as a surrogate safety measure. St-Aubin (2011) studied the safety impacts of highway ramp with restrictions using surrogate safety measures from video data analysis, traditional accident data analysis as well as applying cross sectional and before-and-after comparison methods. The strategy is intended to mitigate traffic safety concerns associated with poor ramp design in urban areas by using pavement-marking techniques. The strategy simply bans lane changings near entrance and exit ramps in order to encourage drivers to perform the lane changing maneuver earlier. The author concludes that this strategy must be applied on a case-by-case basis because there are inconsistencies in the results across areas of study.

The definitions of the surrogate safety measures are adopted from the above literature and organized in Table 1.

Table 1: Surrogate safety measures description (adopted from Gettman & Head (2003))

Surrogate safety measure	Description
Time To Collision (TTC)	Expected time for two vehicles to collide if they remain at their present speed and on the same path.
Post Encroachment Time (PET)	Time lapse between end of encroachment of turning vehicle and the time that the through vehicle actually arrives at the potential point of collision.
Deceleration Rate (DR)	Rate at which crossing vehicle must decelerate to avoid collision.
Speed Differential (SD)	The speed differences between the two vehicles while they are on course of collision.

2.4 High Occupancy Vehicle (HOV) lanes

The proposed calibration methodology in this thesis is applied to high-occupancy vehicle (HOV) lanes. In this section a brief introduction of HOV lanes is presented.

Any auto vehicle carrying two or more persons at the same time can be classified as High Occupancy Vehicle (HOV). Examples of HOVs are private vehicles used by commuters for carpooling and other purposes, public transportation vehicles, taxis, etc. On the other hand, any vehicle carrying only the driver as the sole occupant is identified as a Single Occupancy Vehicle (SOV). If selected lanes along a roadway are specifically designated for the exclusive use of one or more HOV vehicle types, they are referred to as HOV lanes. Otherwise, all the other lanes along a roadway will be referred to as General Purpose (GP) lanes.

For safety and regulation purposes it is important to provide road users with adequate signage with respect to HOV facilities. The identification of HOV lanes is commonly done with a white diamond sign placed at various locations along the road (Figure 1). Although the geometric features of the HOV lanes may be similar to that of the GP lanes, the design and traffic control and operations of HOV lanes may be different from one type of lane to another. For example, with respect to bus-lanes, which is one type of HOV lane, because the vehicles allowed to use the lane are operated by professional drivers, different geometric characteristics (Jang, et al. (2009)) could be used for the design of these lanes (e.g. sight distance, speed, curve radius, etc.). In addition, other specific design elements can be included in the access-egress ramps and/or shoulders as illustrated in Figure 2 and Figure 3 (Dehghani, (1990)). With respect to regulation and operations, the HOV facilities might benefit from additional enforcement technologies ranging from different ITS deployments to more active presence of law enforcement patrols (MTO (2012)).

The HOV lanes can be classified based on four criteria: the type of access/egress, the operational treatment, the type of separation, and the functional classification based on the road type. The first criterion assesses the HOV facilities as either with continuous or with limited access. The HOV facilities with continuous access allow the access of eligible vehicles at any location the designated lane(s).

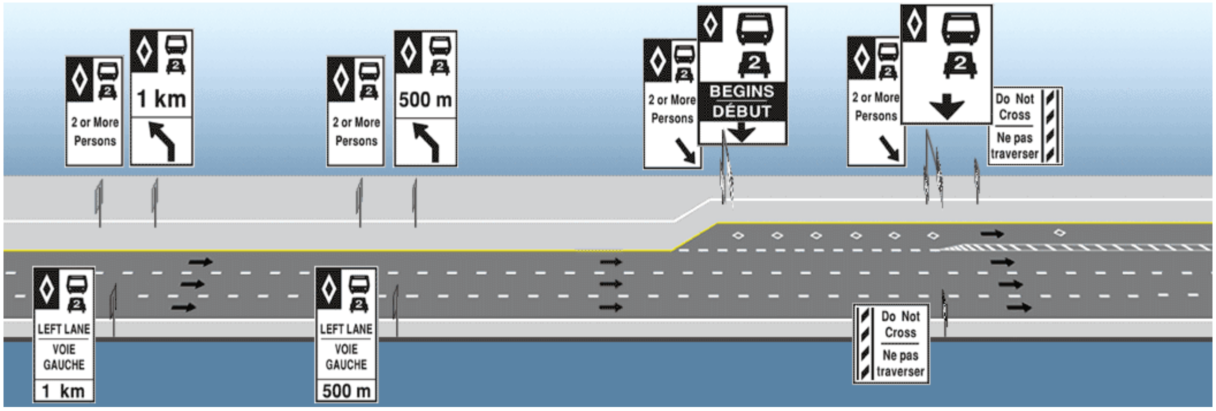


Figure 1: HOV lane identification and related signs (MTO (2012)).

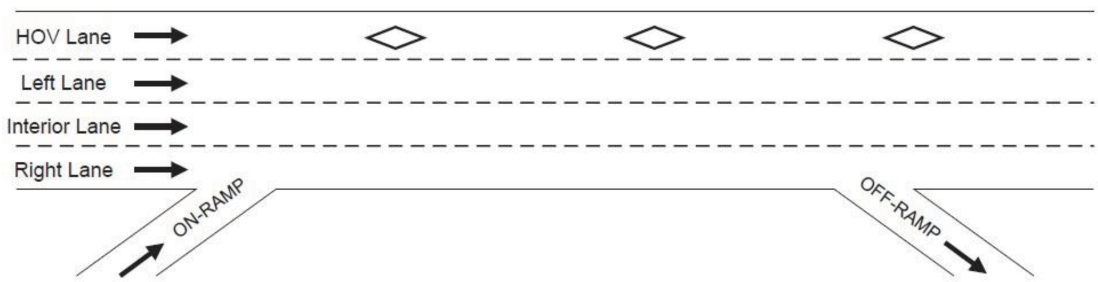


Figure 2: HOV lane with continuous access, (Jang, et al. (2009))

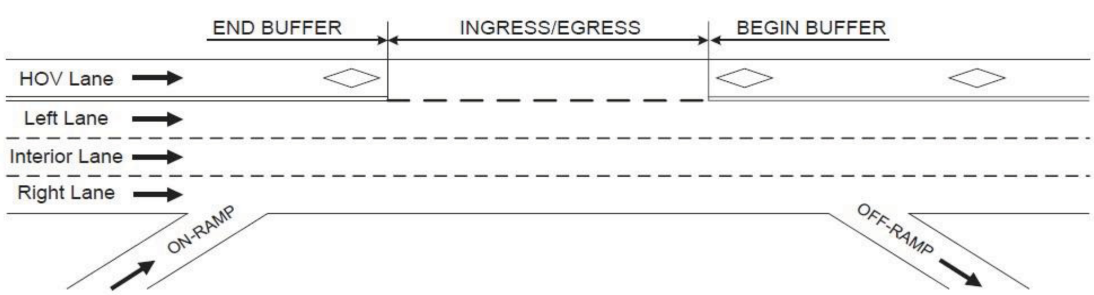


Figure 3: HOV lane with limited access (Jang et al. (2009))

On the other hand, HOV facilities with limited access are built to provide vehicle access at specific locations for ingress and egress (Jang et al. (2009)). To provide this type of HOV lanes, one has to consider a certain degree of separation from the GP lanes.

The second classification criterion focuses on the type of separation between the HOV and GP lanes, and places a HOV lane into one of the three groups: separated by a special pavement marking line, buffer separated, and physical barrier separated HOV lanes. Examples of possible designs are shown in Figure 4 and Figure 5. It can be seen that different types of separation have different benefits as well as drawbacks. For example, separation with just pavement marking is not recommended when road operators expect high speed differentials between the vehicles on the HOV and the GP lanes. On the other hand, a physical barrier is more costly and it may raise issues when emergency vehicles need to access the facility.

The third criterion considers the operational treatment and divides HOV lanes into four groups: concurrent, contraflow, reversible and two-way flow operations. Concurrent HOV lanes allow their users to move in the same direction as the traffic flow on the adjacent GP lane (Figure 4), as opposed to the contraflow HOV lanes that are designed to allow vehicle movements in the opposite direction of traffic flow along the GP lanes (Figure 5 and Figure 6). Usually the contraflow solution used due to constraints related to land development. The third type includes the reversible HOV lanes that allow vehicles movements in the peak direction of the GP lanes, alternatively in the morning and the afternoon peak periods (Figure 7). It can be seen that this design is also warranted when a limited right of way is available (e.g. bridges, mixed residential/commercial zones, etc.). The last type includes the two-way HOV lanes which are typically designed in the middle of the roadway to allow movements on HOV vehicles on both directions along two or more adjacent lanes (MTO (2012) and Ronglong (2010)).

Figure 4: Buffer-separated Concurrent HOV lane (Haljackey (2010))

Figure 5: Barrier-separated contraflow HOV lane (Turnbull (2003))

Figure 6: Contraflow HOV lane (Turnbull (2003))

Figure 7: Reversible HOV lane on the Champlain Bridge in Ottawa(Ball (2012))

Lastly, the fourth criterion categorizes the HOV lanes using the functional classification of highways. Hence, there are two types of HOV facilities: freeway and urban. In most settings the urban HOV lanes are deployed to promote the public transportation services and are placed at the right side. However, specific express lanes (often bus-only) may be implemented in the middle of the roadway to avoid safety issues related to speed differentials or right-turn movements at driveways or intersections

(Technical Committee on Public Transportation Facilities Design (2004), MTBC (2012)). Nevertheless most of the HOV lanes along the freeway are placed on the left side. For example, the barrier-separated HOV lanes which are usually located in the median (Technical Committee on Public Transportation Facilities Design (2004)) as well as most concurrent flow HOV lanes along freeway. However, interactions between HOV and GP lanes should be analyzed because of their influence on safety and travel-time reliability (Technical Committee on Public Transportation Facilities Design (2004)). In some cases where these facilities are used by buses on relatively short distances, the reserved lanes can be located on the right side of the traffic flow to allow for a more cost effective solution in addressing the access/egress design issues (Figure 8 and Figure 9).

