Implementing Artificial Neural Network Based Gap Acceptance Models in The Simulation Model of a Traffic Circle in SUMO

A Thesis

by

Mohammad Bagheri

Submitted to the
Graduate School of Sciences and Engineering

In Partial Fulfillment of the Requirements for

the Degree of

Master of Science

in the

Department of Civil Engineering

Özyeğin University

August 2022

Implementing Artificial Neural Network Based Gap Acceptance Models in The Simulation Model of a Traffic Circle in SUMO

Approved by:

Associate Professor Bekir O. BARTIN, Advisor,

Department of Civil Engineering

Özyeğin University

Assistant Professor TANER YILMAZ,

Department of Civil Engineering

Özyeğin University

Date Approved: 5 August 2022

Professor Ismail Sahin,

Department of Civil Engineering

Yıldız Technical University

This work is dedicated to those whose support and words of encouragement helped me to accomplish this journey successfully, specially my beloved wife who is a great source of motivation for me to fuel my endeavor and diligence. A special feeling of gratitude to my advisor, Dr. Bekir Bartin, of whom I acquired a great deal of experience and knowledge through his kind support, patience and precious guidance. I am very grateful and honored for completing my M.Sc. program under his supervision.

ABSTRACT

The impact of various operational and design alternatives at roundabouts and traffic circles can be evaluated using microscopic simulation tools. Most microscopic simulation softwares utilize default underlying models for this purpose, which may not be generalized to specific facilities. Since the effectiveness of traffic operations at traffic circles and roundabouts is highly affected by the gap rejection–acceptance behavior of drivers, it is essential to accurately model driver's gap acceptance behavior using location-specific data. The objective of this paper was to evaluate the feasibility of implementing an Artificial Neural Network (ANN)-based gap acceptance model in SUMO, using its application programming interface. A traffic circle in New Jersey was chosen as a case study. Separate ANN models for one stop-controlled and two yield-controlled intersections were trained based on the collected ground truth data. The output of the ANN-based model was then compared with the SUMO model, calibrated by modifying the default gap acceptance parameters to match the field data. Based on the analyses results it was concluded that the advantage of the ANN-based model lies not only in the accuracy of the selected output variables in comparison to the observed field values, but also in the realistic vehicle crossings at the uncontrolled intersections in the simulation model.

ÖZETÇE

Dönel kavşaklarda ve trafik dairelerinde çeşitli operasyonel ve tasarım alternatiflerinin etkisi, mikroskobik simülasyon yazılımları kullanılarak değerlendirilebilir. Çoğu mikroskobik simülasyon yazılımı, bu amaç için belirli tesislere genelleştirilemeyecek varsayılan temel modelleri kullanır. Trafik daireleri ve dönel kavşaklardaki trafik operasyonlarının etkinliği, sürücülerin boşluk reddetme-kabul davranışından büyük ölçüde etkilendiğinden, konuma özgü verileri kullanarak sürücünün boşluk kabul davranışını doğru bir şekilde modellemek esastır. Bu makalenin amacı, uygulama programlama arayüzünü kullanarak SUMO'da Artificial Neural Network (ANN)-tabanlı bir boşluk kabul modeli uygulamanın fizibilitesini değerlendirmektir. Örnek olay olarak New Jersey'deki bir trafik çemberi seçilmiştir. Bir durak kontrollü ve iki verim kontrollü kavşak için ayrı ANN modelleri, toplanan yer gerçeği verilerine dayalı olarak eğitilmiştir. ANN tabanlı modelin çıktısı daha sonra SUMO modeliyle karşılaştırıldı ve varsayılan boşluk kabul parametreleri saha verileriyle eşleşecek şekilde değiştirilerek kalibre edildi. Analiz sonuçlarına dayanarak, ANN-tabanlı modelin avantajı, seçilen çıktı değişkenlerinin gözlemlenen alan değerlerine göre doğruluğunda ve ayrıca simülasyon modelinde kontrolsüz kavşaklarda gerçekçi araç geçişlerinde yattığı sonucuna varılmıştır.

ACKNOWLEDGMENTS

Many thanks to my advisor, Dr. Bekir Bartin, who has been an ideal teacher and thesis supervisor, offering advice and encouragement with a perfect blend of insight and patience. I'm proud of, and grateful for, my time working under his supervision.

