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Simulation of Vehicles' Gap Acceptance Decision at Unsignalized Intersections Using SUMO

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Abstract

In this paper, an artificial neural network (ANN)-based gap acceptance behavior model was proposed. The feasibility of implementing this model in a microscopic simulation tool was tested using the application programming interface of Simulation of Urban Mobility (SUMO) simulation package. A stop-controlled intersection in New Jersey was selected as a case study. The simulation model of this intersection was calibrated using ground truth data extracted during the afternoon peak hours. The ANN-based SUMO model was compared to SUMO model with default gap acceptance parameters and the SUMO model with calibrated gap acceptance parameters. The comparison was based on wait time and accepted gap values at the minor approach of the intersection. The results showed that the ANN-based model produced superior results based on the selected outputs. The analysis results also indicated that the ANN-based model leads to significantly more realistic driving behavior of vehicles on the major approach of the intersection.

Keywords: microscopic simulation, artificial neural network, gap acceptance, machine learning, calibration and validation

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1. Introduction

Intersections are the critical facilities of traffic networks in terms of mobility and safety. In the US, nearly 67 percent of fatal intersection crashes occur at unsignalized intersections [1]. In order to determine the effectiveness of various safety countermeasures or alternative operational scenarios, accurate models of such facilities are needed.

The gap acceptance behavior is a crucial concept in the analysis of unsignalized intersections, where the driver on the low priority traffic stream encounters a series of time gaps within the higher priority traffic stream and decides whether to accept the gap and cross or reject and wait for the next gap. The decision-making process for gap acceptance is influenced by various factors such as traffic conditions, roadway geometry, vehicle type, driver characteristics, environmental conditions, etc. The definition of a gap within this context is the time interval between the arrivals of consecutive vehicles before an intersection in mainstream traffic. Thus, the traffic flow rate is a major factor impacting the gap acceptance process [2]-[5].

The relevant literature that focused on modelling and analysis of unsignalized intersections can be grouped into analytical and simulation-based approaches. In the analytical methods, the critical gap is a key parameter used in assessing the safety, delay, and capacity of a traffic stream [6]. The critical gap is defined as the minimum time headway in the mainstream traffic that provides a safe crossing for the minor-approach vehicles [7]. It is not possible to measure critical gap directly in practice, rather it can be estimated by analyzing the values of accepted and rejected gaps. According to the literature, variables such as driver, traffic, and trip characteristics, wait time, vehicle type and weather condition impact the estimation of critical gap [8]-[17]. Various methods were used to estimate the critical gap value. These methods include but not limited to Raff's method, binary probit model, maximum likelihood method as well as approaches that apply various machine learning models such as Decision Tree, Random Forest, Support Vector Machine and so forth [10], [14]-[18]. Nevertheless, not all the estimation methods necessarily produce the same results [20]-[23]. For example, in a study conducted by Dutta and Ahmed [24], the logit method outperformed the clearing time method in terms of estimating the critical gap at a three-legged unsignalized intersection. In addition, Maurya et al. [23] indicated that the estimated critical gap value of the logit method was roughly 0.2 s longer than that of Raff's method.