Figure 8: Bus-lane on the right-side of a freeway near Grenoble (France) (Google ((2009))

Figure 9: Bus-lane on the right-side of the exit of a freeway near Grenoble (France) (Pollet, et al. (2005))

Based on the reviewed literature, it can be said that there exist no definitive guidelines to identify which safety elements should be considered for HOV design. Different HOV deployments should be considered (i.e. adding new lanes, converting GP lanes, using shoulders as reserved lanes, or simply re-aligning the existing roadway by reducing the width of the GP lanes). For each of these solutions there are various road-safety related problems, and many of them are investigated in different studies (Rees (2002); Farnsworth, et al. (1993) ; Case (1997) ; Golob et al. (1990) ; Jang, et al. (2009) ; Lee, et al. (2007)).

CHAPTER 3: METHODOLOGY

This thesis proposes a calibration methodology for traffic simulation models that employ the learning abilities of Artificial Neural Networks (ANNs) and optimization attribute of Genetic Algorithms (GAs). In this chapter the two aforementioned methods are explained. The proposed methodology is also presented. In addition, this chapter will also explain the GA-based calibration method in anticipation of the analysis comparison presented in the subsequent chapter.

3.1 Artificial Neural Network (ANN)

In the third step of the proposed methodology, an ANN is applied for prediction purposes. Artificial Neural Networks are mathematical structures built to emulate the behavior of the brain cells. The network is modeled via different transfer functions which are structured into layers and interconnected through weighted links that emulate the different degrees of connectivity in the brain cells. There exist a variety of structures developed for the artificial neural networks. One of the most commonly used and simplest structures proposed for the use of neural networks is the feedforward structure that is used in this study as well (Figure 10). The neurons in this structure are categorized into three different layers: the input layer, one or more hidden layers, and the output layer. The connections in this structure are directed forward from input layer to output layer. The structure itself forms a crude neural network which is nothing but sets of neurons interconnected through layers with unknown biases and weights. These weights and biases must be adjusted such that the errors between the ANN output and the observed output values must be minimized. This process is called neural network training. There exist many different algorithms developed for ANNs' training. The most common type is the backpropagation algorithm, which is used in this study and explained in the following section.

The backpropagation algorithm is a method used extensively for neural network training purposes. The algorithm is employed in this study as well. Backpropagation assigns some random values to biases and weights initially. The algorithm then adjusts the weights and biases in each iteration by exposing the network to the historical inputs and corresponding outputs with the purpose of minimizing the difference between predicted and real outputs. The new weights (biases) are functions of previous weights (biases), errors and the derivation of errors with respect to each unknown parameter (either biases or weights). This procedure continues until one of predefined termination criteria stops the process. The network then is prepared to be exposed to new input sets of parameters for prediction purposes (Bryson and Ho (1975); Werbos (1974); Alpaydin (2004); Rumelhart et al. (2002)).

The ANN functions in two modes: learning and recalling. Learning can be defined as the process of adjusting the weight and biases by exposing the untrained network to predefined sets of inputs and corresponding outputs with the goal of minimizing the difference between predicted and real outputs. Recalling is the process of exposing the trained network to a set of "unseen" input. The output predicted from this new input data is compared with the corresponding observed output and the quality of the trained network is evaluated (Zayed and Halpin (2005) and Hegazy and Moselhi (1994)).

ANN has been extensively used for data mining, prediction and pattern recognition, and other applications. ANNs have been successfully used when the relationship between the inputs and the outputs is not known or is difficult to model using analytical models (Elwakil (2011); Demuth, Beale, and Hagan (2009)).

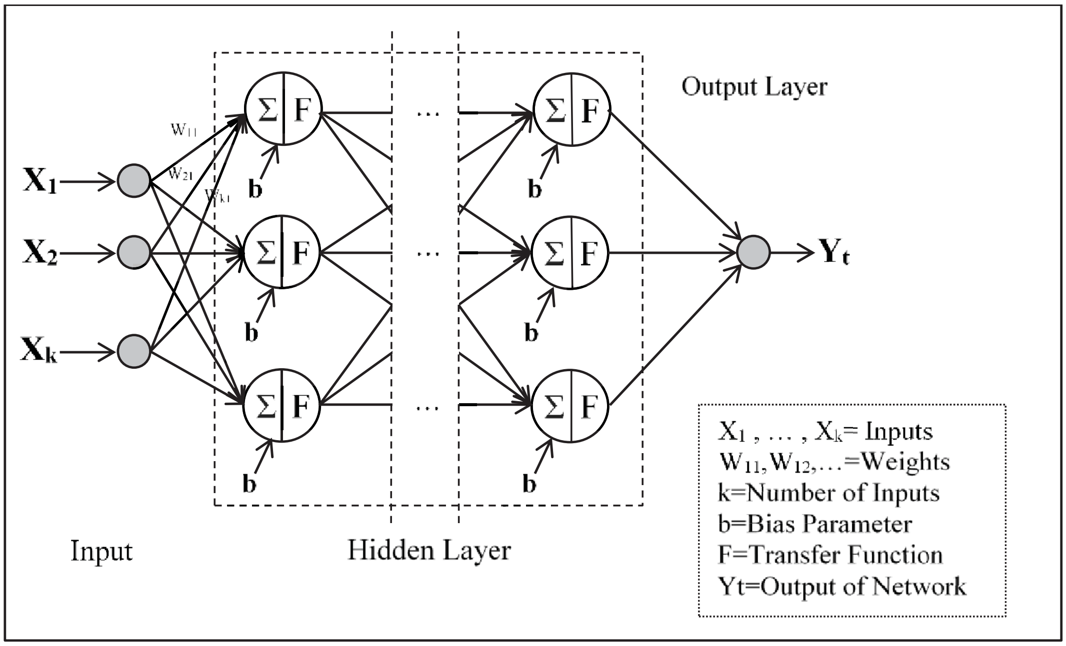


Figure 10: Schematic diagram of a multi-layer feed forward (Zhu, et al. (2007))

In recent years ANNs have been widely used in area of transportation and traffic engineering mainly for two types of applications prediction and data processing. Here are few examples presented for illustrative purposes. Alecsandru and Ishak (2004) used the neural network for short term prediction of traffic speeds. Rouhieh (2010) used the neural network method to make a compromise between safety and performance of an isolated intersection by modifying signal timing configuration. Yi et al. (2010) developed a clustering neural network for safety evaluation. The motivation of using this model was to overcome the complex relationship between the accident data and the considered parameters. Shen et al. (2008) used neural networks to combine several road safety indexes into a unique composite road safety indicator. Juan et al. (2010) also employed backpropagation neural network for safety assessment of a two-lane roadway.

In this study an ANN is employed first to learn the relationship between a given set of parameters and the corresponding simulation outputs and later be used for prediction purposes.

3.2 Genetic Algorithm (GA)

The reviewed literature shows that GA is frequently used for vehicular microscopic simulation calibration. In this study GA is used to implement the optimization process associated with calibration procedure.

GAs are part of evolutionary computing method, developed by Rechenberg in 1960, which has the basis on the Darwinian theory of survival of the fittest. The method was further developed by Holland (1975) into an optimization method. The method originated from the idea of mimicking the natural evolution. In other words, GA solves the optimization problems with step-by-step evolutionary approach in which best solutions are selected to help find better solutions for next steps. Thus, the solution at the final step is the winner or best survivor (Obitko (1998) and Deb (2001)). The GA-based optimization is described next.

Initially a randomly produced set of population is proposed by generating random individuals to start the process with. This population thereafter evolves toward the better generation by means of modifying properties of population while the algorithm proceeds. At each iteration the individuals are evaluated in terms of performance by being exposed to a predefined fitness function; this assigned performance provides the basis for selection and migration to the next step by employing the genetic operators (selection, crossover, and mutation). The algorithm comprises in applying recurrently the following stages for which the schematic view is presented in Figure 11 (Haupt & Haupt (2004)):

1. Generate initial population (Initialization)
2. Evaluate fitness of population
3. Apply selection, crossover, and mutation operators.
4. Generate new population and evaluate its fitness.

The genetic operators and coding are explained in the following sections.

3.2.1 Coding

The genetic algorithm comprises of two spaces, in one space the evaluation of the individuals is conducted and in the other, the genetic operations are applied to individuals to evolve them toward the fittest solution. Coding is the process of assigning the values to gens. The outputs of coding process are chromosomes expressed by row of 0 and 1. The binary codes are representative of real numbers which are converted through a predefined mapping relationship. The area to be explored and searched is converted to binary forms and all operations take place in that domain. On the other hand, decoding converts the binary chromosome to real values; this process prepares the chromosome for performance evaluation process which take place in the real space.