Thanks to the Ozyegin University for awarding me a Dissertation Completion Scholarship, providing me with the financial means to complete this project

Table of Contents

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Controlling the traffic flow at the intersections significantly impacts the overall performance of the complete transport system. Specially unsignalized intersections, where at least one of the movements is controlled by a STOP sign or YIELD sign, are more prone to traffic hazards, delay and congestion [1]. The two-way stop-controlled, all-way stop-controlled, and roundabouts are classified as unsignalized intersections. Roundabouts in particular are considered a popular transportation facility due to their safety, capacity, and environmental advantages [2]. The accurate models of such facilities are necessary to measure the efficiency of various safety countermeasures or alternative operational scenarios.

One of the key factors in assessing the safety and operational performance of roundabouts is the gap acceptance behavior of drivers. In other words, vehicles in the minor stream (low priority) are permitted to cross the intersection provided they find a suitable gap in the major stream (high priority). The gap is in fact the interarrival time of vehicles in the mainstream traffic at the intersection. The gap acceptance decision-making process depends on various external and internal parameters such as vehicular characteristics, intersection characteristics, type of control, opposing flow, psychological and socioeconomic status of drivers, weather, pavement and light conditions, and factors related to the vehicle occupancy.

As mentioned in the literature review section, the impact of various operational and infrastructure changes at roundabouts are evaluated using computer tools that employ analytical or simulation-based methods. There are a wide variety of computerized analysis tools that offer efficient and detailed analysis of transportation facilities. The choice of which computer tool to use depends on the scope of the project and studied area. While the deterministic tools offer an efficient and detailed analysis of roundabouts and estimate the capacity and delay at the approaches, high fidelity simulation tools can present the impact not only at the roundabout but also in the surrounding network, therefore providing a more comprehensive impact analysis of various safety and operational measures. However, the development of an accurate simulation model is a challenging issue because of the complexities in the human-nature behaviour and traffic flow dynamics. Most microscopic simulation tools utilize default underlying models for this purpose, developed based on some specific traffic condition and/or location which may not be generalized to other facilities due to the heterogeneity in driver behavior, demographics, cultural norms, etc. Because the effectiveness of traffic operations at circles and roundabouts is highly affected by the gap rejection–acceptance behavior of drivers [3], it is essential to accurately replicate the driver's behaviour, such as gap acceptance using location-specific models.

To that end, this paper aims to demonstrate the viability of using an artificial neural network (ANN)-based gap acceptance model in a microscopic traffic simulation in lieu of the default gap acceptance model embedded in the simulation package. Collingwood traffic circle in New Jersey was used as a case study. The simulation model of the circle for the morning peak period was developed in Simulation of Urban Mobility (SUMO) simulation software. The gap acceptance models were developed using a Back-Propagation (BP) neural network trained by field data, which was collected as part of an earlier study by Bartin et al. [3]. Then these intersection-specific models were applied in SUMO using its application programming interface (API), named Traffic Control

Interface (TraCI). The validation of the simulation model was then conducted by comparing the selected simulation outputs with those of the observed field data. The analysis results showed the ANN method could be beneficial in terms of accurate replication of drivers' critical gap values as well as realistic driving behavior.

The outline of this thesis study is as follows. The second chapter provides a literature review regarding the main concepts applied in this work. 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 4. Section 5 presents the conclusions and possible future work.

CHAPTER II

LITERATURE REVIEW

The literature study was conducted to highlight the knowledge gap within the concept of vehicle's gap acceptance decision-making, specifically at unsignalized intersections. For this purpose, the literature review is initiated with providing the general information about intersections. As a key feature within this study, the critical gap context, its application, and possible calculation methodologies are introduced. Then, the concept of Artificial Neural Network (ANN) is explained, followed by reviewing its relevant research studies in the domain of vehicle's decision-making process. The traffic simulation plays an important role in this thesis, thus requires understanding theories behind the traffic simulation. The simulation-based techniques are presented in general, and finally there is an introduction of selected SUMO software.