As to the simulation-based approaches, high fidelity traffic simulation packages enable users to model and analyze complex traffic networks. The strength of a simulation model relies on its efficacy in simulating stochastically the driver and traffic interaction in the field condition. Even with the enhanced capability of simulation tools, performing an accurate simulation model is considered a challenging issue due to the complexities in human-nature behavior and traffic flow dynamics. Thus, a validation and calibration process is required to accurately replicate the driver's behavior (e.g., gap acceptance, lane changing, car following and route choice) using ground truth data [25]. The literature review indicates various studies working on calibrating/validating simulation models, effect of their results on decision-making process and evaluating impact of various design and operation alternatives [4], [26]-[31]. Moreover, the default underlying models in simulation tools often are developed based on some specific traffic condition and/or location which may not be generalized to other traffic situations. This necessitates the development of location-specific driving behavior models using comprehensive field data. For example, Bartin et al. [27] applied the binary probit model based on extensive field data to model the gap acceptance behavior of drivers in two unconventional traffic circles in New Jersey. They used the application programming interface (API) feature of Paramics simulation software, to replicate site-specific gap acceptance behavior of drivers, instead of the default gap acceptance model of Paramics. Their results were promising in terms of predicting accepted gap time using the probit model. Also, in another study, Bartin [28] applied the reinforcement learning approach to model the gap acceptance decisions of drivers using the same observed data that were used in [27]. The study indicated that the Q-learning reinforcement algorithm can yield high level of accuracy in terms of validation when simulating the gap acceptance behavior of drivers in a microscopic simulation model. In fact, machine learning methods in some cases outperform the statistical methods due to their ability to handle outliers and missing values as well as their independency from predefined correlations between exogenous and endogenous variables [32]. Nagalla et al. [33] investigated the left-turn gap acceptance decision at an unsignalized intersection using support vector machine (SVM), random forest (RF), and decision tree (DT) models. They showed that DT and SVM indicate considerably different results and the RF model was more robust than the DT and SVM models. Furthermore, simulation-based methods are more preferable and convenient than analytical methods, which require many efforts to collect field data and process them for model development. Dutta and Ahmed [24] demonstrated that the difference between critical gaps obtained from the simulation and field data for both logit and clearing time methods is not more than 10 percent.

To that end, the objective of this study is to present the feasibility of applying an artificial neural network (ANN)-based gap acceptance model in a microscopic traffic simulation, in which the drivers' individual gap acceptance decision is represented without relying on the default mechanism provided in the simulation package. For this purpose, first an ANN is used as the state-action mapping function to train drivers for their gap acceptance, then the model is tested using the API feature of SUMO, a microscopic simulation tool, to check the compatibility of the simulation model with the field condition. The proposed approach is tested on the simulation model of a stop-controlled intersection located at Collingwood traffic in New Jersey. The real-world data were collected and processed as part of the analyses presented in Bartin et al. [27].

The outline of the paper is as follows. The next section presents the methodology of implementing the ANN-based gap acceptance model using SUMO API. The case study, data collected, and analyses results are presented in section 3. Section 4 presents the conclusions and possible future work.

2. Methodology

The methodology used in this study is twofold. First, the ANN method was used to model drivers' gap acceptance behavior based on the collected ground truth data. Second, a microscopic simulation model was developed to test the feasibility of implementing the ANN-based gap acceptance behavior in lieu of the default behavior embedded in the simulation package. The performance of this approach was tested by comparing the simulation outputs with those extracted from the ground-truth data. Two output variables were used for this purpose, namely, wait time at the intersection and accepted gaps.

The application of ANN has expanded to a wide variety of disciplines including the transportation and traffic domain. ANN method is a good fit for modeling traffic with heterogenous drivers where their interaction is discontinuous, nonlinear and complex [34]. The main mechanism of ANN is to extract the underlying structure that relates explanatory variables to target variable from a set of sufficient real-world data. The application of ANN in transportation domain has been widely used during the last decades [35]-[40]. For example, Zheng et al. [41] used ANN to estimate the driver's lane-changing behavior and compared it with the multi-nominal logit (MNL) model. They indicated that the ANN outperformed the MNL in terms of accuracy of estimating lane-changing samples. In another study, an ANN model was trained to replicate the driver's car-following model using naturalistic driving data [42]. The results were compared with an alternative approach, Gazis-Herman-Rotery (GHR) model. The performance of ANN in capturing driver's car-following behavior was higher than that of GHR model. To the best of the authors' knowledge, the application of ANN has not been investigated in the gap acceptance decision context.