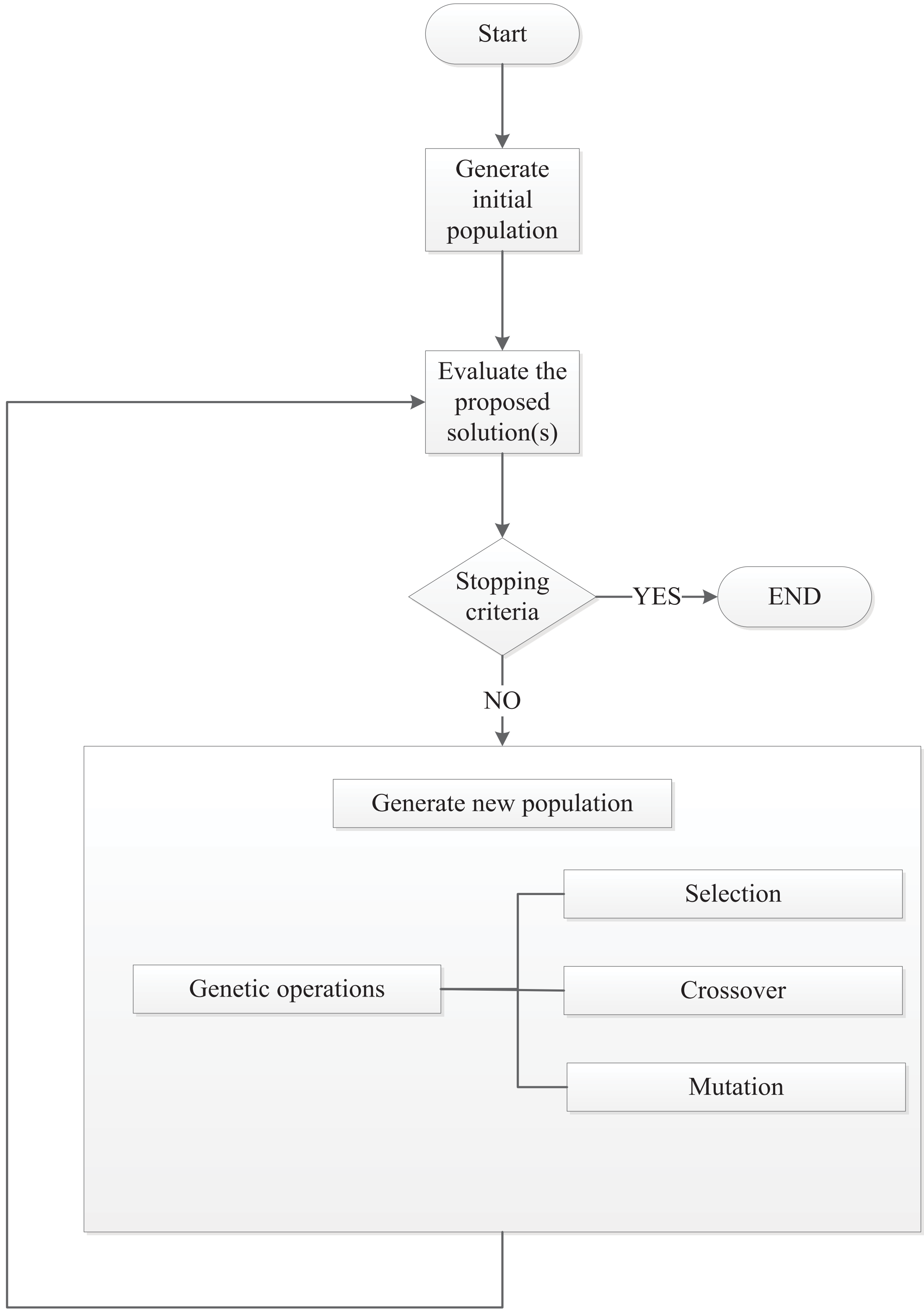


Figure 11: Schematic diagram of GA (adopted from Turban (1990))

3.2.2 Selection

Selection is the process of selecting the best individuals in the population to be used to form new generation. A generic selection algorithm follows the following steps:

1. All individuals are evaluated by being exposed to fitness function and all the assigned fitness values are normalized.
2. The individuals are ranked with respect to their performances (fitness values).
3. The cumulative fitness values of each individual is calculated (fitness value of the individual plus all former individuals of the ranking).
4. A random number between 0 and 1 is generated.
5. The first cumulative fitness value bigger than the generated random number is the selected parent.

These steps have to be repeated until a predefined number of individuals are selected for reproduction of the next generation. This collection of new individuals is called mating pool.

3.2.3 Crossover

Crossover is the act of taking more than one parent solution and reproducing a child solution by mixing the parents' properties. There exist many different methods developed for crossover implementation. The one that is widely used and the most basic is one-point crossover which is explained here. In this method a single point in both parent chromosomes is chosen randomly and the genes before and after that point are swapped between the two. **Error! Reference source not found.** Figure 12 schematically presents he explained technique and makes a better understanding of the technique.

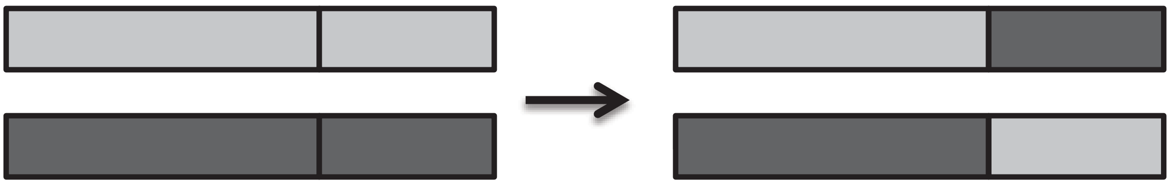


Figure 12: One point crossover illustration

3.2.4 Mutation

Mutation is the process of altering the value of a property (gen) which is randomly selected in chromosome. Mutation can cause noticeable change in the solution. This allows GA to search globally for the optimal solution and not get stuck in local optima. Mutation rate in the algorithm is defined by user. High rate of mutation causes some deficiency in wisely searching for local optima and make the algorithm a random search instead.

To provide a better understanding about the mutation process, two of the developed methods for mutation are presented here. Flip Bit is a mutation method that randomly selects a gen in the chromosome and flips the bit value. As an example, 1 0 1 0 1 0 1 is transformed into 1 0 1 0 1 1 1. Non-Uniform is another mutation method that adjusts the mutation rate while the algorithm proceeds; initially it allows high rate of mutation and consequently more freedom to search the domain. The mutation rate is decreased as the algorithm proceeds.

3.3 GA-Based Calibration Methodology

As the proposed methodology is later compared to the GA-based only calibration in terms of optimization speed and accuracy, the GA-based calibration method is briefly explained in this section. Figure 13 illustrates the flowchart of GA-based calibration method. The procedure comprises the steps below:

1. First the network has to be coded into the simulation platform which is VISSIM in our case. This includes the geometric configurations and collected traffic data (volumes, speed, types of vehicles, etc.).
2. Next step is to determine what the parameters of simulation platform are that affect the network performances of the model. As was mentioned, there are two different ways for effective parameter detection, one is based on experts' opinions who have the knowledge about the area of study. The other approach which is employed in this study is to conduct a sensitivity analysis that investigate the changes in network performance while keeping constant some parameters and changing the value of other(s).
3. In this step the GA must be integrated with the simulation platform using the existing interfaces such as Application Programming Interfaces (API) or Component Object Model (COM) interfaces. In this study VISSIM COM interface is used to integrate GA with simulation platform. Figure 14 presents a schematic diagram of how the simulation platform can be controlled through the COM interface and how the GA can be integrated into simulation platform.
4. In the next step, the GA is employed to find the optimal set of effective parameters that best replicate the performance on real life. The algorithm proposes

some sets of the calibration parameters and each set is evaluated by the simulation platform.

5. In this step, the termination criteria are tested and the calibration process will stop only if one of termination criteria (number of generation, fitness limit, time limit, etc.) is met.
6. Once the optimization process is stopped, the resulted parameters must be validated against field observation(s). It means that the parameters must be plugged to the model and the outputs of simulation with different seeds be equal or have ignorable difference with observed network performance value(s) in the field. Otherwise, the parameters of GA must be modified and the procedure be followed from step 4.

These steps will be followed until a desired set of parameters is achieved upon which the model can accurately replicate the real-life traffic conditions.

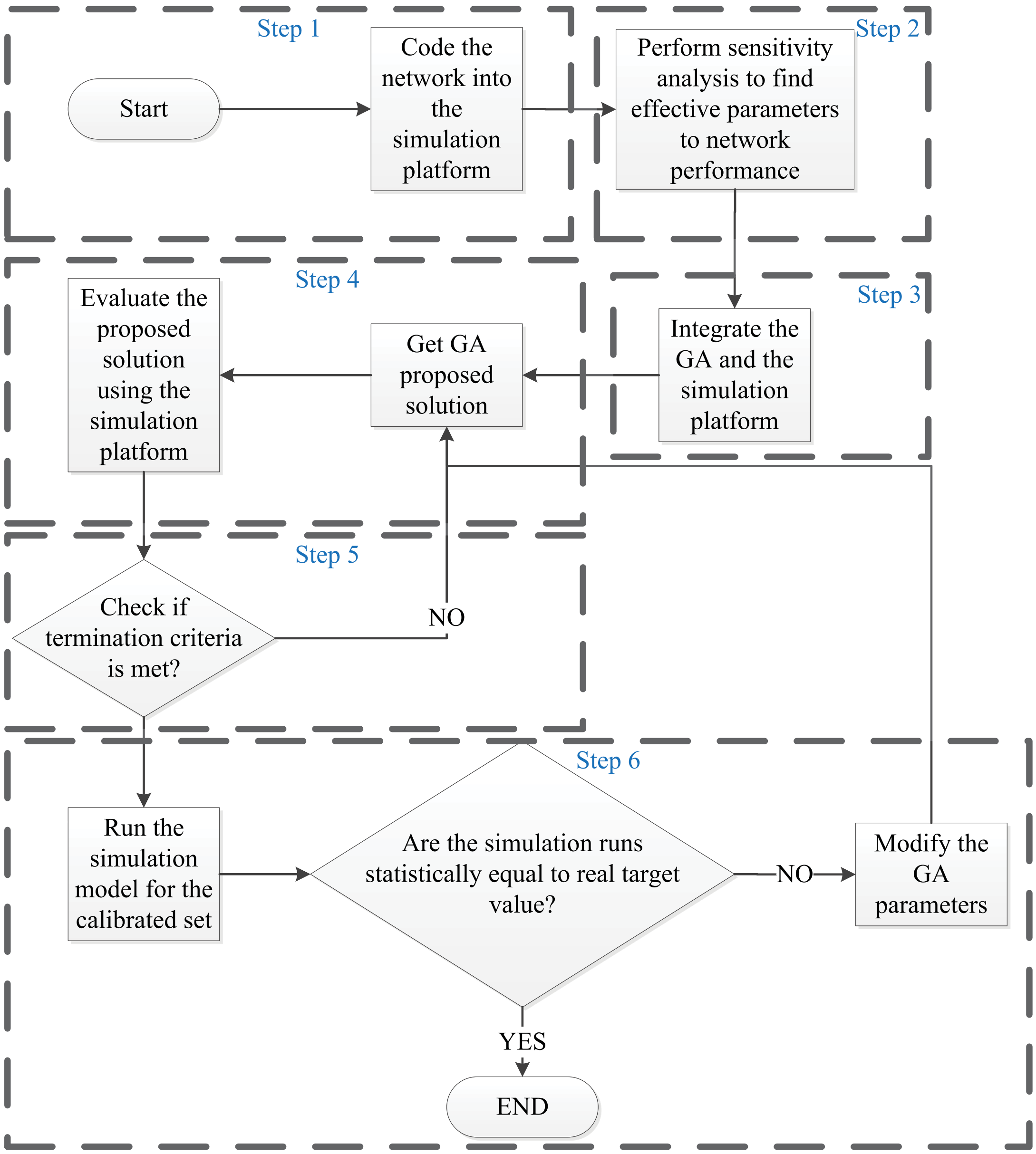


Figure 13: Flowchart of GA-based calibration method

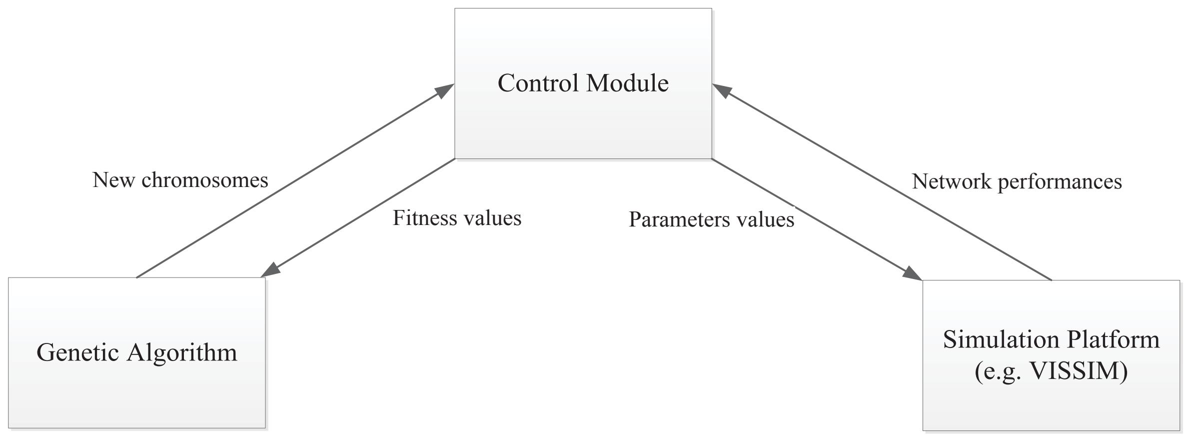


Figure 14: Schematic diagram of COM interface (adopted and modified from Cheu, et al. (1998)).