2.1 Intersections

Intersections are locations in the transportation network where multiple roads are intersecting each other. Controlling the traffic flow at the intersections has a significant impact on the overall performance of the complete transport system. There are two types of intersections that are classified based on traffic control measures, signalized intersections (intersections controlled by traffic signals) and unsignalized intersections; the latter is divided into four subcategories, uncontrolled intersections, stop sign-controlled intersections, yield sign-controlled intersection and roundabout [4]. The operations of unsignalized intersections oblige the vehicles in minor road to make decision about the size of gap in the major street, to whether accept the gap and cross/merge into the mainstream or not. For example, Figure 1 shows three types of unsignalized intersections, the two-way stop-controlled (TWSC), all-way stop-controlled (AWSC) and roundabout [5]. At a two-way stop-controlled (TWSC) intersection (Figure 1.a), the left turn and through movements in the major road have priority over the left-turn and through movements of minor road. On the other hand, these movements of minor street have priority over the right-turn movement in the major road. Thus, the capacity of minor approaches is a function of these priority rules combined with the geometry and relative demand of each movement. The AWSC intersections are operated slightly different than TWSC intersections as the first arriving vehicle is prioritized over the later arriving vehicle. Thus, the priority rules within these intersections are independent of drivers' gap acceptance, rather it depends on the position of the vehicles relative to the other vehicles at intersection when they approach the stop bar. The demand size at each approach impacts the capacity of the other approach in a way that increasing the demand in one approach reduces the capacity in the other approach. Roundabouts are the traffic circles where the vehicles flow around a central island in one direction, and are more advantageous in terms of operational performance, safety and other benefits [6]. At the modern roundabouts, the vehicles on the entrance lanes (minor road) have to yield to the vehicles on the circulating lanes (major road) by judging the gaps within the circulating traffic. Comparing with the right-turn movement of a stop-controlled approach, the roundabouts approach has higher capacity and lower delay.

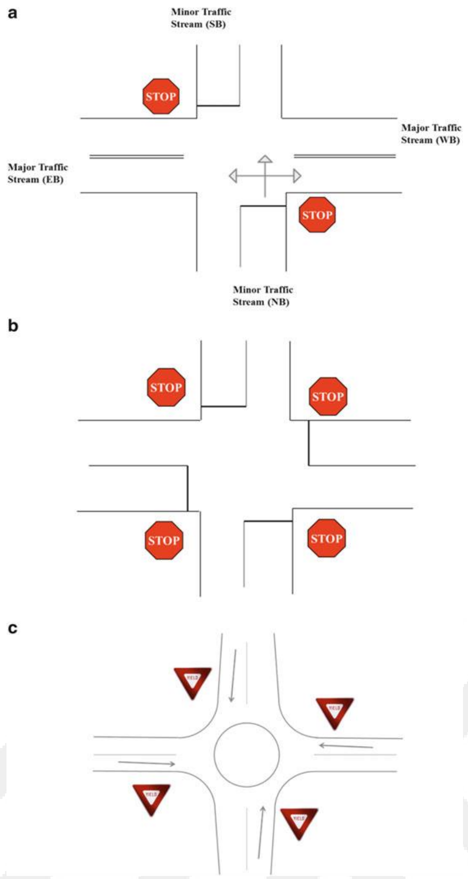

Figure 1: Three types of unsignalized intersections: (a) TWSC, (b) AWSC, and (c) Roundabout [5].

The trajectory of a vehicle approaching a stop sign and that of a vehicle approaching a yield sign is shown in Figure 2. According to this figure, the yield-sign intersection produces smaller travel time and lower delay for the minor traffic stream. It is important to measure the performance of any unsignalized intersection by analysing the capacity of the minor road and calculating the average delay to achieve an expected level-of-service. Using the gap acceptance theory one can calculate the entrance capacity, delay, and queue length. For example, the roundabout capacity is highly influenced by the gap acceptance behavior of drivers. According to the Highway Capacity Manual (HCM) [7], the capacity of a roundabout can be calculated based on various parameters, one of which is the critical gap. There is a sundry of research works trying to measure the capacity of roundabout using the gap acceptance theory [8]- [10].

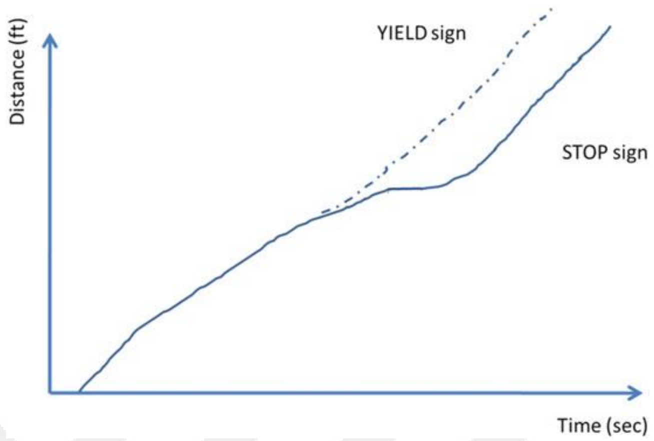

Figure 2: Trajectory of vehicle approaching a stop sign (TWSC) vs. a yield sign [5].