2.1. Description of the ANN-Model

A feedforward backpropagation neural network is utilized as the state-mapping function for predicting the driver's decision. The training process is the adjustment of weights and bias by calculating the error between actual output action and predicted output action and propagating it back to each neuron in the network. This process is iterated until the weights between layers converge and the error propagation is minimized. The gradient descent algorithm acts as the learning rules to gradually estimate the driver decisions from the input and output data during the training episodes. The Keras library is used for developing and training the ANN model in Python.

The ANN in the proposed model consists of five layers (an input layer, three hidden layers, and an output layer). The input layer includes four vectors containing: Time Headway (TH) or interarrival time of mainstream vehicles, type of vehicle at the minor approach (passenger car and truck), wait time of vehicle at the minor approach and the lane index of mainstream vehicles.

The summation of bias and weighted inputs is the input of activation function in the next (hidden) layer. The activation function in all units of hidden layers is Rectified Linear Unit (ReLU). There are sixteen neurons in each hidden layer. The last layer is the output layer with only one neuron and sigmoid activation function. Based on a defined threshold, the ANN model predicts whether accept or reject the gap. The procedure concerning hyperparameter tuning and selecting a suitable architecture for the presented ANN model was accomplished by trial and error where the main objective was to obtain the maximum accuracy and minimum loss while controlling the balance between bias and variance. The model was trained with 80% of data and validated with 20% of data. Binary Cross Entropy was used as loss function and Stochastic Gradient Descent as the optimizer with learning rate of 0.005. The model was converged after 1760 epochs which resulted in an accuracy of 97%.

2.2. Implementing the ANN-Model in SUMO

To implement the ANN model, SUMO microscopic simulation software is utilized [43]. SUMO's Application Programming Interface (API), known as TraCI (Traffic Control Interface), allows modelers to control the behavior of all simulation objects, adjust many of its default traffic models during the simulation as well as implement their own models instead of using underlying default traffic models.

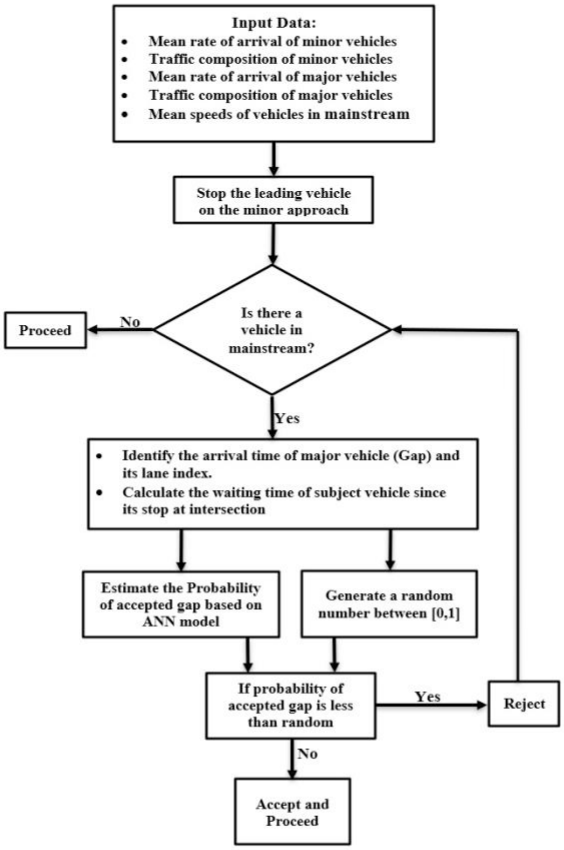

Fig. 1 The flowchart of decision-making process

Fig. 1 presents the implementation of the ANN-based gap acceptance model at a stop-controlled intersection using SUMO TraCI. The average arrival rate of vehicles on the minor and major roads, the traffic composition on the minor and major roads, and the average speed of vehicles on major road are defined as the input data for the simulation. Any vehicle that enters the minor road receives a stop command and comes to a complete halt at the stop sign behind the intersection. At each time step (0.1 seconds) the model checks for any vehicle in the mainstream, if there is no vehicle, the subject vehicle is allowed to proceed and cross the intersection. Otherwise, it detects the leading vehicle on the approach link, determines its speed and distance from the intersection and calculates its arrival time to the intersection. Therefore, the probability of accepting gap for every major vehicle at each location and at each simulation time step is estimated based on the developed ANN model. This probability value is then compared with a uniformly generated random number between [0,1]: if the probability is greater than the random number the vehicle would accept the gap and cross the intersection otherwise it would reject the gap and wait for the next vehicle.