3.4 Proposed Methodology

Through investigating the current state of practice of vehicular microscopic calibration model, it was concluded that the most time consuming part is when repetitive simulation runs are required to evaluate a proposed set of parameters. To improve the optimization speed of calibration, one possible solution is to reduce the number of simulations without the negative impact on the results' accuracy. A faster procedure that could provide the network simulated output would be ideal. The intuitive complexity associated with the simulation platforms and the developed model, along with the intense computations required for large scale networks suggest that ANNs could be a good candidate for the required task. ANNs are capable of detecting the complex relationship between the inputs and corresponding outputs. Thus an ANN technique is employed to capture the relationship between the input parameters of the simulation model and the simulation results. The purpose is to use the trained ANN for predicting simulation outputs rather than using the time consuming simulation model itself.

The proposed methodology synergistically combines the application of ANN and GA to get advantages of learning capabilities of ANN and optimization abilities of GA to calibrate vehicular microscopic simulation models. The GA application is employed to minimize the difference between the simulated network performance which is predicted by the trained ANN and the real network performance. The methodology is thoroughly explained in the following steps in accordance to the flowchart of the methodology which is illustrated in Figure 15.

1. First the network must be coded into the simulation platform. This includes all the collected data with regard to geometry (e.g. number and lanes, radius of curves, etc.) and traffic data (volume, speed, type of vehicles, etc.).
2. Next step is to find out what controlling parameters of simulation model affect the model in terms of network performance. In accordance to the reviewed literature, there exist two types of approaches to address this issue. First is to refer to experts' opinions that have the knowledge about the area of study (Hellinga (1998)) and second is to conduct a sensitivity analysis. Sensitivity analysis investigates the changes in network performance while keeping constant the effect of some parameters and changing the values of other(s) (Zhizhou and Jian (2005)). In the proposed methodology, the second alternative is chosen to detect the effective parameters.
3. The ANN application is employed to capture the hidden and complex relationship between the effective parameters and corresponding simulated network performance. The ANN needs to be trained given the effective parameters and the corresponding outputs. An experiment needs to be designed to provide the inputs and outputs for ANN training process. Since the ANNs do not consider the inter-

relationship between the input parameters, the inputs must be un-correlated. Latin Hypercube Sampling (LHS) is employed to design the experiment. LHS takes the ranges of parameters and the number of sets of parameters to be designed and provides the designed sets such that the whole ranges of all parameters are covered and there is the least correlation between the parameters (Lophaven, Nielsen, and Søndergaard (2002)). Each of these sets has to be evaluated when the simulation model is run upon them to get the corresponding output.

4. The next step is to test whether the distribution of simulation results include the real value or not. Based on the studies of Park (2006), if not, some modifications have to be applied to the ranges of effective parameters.
5. After successfully designing the parameters and evaluating the corresponding outputs, they must be inputted to neural network for training purposes. The inputs to the network are the designed sets of parameters and the outputs are the corresponding simulation output to each set. The performance of the network is evaluated based on the difference between the real and predicted values. The training process will stop when one of termination criteria (e.g. number of epochs, number of fails in validation measure improvement, etc.) is met. Changes in the training parameters can change the performance; this can be used when higher level of accuracies are required. Once the neural network is properly trained, it can be used further for prediction purposes.
6. In this step, GA is employed to search for the optimal set of effective parameters upon which the simulation model can replicate the real-life traffic conditions. The objective function to be minimized by GA is defined as difference between real performance measure of network and predicted network performance which is

calculated by the trained neural network. The GA stops searching for optimal solution when one of its termination criteria (number of generation, fitness limit, time limit, etc.) is met. Then the simulation model is run upon the calibrated set of parameters and the network performance(s) is evaluated for different seeds. This collection of network performance values is later used for validating the results of calibration process.

7. The proposed set of calibration parameters by GA must be validated with respect to replicating the real-life traffic conditions. To this purpose, the output values of network performance(s) collected in previous step must be statistically equivalent to the field observed network performance(s). The average absolute relative errors are calculated to test the equality of the two. If higher level of accuracy is required, changes in the GA parameters helps.

This process will continue until the desired set of parameters that replicate accurately the real-life traffic conditions is achieved. The main point is that utilizing the trained ANN instead of the simulation runs for prediction purposes can drastically expedite the calibration process.

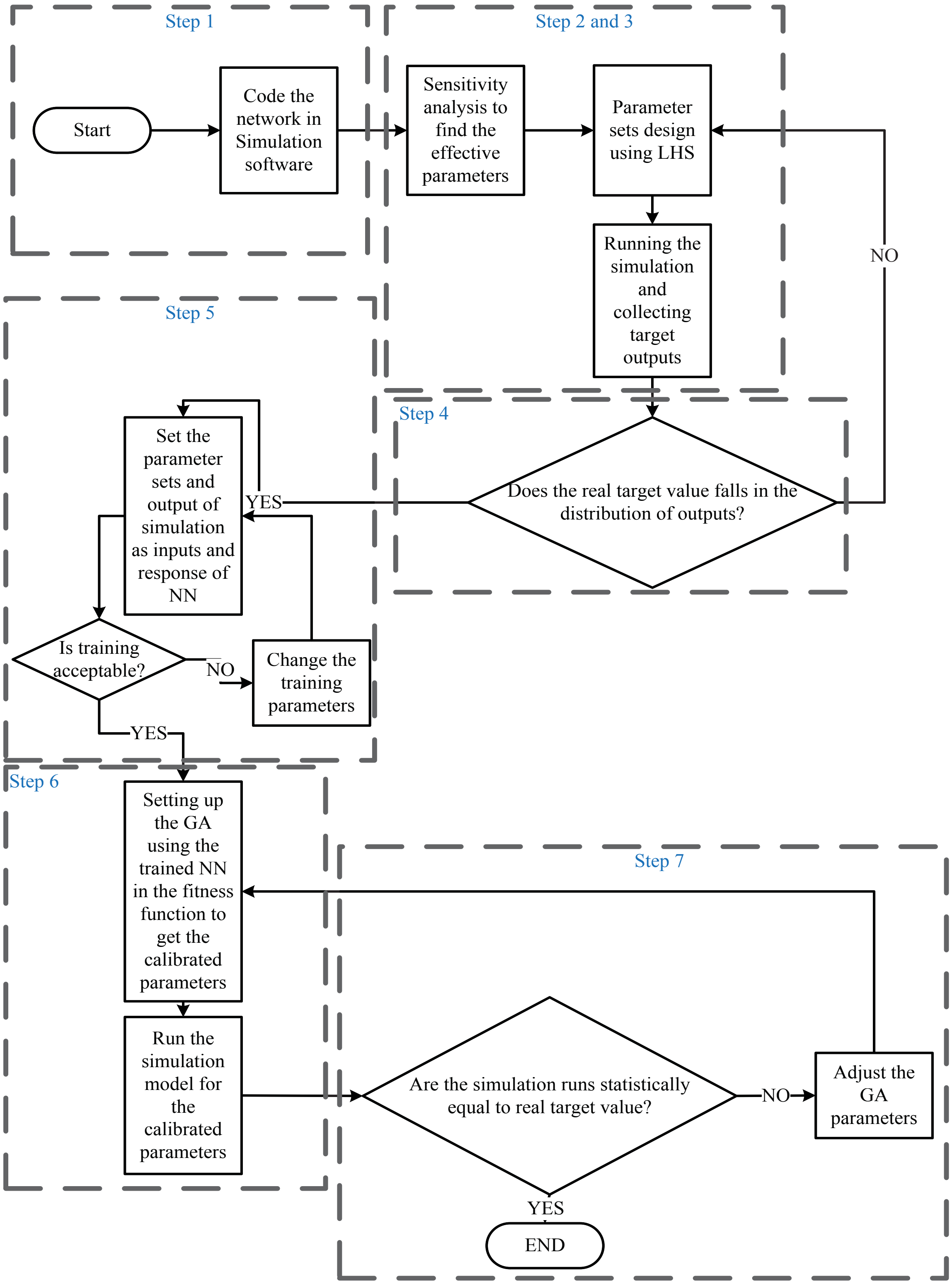


Figure 15: Flowchart of the ANN-GA calibration methodology

CHAPTER 4: DATA COLLECTION AND PROCESSING

This chapter includes information about the necessary data for this research, the available sources and the techniques used to process the collected data.

4.1 Scope of Data Collection

To replicate the observed traffic conditions, it is necessary to use traffic data from the study area. This research study used the data collected as part of a Ministère des Transports du Québec (MTQ) project that investigates the safety of high-occupancy vehicle lanes (HOV) lanes in province of Québec. However, the microscopic simulation calibration methodology is independent of type of transportation facility used. In this study two study areas were used: Highway A-15 and A-25 in Québec, Canada for which a description is presented in Chapter 5.

There exist two different data sources needed to model the selected study areas using VISSIM: highway geometric alignment information (e.g. number of lanes, radius of the curves, width of lanes, etc.) and traffic operations data (e.g. traffic flow volume, types of vehicles, distributions of vehicles' speed, etc.).