2.2 *Principals of Gap Acceptance*

Drivers at unsignalized intersections should make decisions about the safe crossing or merging into the conflicting traffic stream. They should seek gaps that are acceptable for them and consider other drivers in the higher priority stream. In other words, vehicles in the minor stream (low priority) are permitted to cross the intersection provided that they find a suitable gap in the major stream (high priority). The accepted gap means that the gap is large enough to allow the vehicle on minor road to cross the intersection and the rejected gap means the gap is very small that the vehicle on minor stream refuses to cross the intersection. This process is known as the gap acceptance. A gap is usually defined as the time headway between the rear bumper of the first vehicle and the front bumper of the second vehicle and is usually measured in seconds [11], see Figure 3; however, some references also define it as the time headway between successive vehicle arrivals. This study used the first definition and referred to the first one simply as the time headway. Gap acceptance models are used to predict the acceptance or rejection of a particular size gap by a driver or group of drivers under a given set of specific conditions.

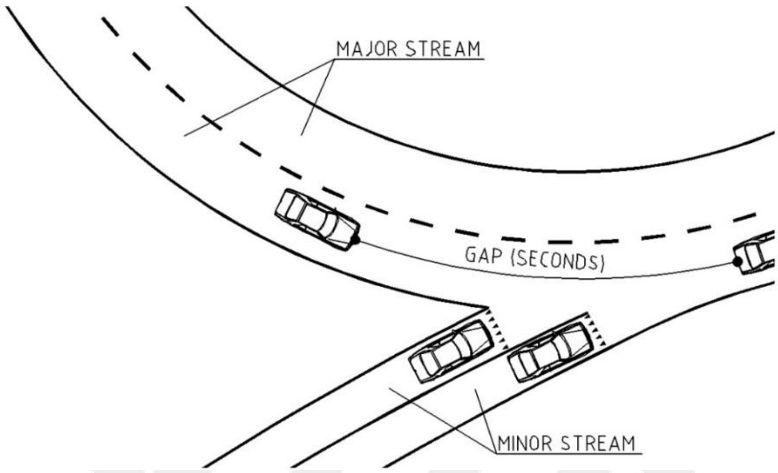

Figure 3: The gap definition [5].

2.3 Critical Gap

To better understand the gap acceptance behavior at unsignalized intersections and to conduct intersection-related safety and operations analysis, the concept of the critical gap has been introduced and refers to a judgment threshold to whether a minor-road vehicle can cross the intersection. By definition, the critical gap is the minimum time headway in the mainstream that is acceptable to a driver on the minor road [7]. It is not possible to directly observe the critical gap, rather it can be measured by analyzing the accepted and rejected gaps. The value of the critical gap depends on various parameters such as traffic conditions, driver characteristics, weather conditions, vehicle type, and so on [12]-[17]. It is necessary to collect a wide set of accepted critical gap values from various scenarios to apply for an extensive range of engineering application related to intersections, such as traffic control analysis, roadway geometric design, safety and capacity analyses. There are two ways of modelling the critical gap values, the deterministic approach and the probabilistic approach [18]. The deterministic approach treats the critical gap value as a single average value, assuming that the gaps larger than the critical gap are accepted gaps and smaller than the critical gap are rejected gaps. While the probabilistic method takes into account the inconsistency and heterogeneity in the gap acceptance behavior of drivers in the minor stream and treats the critical gap as a random variable. During the recent years various techniques have been developed to calculate the critical gap value. However, each of these methods has advantages and disadvantages and differs in level of complexity, assumptions, and ease of use. A brief description of some of these methods are summarized as follow [19]-[21].