3. Case Study

A stop-controlled intersection studied by Bartin et al. [27] was selected for the analyses used here. The selected intersection was part of the old design of Collingwood Circle in New Jersey, which was later redesigned as a modern roundabout. The raw field data borrowed from Bartin et al. [27] was processed for afternoon peak period, 3 pm to 5 pm, to extract the variables used in the gap acceptance model. The extracted data include (1) vehicle counts with percentage distributions of trucks and passenger cars, (2) vehicle interarrival times at mainstream, (3) vehicle wait-times before stop sign on minor road, (4) the lane index of vehicles at mainstream and (5) gap acceptance/rejection times at the stop sign. The accepted gap and average wait-time of observed data during the afternoon peak period are presented in Table 1.

Three gap acceptance behavior models were compared. First is the default SUMO gap acceptance behavior. Second is the calibrated SUMO gap acceptance behavior. Third is the use of the proposed ANN-based gap acceptance behavior implemented in SUMO TraCI.

The default gap acceptance mechanism embedded in SUMO is based on several parameters. These are maximum speed and deceleration of vehicles, wait time, impatience of drivers and minimum time gap when passing ahead of a prioritized vehicle. The detailed information on the default gap acceptance mechanism of SUMO can be found in [44]. To explain briefly, when a vehicle in low priority approach stops behind the intersection, it checks the high priority road for any approaching vehicle, then it decides to enter the intersection if the time difference between its expected arrival at the intersection and the expected arrival of the high priority vehicle to the intersection is greater than the minimum time gap i.e., critical gap. In addition, impatience is another factor that affects the decision-making process. Vehicles with high impatience tend to enter the intersection aggressively without considering the right of way rules. This parameter has a direct relationship with the wait time, i.e., it increases while a vehicle is waiting to pass an intersection. SUMO allows users to customize the aforementioned parameters to calibrate the gap acceptance in the stop-controlled intersection.

Two output variables were used for comparing the three gap acceptance models, namely wait time and accepted gap. Based on the central limit theorem, the sampling distributions of the output variables are based on a Gaussian distribution with unknown variances regardless of their initial distributions. The model was simulated with various 20 seeds so that the model outputs achieved a 95% confidence interval with a relative error of 5%. To find the 95% confidence interval for the population mean with a Student's *t*-distribution, the obtained values of the selected output variables were used.

Table 1 presents the observed statistics on wait time and acceptance gap, as well the 95% confidence interval for the outputs produced by SUMO default, SUMO calibrated and ANN-based models. In the calibrated SUMO, the default parameters were modified as part of the calibration process to obtain the closest output values to the observed outputs. It should be noted that the wait time shown in Table 1 do not include the queuing time. In addition, the runtime is the time that takes to complete a simulation run.

Table 1 Observed and simulated outputs

	Runtime (s)	Accepted Gap (s)	K-S test (%)	Wait Time (s)	K-S test (%)
Observed (Average)	-	5.5	-	14.6	-
SUMO Default	35	[7.1-7.8]	0	[54.6-62.9]	0
SUMO Calibrated	30	[4.8-5.1]	0	[13.2-14.6]	3
ANN-based Model	280	[5.3-5.6]	0	[13.9-14.9]	1

It can be observed in Table 1 that the SUMO simulation with default parameters fails to replicate the actual conditions at the selected intersection, where the wait time is significantly higher than that of the observed one. The calibrated SUMO model yields far superior results as the wait time is nearly within the 95% confidence level, yet the accepted gap interval does not cover the average observed accepted gap value. The ANN-based model produces slightly better results than those of the calibrated SUMO model. Furthermore, the Kolmogorov–Smirnov (K-S) test was conducted to compare the output distributions of accepted gap and wait time for simulated and observed models. The null hypothesis that two variables have similar distribution is rejected when the p-value is less than the significance level (1 percent). Despite that the gap acceptance distributions appear to be close, the K-S test failed for these variables because their p-value is less than 1 percent.