The following resources have been used for compiling the data necessary to build the traffic simulation models: Google Maps ® and Google Earth ® publicly available versions, and information about HOV lanes in the Montreal metropolitan area available from MTQ. In addition, vehicular traffic flows at the selected HOV lanes were video recorded and analyzed.

Google Maps ® and Google Earth ® were used to extract geometric characteristics of the selected study areas. Characteristics such as number of lanes and type of separation of HOV lanes are extracted by use street view feature of Google Maps and they are further verified by the dataset provided by MTQ. For traffic data, hours of video data were collected from the field. Two different camera were used for data collection. One camera was the Vivotek IP8151 camera with 800*600 pixels resolution and mounted on top of a 25 ft (7.62 m) pole. The other camera used was the GoPro Hero3 with a resolution of 960*720 pixels and that was mounted on the barrier of the road using the camera's handlebar.

4.2 Video Data Analysis Technique

Video data analysis was conducted using the feature-based tracking open-source software developed by Saunier (2012). To extract the traffic information from the processed video recordings, the following procedure was followed.

First, the calibration of the video camera was performed. To determine the vehicular change in position over time, vehicular headway and other similar information, one needs to transform 2-D image space into 3-D real space. Therefore, some control points with known real and the corresponding image coordinates were identified. In this camera calibration step a transformation matrix, called homography-matrix, was calculated based on real and image coordinates of known control points. Thereafter, the homograohy-matrix was used to transform coordinates of all objects from the image space to the real space. This transformation was applied to all the frames of the recorded video.

After the camera calibration was completed, an image masking was defined. This was necessary to process separately the vehicular traffic on individual lanes as well as to help eliminate the noises in the surrounding environment. This mask was also applied to all the recordings.

Once the coordinates were transformed to the real space and the mask was defined on the area of interest, the moving points were detected when the developed algorithm proceeded through the video frames. The detected moving points are called features. The results were saved into a database and further analysis was implemented on basis of the built database.

The database comprises all the moving points including oftentimes multiple features in a single moving object. These points are required to be joined to form a uniform object because otherwise later the extracted trajectories would not reflect the realistic presentation of moving objects. The developed algorithm which is based on finding the similar pattern in the detected object (e.g. having the same speed while being so close) joined the points to form the objects. The resulted objects were also saved to the database.

The database to this step comprised the detected objects and the corresponding real coordinates through time. Therefore, the trajectories were extracted from the database by simply tracking the coordinates for each objects in time. The trajectories were calculated and saved into the database consequently.

Trajectories are an informative source from which variety of information can be extracted about the objects. Information such as speeds, safety indices (e.g. TTC, PET, GT, etc.), acceleration, etc. are some examples. In our research group a Python script has been developed to extract the speed from the video data.

The advantage of the video processing software used in this thesis is that it falls under the open source category and one can adjust its processing abilities to fit the specific needs of the processed video. However, the software is not yet a complete, versatile traffic analysis tool. For example, it is known to that the results are less accurate when the analyzed videos contain stop-and-go traffic conditions. However, to avoid these problems the data used for processing was carefully selected and the results were manually validated to remove the records that indicate vehicular speeds that are unrealistic when compared with observed conditions.

CHAPTER 5: SIMULATION RESULTS AND ANALYSIS

To demonstrate the feasibility of the proposed calibration method for microscopic vehicular traffic models, two real-world study areas were used. The two study areas are selected from the Montreal highway network and each of them includes a reserved lane section. The two cases are different in the type of access.

In this chapter, first an introduction is provided with detailed information about the two study areas. Next, for each of the two case studies the VISSIM model is developed and explained in preparation for calibration methodology applications. First the proposed ANN-GA based calibration method is employed and second, the comparison GA only calibration method is applied to the same two case studies. Finally, the results of both calibration methods are compared based on the results' accuracy and optimization speed criteria.

5.1 Location and Traffic Operation Characteristics

This section presents an introduction about the location and traffic operation characteristics of each of the cases of study.

5.1.1 Highway A-25

Highway A-25 is a three-lane freeway located in Lanaudière region of Québec with a total length of about 49 km connecting Longueuil to east Montréal. The posted speed limit through the highway is 60-100 km/hr. The A-25 section has a 4-km long reserved lane for buses, taxis and passenger vehicles with two or more occupants open specifically during the morning and afternoon rush hours. The access to the HOV lane is limited and is separated by pavement markings.

For geometric data Google Earth® and Google Maps® were used to find the number of lanes and approximate lane width; one snapshot of Google Maps® of the area was later used for geometric modeling of the case study into VISSIM. MTQ inventory of reserved lanes was used to verify this information. Video analysis technique was employed to collect the traffic data from the area of study. Figure 16 presents a map of the studied area and identifies the data collection point located on pedestrian overpass. The location was selected for two main reasons. First, it gives a very good, wide spread view along the direction of traffic. Second, the camera was set up on an overpass pedestrian bridge and was not visible to the drivers, therefore, it is expected that it had no effect on drivers' behavior (i.e. when drivers observe that monitoring devices are present, they adjust their behavior and the collected traffic data becomes less representative of the prevailing conditions). The data was collected from 6AM to 12PM for the south direction and from 12PM to 6PM for the north direction. Only the peak-hour was used in this study. These hours of data collection include HOV-lane operation hours and when they are open to all types of vehicles. This allows for a comparison between driving behavior along the HOV-lane versus the driving behavior along the non-HOV operation. The results of data collection are summarized in Table 2.

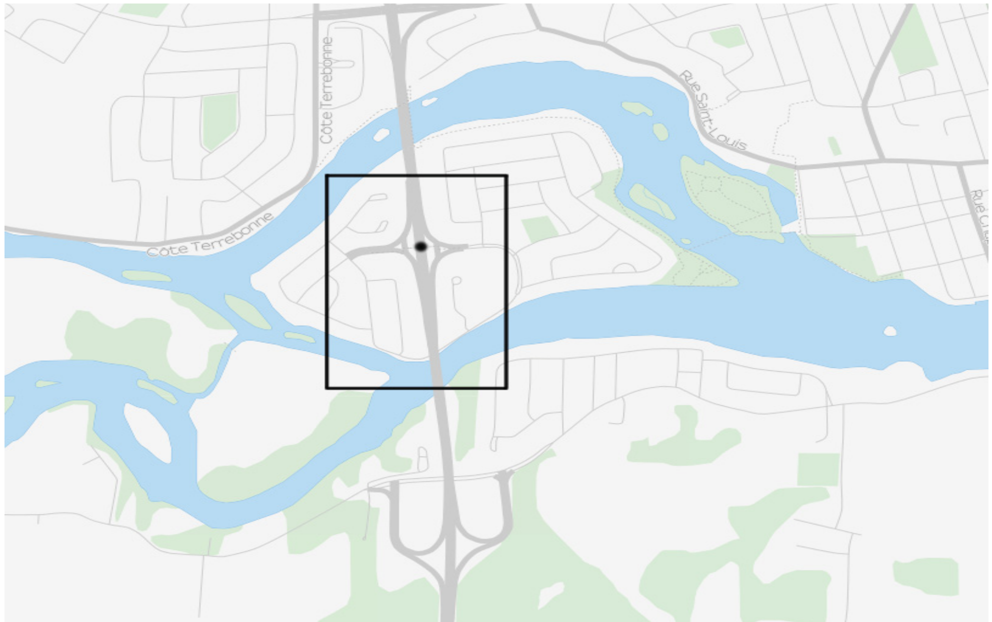


Figure 16: Map and data collection point of Highway A-25

Table 2: Summary of characteristics of the Highway A-25, both directions

		A-25(North Bound)	A-25(South Bound)
Geometric Characteristics	Peak hour	5-6 PM	7-8 AM
	Number of lanes	2 GP lanes+1 HOV lane	2 GP lanes+1 HOV lane
	Placement of HOV lane	Outermost lane (right side)	Outermost lane (right side)
	Type of Access	Limited access	Limited access
	Length of HOV-equipped section (Km)	4	4
Traffic Characteristics	HOV Vol. (veh/h)	1158	807
	GP Vol.(veh/h)	2715	2294
	Total Vol. (veh/h)	3873	3101
	Speed limit(km/h)	60-100	60-100
	HOV average speed± Standard deviation(km/h)	63.4±7.24	85.3±13.08
	GP average speed± Standard deviation(km/h)	42.9±11.27	61.4±18.78

5.1.2 Highway A-15

Highway A-15 is located in western Québec that connects A-87 at border of Canada and US all the way to Sainte-Agathe-des-Monts. The A-15 is equipped with about nine kilometers of continuous reserved lane accessible to passenger vehicles with at least two occupants, taxis, and buses during the peak hours. The type of separation is by means of pavement marking and the maximum permitted speed along the corridor is 100 km/h.

Similar to the previous study area, the same data sources were used to build the network (i.e. Google Maps® products and MTQ highway inventory). Video recordings of traffic at the location identified in Figure 17. The data was collected from 14-17:30 for north bound direction on two different weekdays. These hours of data collection include HOV-lane operation hours and when they are open to all types of vehicles. This provides the opportunity to make a comparison between driving behavior of HOV-lane operation and non-HOV operation in future research. The results of data collection are summarized in Table 3.