Gap acceptance curve: based on both theoretical and empirical considerations, if a dependent variable is binary, the target variable takes the shape of curvilinear, which means that the target variable takes the shape of tilted “S” with the value of 0 or 1 as asymptotes. The cumulative probability of accepting a gap of a specific length is the dependent variables of this response curve. The critical gap value may be calculated as the *x*-value corresponding to the 0.5 probability. The probability is calculated as follow [22]:

$$P_i = \frac{d_i}{N}\,, \qquad 0 < P < 1 \tag{1}$$

where P_i = cumulative probability of accepting a gap of time length i; d_i = number of gaps accepted of time length i or less; and N = total number of events.

Greenshields method: this method is proposed by Greenshield et al. [23] that utilizes a histogram to represent the frequency of acceptances and rejections for each gap range. The horizontal axis of the histogram is the gap-size range, and the vertical axis is the number of gaps accepted (positive value) or rejected (negative value) of a certain gap range. The critical gap is identified as the minimum time gap that is acceptable for more than 50 percent of the drivers. Figure 4 shows an example of Greenshields method for a specific type of vehicles performing right-turning manoeuvre at an intersection [23]. As can be seen from this figure, the critical gap in around 8.2 seconds, i.e., three vehicles rejected, and three drivers accepted the gaps between 8 and 8.5 seconds. This method is very simple, however small sample sizes may influence and distort the analyses.

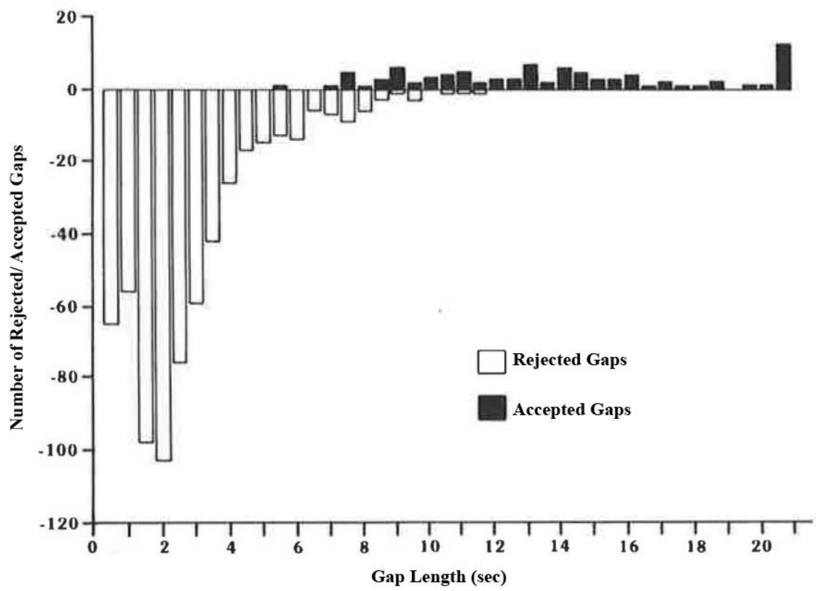

Figure 4: Greenshields method plot for a sample vehicle [24].

Raff method: Raff and Hart [25] defined the critical gap, as the size gap, T, for which the number of rejected gaps longer than T is equal to the number of accepted gaps shorter than T. The acceptance curve is obtained by a cumulative curve that indicates the total number of accepted gaps with gap size less than the given gap size. The rejection curve is created based on the total number of rejected gaps with gap size larger than the given gap size. The original Raff method only considers lag acceptance and rejection data. More recent studies used the combination of lag and gap data and indicated that the acceptance of gaps and lags is not significantly different from each other and that the lag and gap data can be combined [26], [27]. Figure 5 demonstrates the Raff method's plot, on which the critical gap value of a five-axle trucks turning right is 8.5 seconds.