Although the calibrated SUMO and ANN-based models produce similar results, it should be noted that the comparison is based on only the outputs extracted at the minor approach. During the simulation runs in SUMO calibrated model, it was observed that the vehicles on the major road frequently decelerated at the intersection, often coming to a full stop as the vehicles on the minor approach accepted unrealistically low gaps. This is due to the impatience parameter used by SUMO, where, as vehicles wait for more than a certain threshold, they start ignoring the priority rules. As a result, even though the calculated accepted gap within TraCI appears "reasonable", the actual gap is not. The accepted gap calculation in TraCI is coded as distance over time, therefore it measures the estimated time the vehicle on the major road arrives at the intersection based on its instantaneous speed. However, as vehicles decelerate sharply before the intersection, the calculated accepted gap falls within the reasonable bounds, as shown in Table 1.

In order to inspect this deceleration behavior, the speed and acceleration trajectories of vehicles on the major approach were generated for every three scenarios, as shown in Fig. 2 and Fig. 3, respectively. In these figures, the arithmetic average speed and acceleration are shown along with their upper and lower bounds. The position is the distance between point at the main road and end of the intersection in meters.

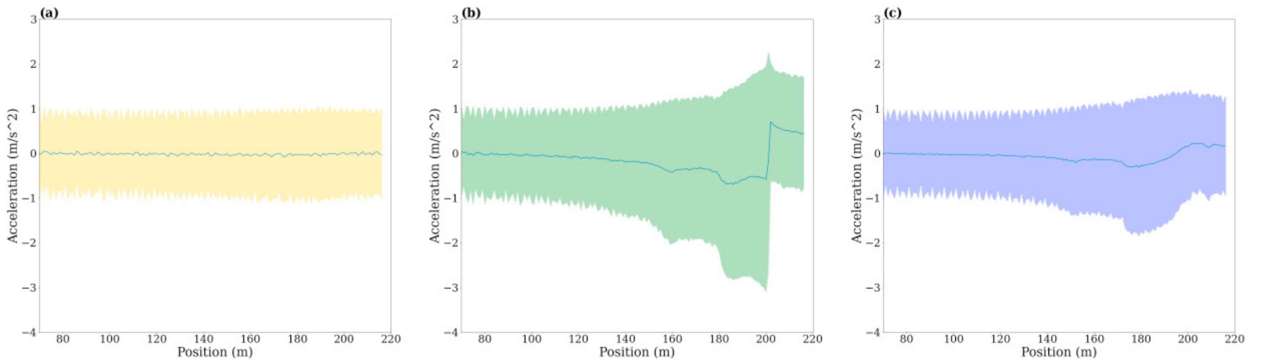

Fig. 2 The acceleration trajectory of major vehicles (a) SUMO default, (b) SUMO calibrated and (c) ANN-based model