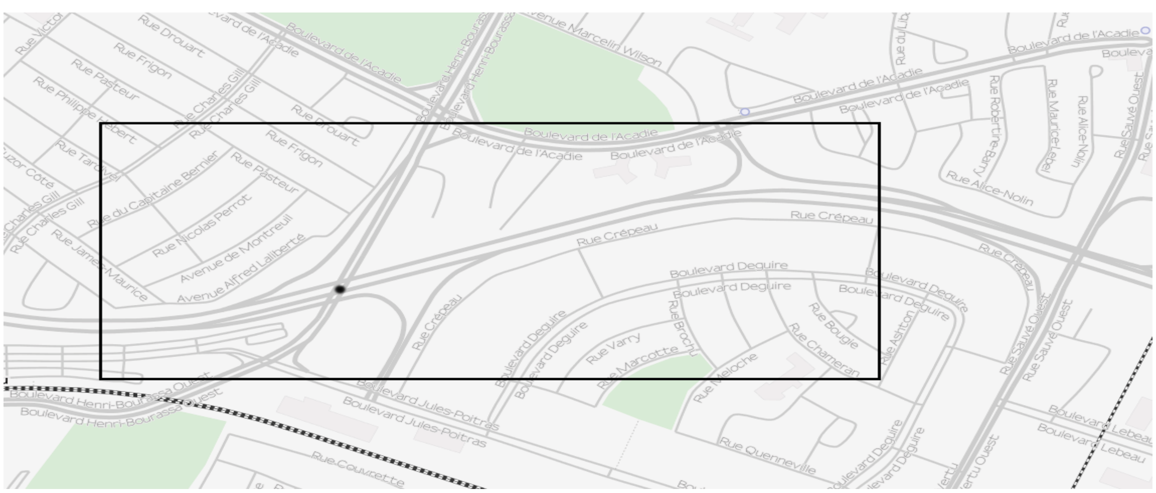


Figure 17: Map and data collection point for Highway A-15

Table 3: Characteristics of Highway A-15, North

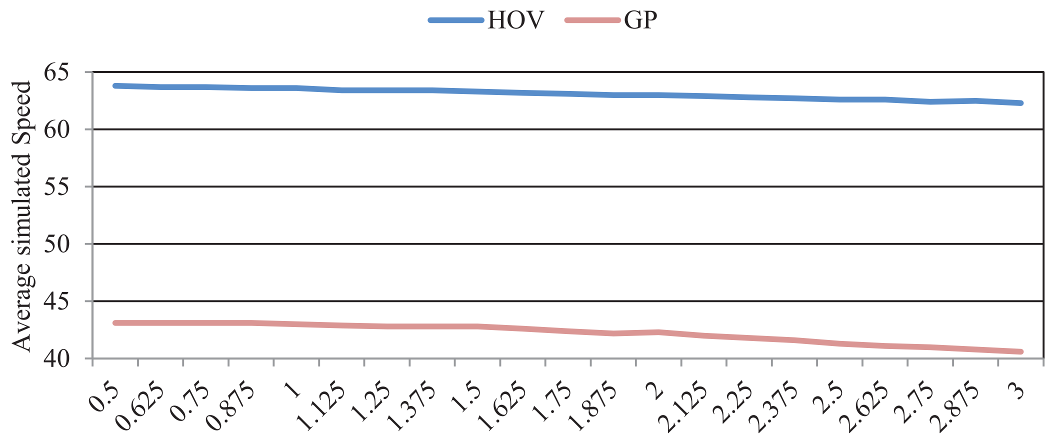
Geometric Characteristics	Peak hour	3-4 PM
	Number of lanes	3 GP lanes+1 HOV lane
	Placement of HOV lane	Innermost lane (left side)
	Type of Access	Continuous Access
	Length of HOV-equipped section (Km)	9
Traffic Characteristics	HOV Vol. (veh/h)	1551
	GP Vol.(veh/h)	4069
	Total Vol. (veh/h)	5620
	Speed limit(km/h)	60-100
	HOV average speed± Standard deviation(km/h)	120.9±12.65
	GP average speed± Standard deviation(km/h)	109.2±16.06

5.2 VISSIM Model Development

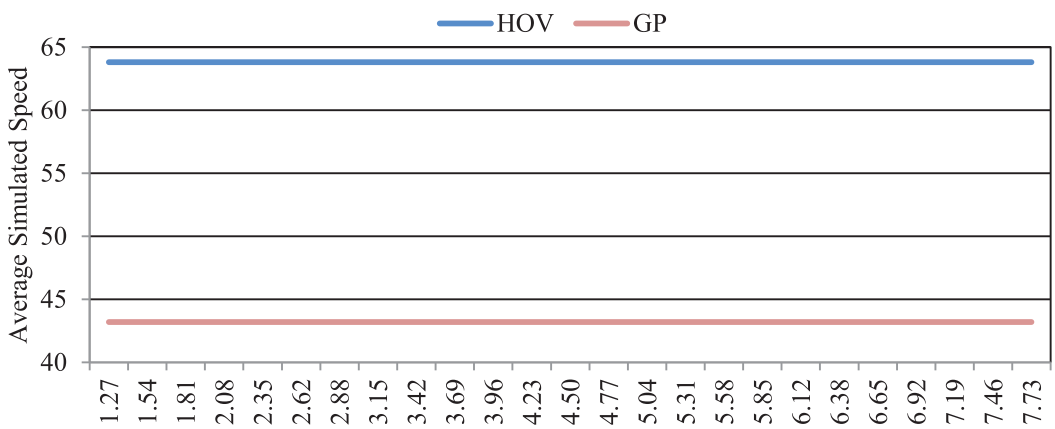
The following steps have been followed to model the areas of study with VISSIM. First, a snapshot of Google Maps® was used to geometrically define selected highway segment into VISSIM coordinates system (e.g. the number of lanes, the lanes width, lanes usage restriction, etc.). Second, the collected and processed vehicular traffic input from the study area (i.e. traffic volume, traffic mix and speed distribution) were coded into the simulation model. Finally, for the purpose of determining the performance measures of the highway segment several data collection sensors (i.e. virtual traffic detectors) were defined in the model. To be able to properly calibrate the microscopic simulation model, the virtual traffic detectors were placed at the same location where the vehicular traffic was video-recorded. The network performance measure used for this case study was the average vehicular speed. The model was calibrated separately for the southbound and northbound directions for the corresponding peak hours, morning and afternoon, respectively.

5.3 Calibration of the Model Using the Proposed Methodology

The steps of the developed calibration methodology were applied to the defined VISSIM model of the A-25 and A-15 highways. First, a sensitivity analysis is conducted to identify the parameters that have the most significant impact on the model's performance measure (i.e. average vehicular speed). A total number of 150 distinct simulations were ran. All the runs were performed automatically via a developed Visual Basic program using the VISSIM's COM interface module. The program changes the values of one parameter at a time and accumulates the average speeds from the virtual traffic detectors. A visual inspection of the plots similar to the ones shown in Figure 18 and Figure 19 helps to determine whether a model parameter affects significantly the average vehicular speed as it changes its values in the specified range. From Figure 18 and Figure 19 it can be seen that the network performance (average speed) is not changing with variations in the CC8 values, while it is sensitive with the changes in CC1. Therefore, it can be concluded that under the tested conditions, CC1 is an effective parameter on the network performance measure while CC8 has no effect on network performance. Table 3 lists the parameters determined to have a significant effect on the model's performance and their definitions.



a) Calibration parameter CC1



b) Calibration parameter CC8

Figure 18: Sample illustration of sensitivity analysis for A-25

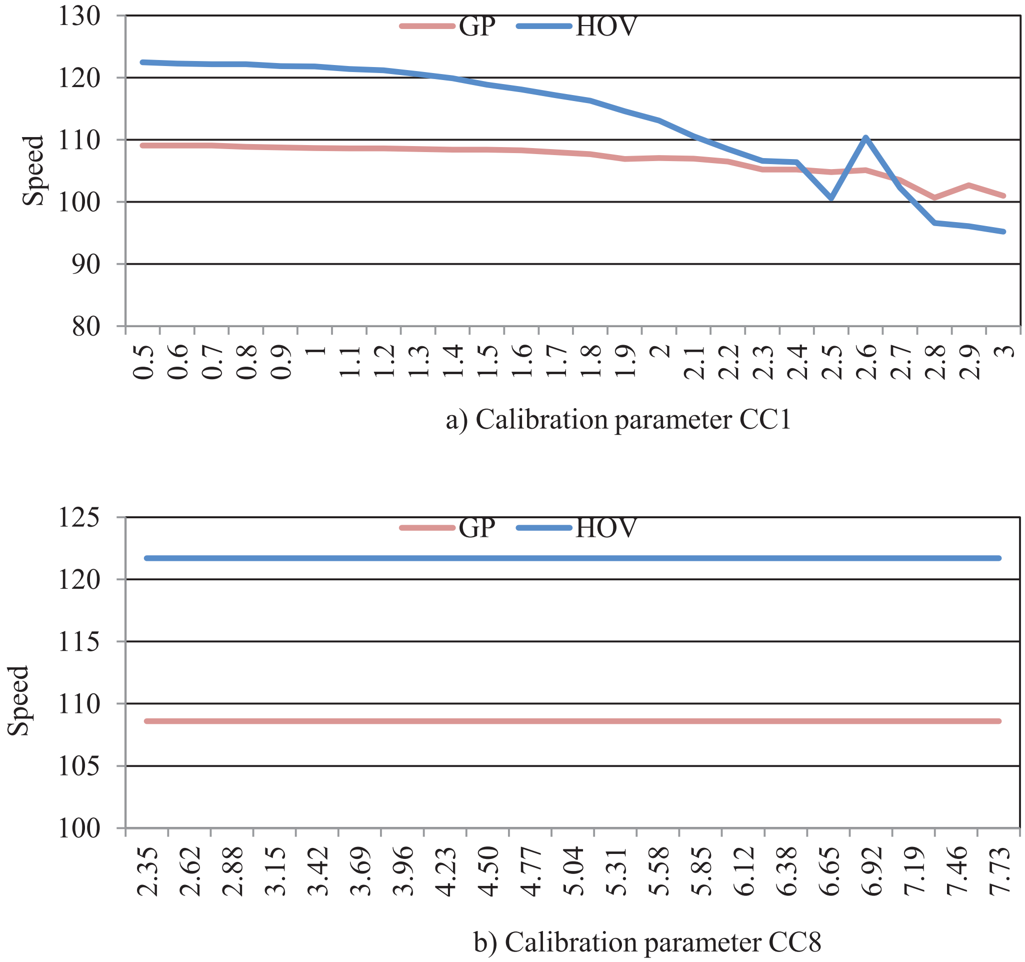


Figure 19: Sample illustration of sensitivity analysis for A-15

Table 4:Definition of effective parameters (adopted from PTV (2011))

Effective Parameters	Definition
CC1	The headway time that the driver wants to keep, the more the value is, the more cautious the driver is.
CC2	Following variation, restricting the longitudinal oscillation* or safety distance variation.
CC4	CC4 and CC5 control the speed differences in the following state. Smaller values results in more sensitive reaction of drivers.
CC5	CC4 and CC5 control the speed differences in the following state. Smaller values results in more sensitive reaction of drivers.
CC6	Influence of distance on speed oscillation* while in following process. Larger values lead speed oscillation with increasing distance.
CC7	Actual acceleration during the oscillation process.

*Where speed oscillation refers to repetitive of speed variation in either time or space.

In the next step LHS was used to combine different parameter values into sets of parameters while the selected parameters remain un-correlated. A MATLAB program was developed to generate the parameter sets. The MATLAB script uses the number of sets (which is 150) and the range of values for each parameter as the input arguments and generates the sets of parameters. A correlation matrix is calculated to verify that the parameters are un-correlated. It can be seen from Table 5 and Table 6 that there exists almost no correlation between the designed parameters.

Table 5: Correlation matrix of parameters for A-25

	CC1	CC2	CC4	CC5	CC6	CC7
CC1	1	-0.006	0.007	0.007	0.004	0.006
CC2	-0.006	1	0.007	0.004	0	0.007
CC4	0.007	0.007	1	-0.001	0.006	-0.005
CC5	0.007	0.004	-0.001	1	0.007	-0.002
CC6	0.004	0	0.006	0.007	1	0.006
CC7	0.006	0.007	-0.005	-0.002	0.006	1

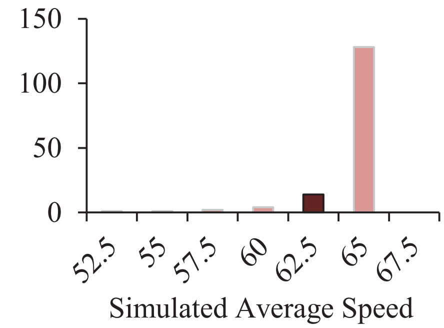
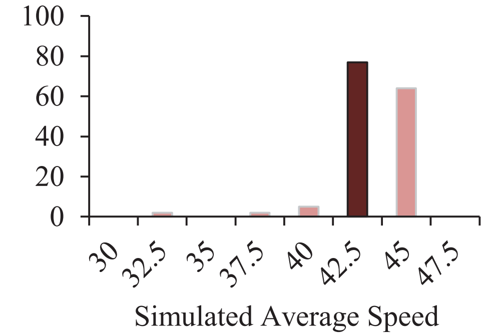
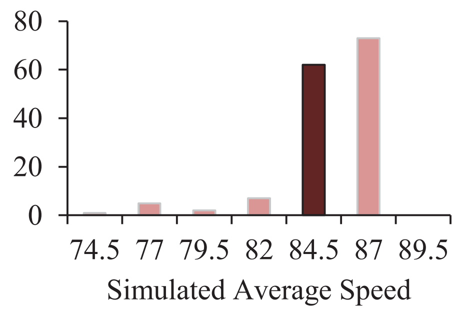
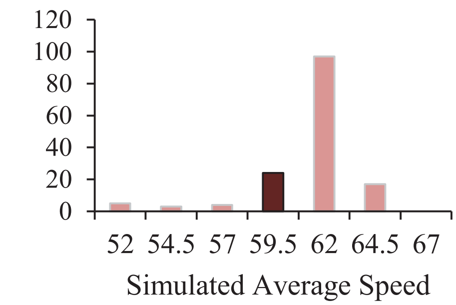
Table 6: Correlation matrix of parameters for A-15 North

	CC0	CC1	CC2	CC4	CC5	CC6	CC7
CC0	1.000	-0.006	-0.003	-0.006	0.006	0.003	-0.006
CC1	-0.006	1.000	0.007	-0.005	0.008	0.006	-0.007
CC2	-0.003	0.007	1.000	0.006	-0.004	-0.006	0.005
CC4	-0.006	-0.005	0.006	1.000	0.009	0.005	-0.006
CC5	0.006	0.008	-0.004	0.009	1.000	-0.005	0.004
CC6	0.003	0.006	-0.006	0.005	-0.005	1.000	0.006
CC7	-0.006	-0.007	0.005	-0.006	0.004	0.006	1.000

The generated parameter sets are used into the simulation model through a Visual Basic script that stores the corresponding simulation model performance measures (i.e. average vehicular speed).

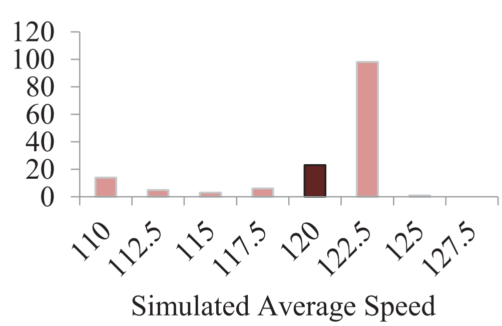
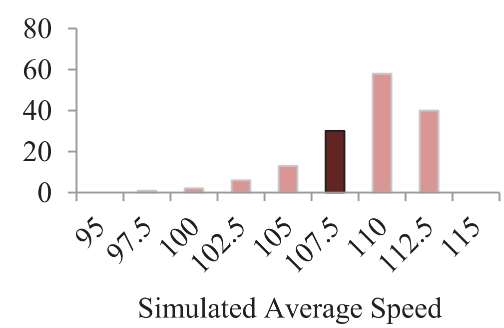
Table 7 and Table 8 show the frequency distributions functions of simulated average speeds and how they include the observed average speed values. It can be seen that the observed values are within the frequency distribution of the simulated average speeds.

Table 7: Frequency distribution of average simulated speed (in km/h) including the observed field speed*

	HOV lane	GP lanes
A-25 North		
A-25 South		

*the bar including the observed field speed colored in dark red

Table 8: Frequency distribution of average simulated speed (in km/h) including the observed field speed*

	HOV lane	GP lanes
A-15 North		

The designed sets and the corresponding outputs of the software must be inputted as the inputs and outputs of ANN to be trained. A feed forward backpropagation (Levenberg–Marquardt) ANN is employed for predictive purposes and a developed script in MATLAB is used for ANN training implementation. The structures of ANNs are determined based on best performance of testing data and the results are summarized in Table 9 and Table 10. The validation measure is considered to be mean of square error (MSE). Considering the mean square errors of testing dataset and the order of speed data which varies from 32.5-80 km/h for A-25 and 97.5-125 km/h for A-15, it can be concluded that the ANN is able to predict the simulation output values at an acceptable level of accuracy (less than 5% of Average Absolute Relative Error (AARE) which is defined in the Equation [1]).

$$[1] \qquad \text{Average Absolute Relative Error (AARE)} = \frac{1}{N} \times \sum_{i=1}^{N} \left| \frac{SS(i) - AS}{AS} \right|$$

Where SS(i) is the simulated speed from the simulation model with the i^{th} seed and AS is the actual speed collected from the field. N in the formula represents the total number of seeds.

Table 9: The neural network structure and the resulted training efficiency for A-25

	A-25 North		A-25 South	
	GP	HOV	GP	HOV
Number of neurons in the hidden layer 1	8	5	4	3
Number of neurons in the hidden layer 2	4	9	7	13
MSE* of the trained network for testing dataset	0.12	0.37	0.35	0.13

Table 10: The neural network structure and the resulted training efficiency for A-15

	A-15 North	
	GP	HOV
Number of neurons in the hidden layer 1	9	4
Number of neurons in the hidden layer 2	6	13
MSE of testing dataset	0.45	0.29

In the next step, the trained ANN was used to predict the simulation output for different values of the modeling parameters. The trained ANN was used to generate the expected simulated average speed corresponding to the various input sets of parameters in the GA optimization process. This allowed for a faster calibration process as demonstrated later in the algorithm performance comparison section.

The GA toolbox in MATLAB was used to minimize the difference between the predicted and the real speed by modifying the input simulation parameter set. The multi-objective optimization shown in Equation [2] is defined to minimize the predicted average speeds on both types of lanes, the high-occupancy vehicle and the general purpose lanes. In the objective function defined in Equation [2], PS represents the predicted speed, generated by the ANN, and AS is the actual average speed observed at the data collection site.

$$[2] \qquad \text{Objective function= Minimize (} \left|\frac{\text{PS} - \text{AS}}{\text{AS}}\right|_{HOV} + \left|\frac{\text{PS} - \text{AS}}{\text{AS}}\right|_{GP} \text{)}$$

The objective function defined as a minimization of the absolute relative error of average speed, allows for the inclusion of other optimization criteria in a similar fashion, regardless the magnitude or the measuring units.

For all the scenarios, the GA parameter values were selected to be 20 for the population size and 50 for the number of generations. The roulette wheel functions was chosen during the selection, intermediate cross over was selected during the crossover stage, and adaptive feasible function was used during mutation stage (MathWork (2013)). The GA optimization yielded a set of calibrated parameters values. These values were used in VISSIM to evaluate the vehicular average speed, which was validated against the observed traffic average speed. The VISSIM model was ran using 50 different random seeds to take into account the probabilistic nature associated with the traffic model. The average absolute relative errors are calculated based on Equation [1] and depicted in Figure 20 and Figure 21. It is shown that the calibrated model yields errors in the average vehicular speed that are very small, between 3% and 5%, while the un-calibrated model has errors between 14% and 18.5%.

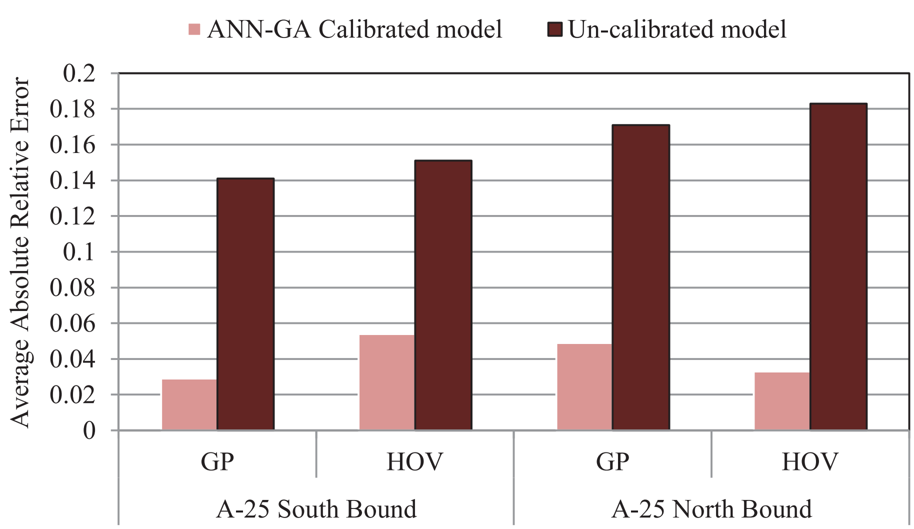


Figure 20: Comparison of resulted average absolute relative errors of ANN-GA calibrated model with un-calibrated model

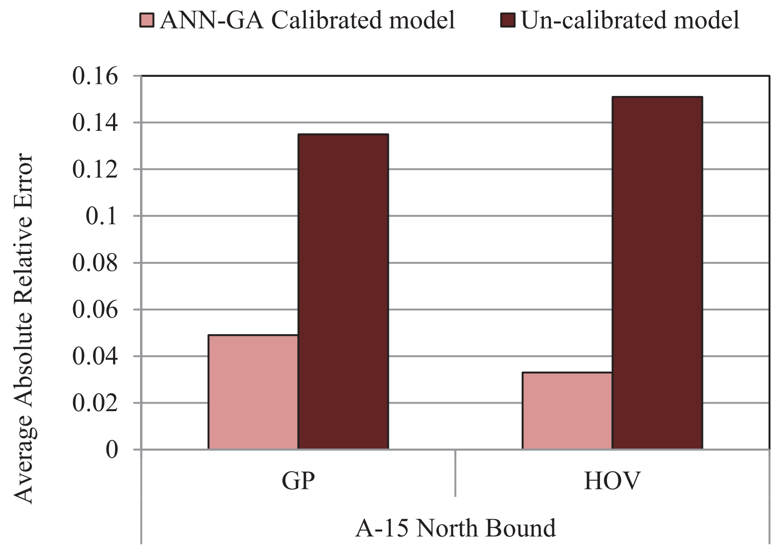


Figure 21:Comparison of resulted average absolute relative error of ANN-GA calibrated model with un-calibrated model

It can be concluded that in comparison to the un-calibrated model, the ANN-GA based calibrated model leads to more accurate reflection of driving behavior of the study areas.