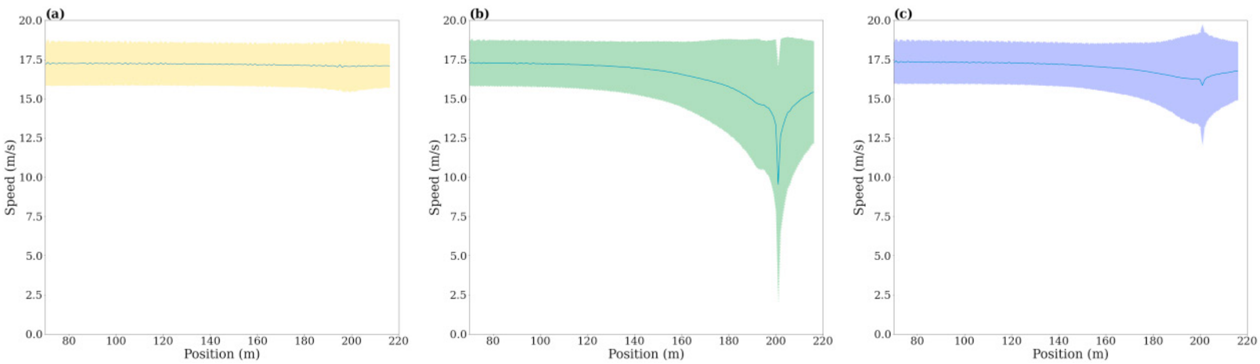

Fig. 3 The speed trajectory of major vehicles (a) SUMO default, (b) SUMO calibrated and (c) ANN-based model

The figures indicate that the default SUMO shows a consistent behavior regarding speed and acceleration, which means that the major vehicles do not change their deceleration or speed at the visibility distance and at the intersection. On the other hand, there is an inconsistency in the speed profile of higher priority vehicles in the calibrated SUMO model. In other words, most of the low priority vehicles are rushing through the intersection which causes the major vehicles to decelerate or slow down when approaching and passing the intersection (around position 200 m), so that affects the overall performance of the traffic network in terms of travel time and safety. However, this inconsistency in ANN model is insignificant and most of the vehicles on major road continue their route without slowing down. In that respect, it can be argued that the proposed ANN-based model yields promising results as opposed to the SUMO model calibrated using default parameters.

4. Conclusions

In this paper, an ANN-based gap acceptance behavior model was proposed and implemented in the simulation model of a stop-controlled intersection in SUMO. Enhancements in computing power and the availability of simulation packages have oriented traffic engineers and practitioners to implement simulation-based approaches to predict the impact of operational and safety measures. There are numerous off-the-shelf simulation packages that enable users to simulate traffic facilities. However, an accurate calibration/validation is required to replicate the driver's traffic behavior in the real-world condition. The underlying models in most of these simulation tools cannot and should not be directly used without a comprehensive calibration and validation process. Performing a thorough calibration and validation process depends on the capacity of the selected simulation tools' ability of allowing users to implement their own traffic models. The simulation software used in this study is SUMO which is an open-source user-friendly microscopic simulation tool. TraCI, the application programming interface of SUMO, allows users to customize and implement their own algorithms.

The gap acceptance decision of drivers was modelled by training an ANN model based on an extensive real-world data, collected at a stop-controlled intersection in New Jersey. The ANN-based gap acceptance model was then implemented in SUMO using its API capability to reproduce driver's behavior when crossing an intersection. The proposed model was compared with default SUMO and calibrated SUMO based on the wait time and accepted gaps of the vehicles at the minor approach. The results indicated that both ANN scenario and calibrated SUMO scenario produced nearly similar outputs regarding the accurate estimation of observed variables. However, unrealistic behavior of the vehicles on the major approach was detected based on the inspection of their speed and acceleration trajectories. To put it differently, higher priority vehicles had to decelerate or even stop as a result the lower priority vehicles at the stop sign accepting very small gaps due to impatience. This deviated from the observed behavior at the intersection. Therefore, any output measures that could be extracted from the simulation model, such as surrogate safety measures, would certainly be flawed. On the other hand, such unrealistic gap acceptance behavior was not observed in the ANN-based gap acceptance model.

The future work will include the implementation of the ANN-based driving behavior models in more complex decision-making environments such as gap acceptance at yield-controlled intersections as studied in Bartin et al. [27] and lane changing manoeuvres as studied in Liu et al. [45].

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