5.4 Comparison of ANN-GA and GA Calibration Methods

To demonstrate the benefits of the proposed calibration methodology both case studies (A15 and A25) were also calibrated using the GA only method. The implementation of GA-based calibration method was programed via Visual Basic and MATLAB. From MATLAB the GA toolbox was used for algorithm implementation. The results that are presented here in Table 11 are those of employing the MATLAB programming as the interface between the simulation model and GA. Optimization speed was computed using a MATLAB script that starts and ends with the optimization procedure.

Table 11: Optimization speed comparison of different calibration methods (Second)

	GA-based Calibration	ANN-GA Calibration
A-15 North	38023.75	64.75
A-25 North	34078.95	69.46
A-25 South	31388.10	62.63

In the Table 11 it can be seen that the ANN-GA calibration method is incomparably faster than the GA calibration. However, the accuracy of the calibrated model applied to the same study area is not as good. It can be seen from Figure 22 that the accuracy of the results is best when the GA-only calibration method is used. Nevertheless, the accuracy of the ANN-GA calibration method is in the range of 3-5%, while the accuracy of the GA-only in the range of 1-4% average absolute relative error. In many traffic simulation applications, this difference in the network performance is not affecting significantly the simulation results. The average absolute relative errors are calculated based on the Equation [1] and the results are presented in Figure 22. As can be seen, GA only method performs better than the ANN-GA for all the cases.

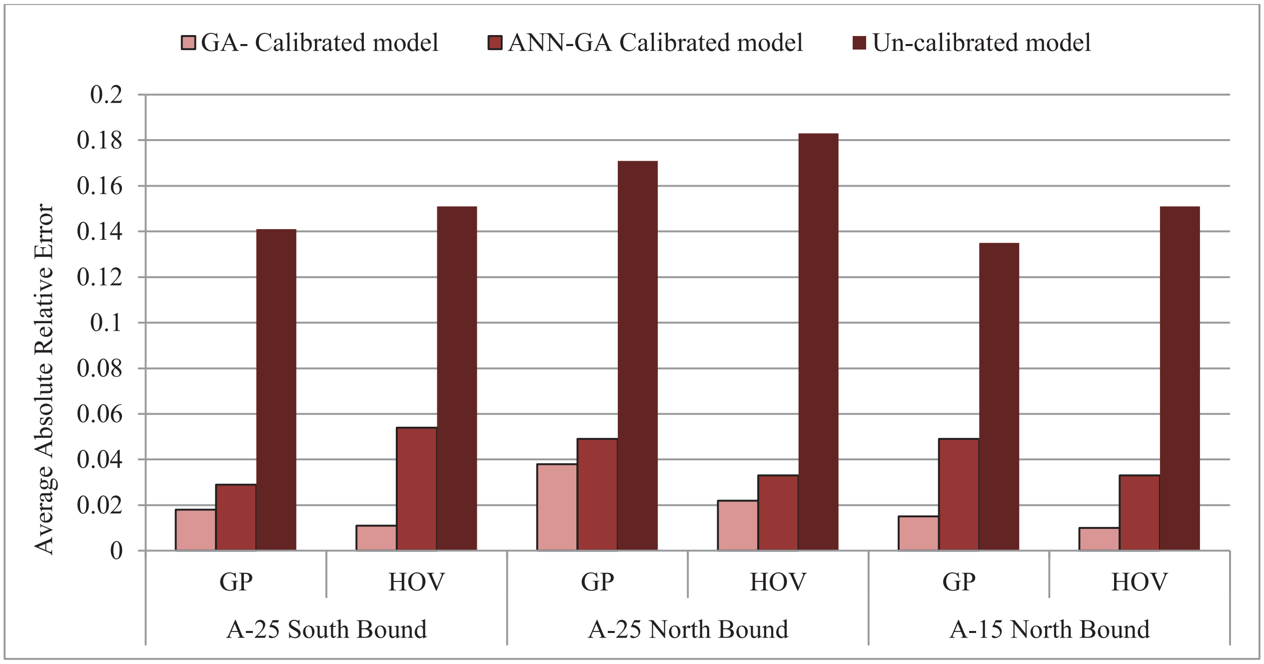


Figure 22: Average absolute relative error comparison (percentage)

To highlight the importance of calibration, next chapter demonstrates a traffic safety analysis.

5.5 Before-After Calibration Safety Comparison

It was mentioned in the literature review chapter that due to the drawbacks associated with direct measurements and analysis of accident data, the road safety assessment methods are shifting toward conflict analysis instead, that is potential for accident occurrence. In this thesis, to highlight the effect of proper calibration of vehicular microscopic simulation models used in traffic safety modeling, a before-after calibration conflict analysis is presented. The conflicts are extracted via SSAM (a software model developed by FHWA for conflict analysis) based on the trajectories of individual vehicles information available from VISSIM. The time to collision (TTC) is considered as the surrogate safety measure in the SSAM model. Based on the exiting literature, the critical TTC value is set to 1.5 second (i.e. interactions with TTC less than 1.5 seconds are considered as potential conflicts). The SSAM analysis was applied to both calibrated and un-calibrated VISSIM models and the results are summarized in Table 12.

Table 12: Before-and-after calibration safety indicator analysis

	A-15 North		A-25 North		A-25 South	
	Before	After	Before	After	Before	After
Rear-end Conflict Frequency	1	3	No Conflict	1	2	6
Lane Changing conflicts Frequency	18	4	No Conflict	6	5	10
Mean of speed differential(m/s)	4.72	6.57	N/A	4.5	7	6.76
Mean of TTC (sec)	0.06	0.02	N/A	0.31	0.61	0.12
Mean of PET (sec)	0.02	0.04	N/A	0.37	0.34	0.14
Deceleration Rate(m/sec^2)	-4.87	-5.09	N/A	-5.85	-5.6	-6.68

As it can be seen, the safety indices are significantly different between the un-calibrated and the calibrated model. This demonstrates how calibration can affect the analysis of traffic models. While this case is a very basic one, it clearly shows the calibration of traffic models is important and more work is identified in the concluding chapter of the thesis.

CHAPTER 6: CONCLUSIONS AND FUTURE WORK

4.1 Concluding Remarks

As shown in the reviewed literature, many studies investigated various issues related to the calibration of vehicular microscopic simulation models. However, there are not many studies that attempted to improve the calibration speed, one of the concerns in the calibration area in some studies. This thesis proposed a new calibration methodology that provides transportation professionals with an efficient way to calibrate vehicular microscopic simulation models. The methodology is a synergetic combination of an ANN, applied in order to replicate the expected output of a microscopic simulator, and a GA used to search for optimal sets of parameters that best replicate the observed behaviors. The GA uses the objective function defined by the trained ANN.

The efficiency of the newly developed calibration method was demonstrated with two case studies. It was shown that the proposed calibration method requires less computation time when compared to another similar calibration methodology that uses a standalone GA-based calibration. With about 5% and less average absolute relative error for all case studies, it can be concluded that the calibrated parameter sets can accurately replicate the observed network performances. In addition, it was shown that while there is no significant impact on the accuracy of the simulation results, the speed benefits are tremendous. When applied to the two highway segments the newly developed calibration method completed in less than two minutes, while the classical GA calibration took more than 10 hours to complete. The calibration results were compared with those of the standalone GA model and it was found that it has relatively lower accuracy. This difference in accuracy can be associated to the small errors in the ANN prediction. However, it was found that the inherent lower accuracy is too small to have a significant impact on the application results. The proposed calibration method was used to evaluate the road safety of the tested case studies using Surrogate Safety Assessment Model (SSAM) developed by FHWA. It is shown that the safety indices differ from before to after calibration, demonstrating the importance of calibration and how this affects vehicular traffic analysis.

All in all, it can be concluded that the proposed calibration method is significantly faster than other GA-based methods. The following points are summarize the main contributions of this research:

- The proposed methodology can provide researchers and practitioners with an efficient calibration method that is much faster than the existing GA-based methods.
- The method is more proficient than other existing methods (i.e. genetic algorithms or simulated annealing) because the ANN preparation can be done in advance while for the other methods the whole process of calibration would be conducted after the calibration is required.

6.2 Future Work

More work is envisioned to improve the proposed calibration method. While, the calibration was validated using the average vehicular speed, it will be important to evaluate it against other network performance measures such as average travel time, lane changing behavior, etc. Another improvement is planned in the area of safety analysis that is currently under development. For example, the safety indices could be extracted from vehicles' trajectories and the effective parameters of simulation model could be adjusted to identify the highest correlation between the simulated and real world conflicts.

The proposed calibration method should be applied to other transportation facilities (e.g. urban arterials, intersections, etc.) to test its versatility.

Another possible avenue to improve the accuracy of the calibrated model while maintain a good calibration speed is to develop a hybrid model that combines ANN-GA method with a standalone GA or SA calibration. The calibration process could be started with the ANN-GA approach and when the solution reaches a certain level of accuracy, the standalone GA or SA optimization could be used to refine the calibration parameters.

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