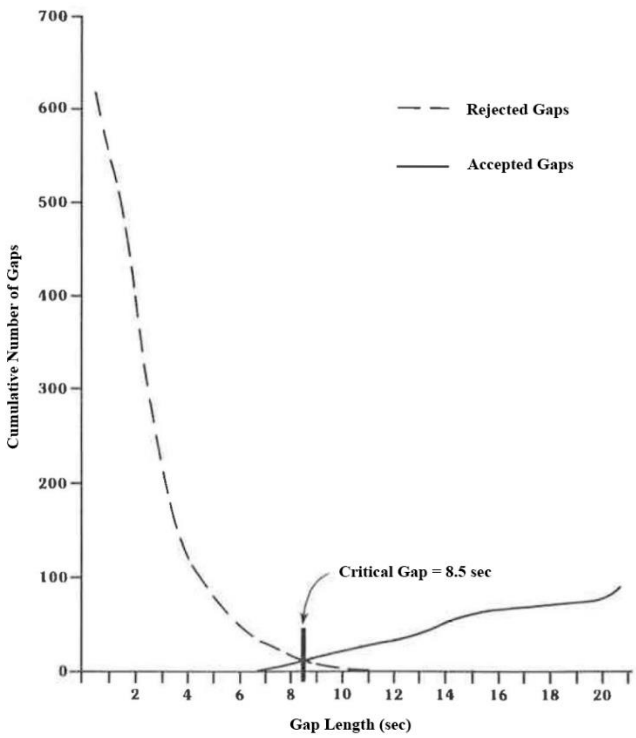

Figure 5: Raff method plot for a sample vehicle [24].

Logit Method: the logit method, which is also known as logistic regression method, uses the logistic function to model the gap acceptance and rejection decisions as the binomial response of gap size. This function is curvilinear, however it can be easily linearized using the logistic, or logit, transformation. The critical gap is defined as the gap sized related to a certain level of acceptance probability (e.g., 50% or 85%). The probability function for the logistic model is [28]:

$$P = \frac{1}{1 + \exp\left(-(\beta_0 + \beta_1 X)\right)} \tag{2}$$

Where P is the probability of accepting a gap; X is the variable related to the gap acceptance, i.e., gap length; and β_0, β_1 are the regression coefficients. This function can be linearized using:

$$P' = \ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X \qquad (3)$$

where P' equals the transformed probability. For instance, according to the Figure 6, the 50 percent of a specific vehicle at an intersection accepts a gap 8.52 seconds and 85 percent of them accepts a gap of 10.06 seconds.

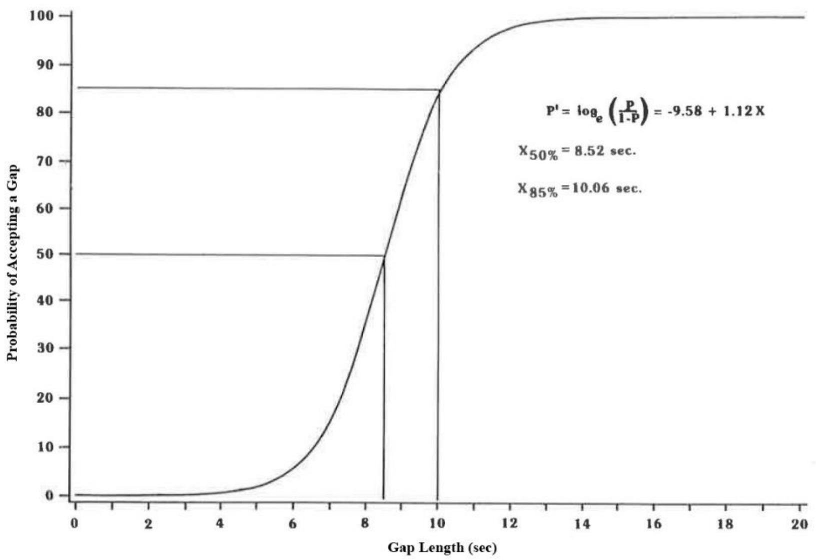

Figure 6: Logit method plot for a sample vehicle [24].

Maximum likelihood method: the main assumption in this method is that the critical gaps for a given vehicle population follow a lognormal distribution and the general critical gap for the population is the mean critical gap [29]. The critical gap is calculated using the distribution coefficients that maximize the likelihood of the critical gap for an individual lower than the actual accepted gap and higher than the highest rejected gap. McGowen and Stanley improved the maximum likelihood method to analyse data with only accepted gaps or rejected gaps [30]. The maximum likelihood method may be a reliable method in the presence of inhomogeneous vehicle population.

Probability equilibrium: In this method the critical gap is estimated based on cumulative distributions of accepted and rejected gaps [31]. The method does not require any presumption regarding data distribution, although it needs less computation than the maximum likelihood method.

Probit analysis: this method is a statistical technique employed to treat the percentages of a population making binomial responses to increasingly severe values of a stimulus [32]. In the gap acceptance theory, the size of gap is equal to the value of the stimulus. The equation of probit transformation follows:

$$y = 5.0 + \frac{x - \mu}{\sigma} \tag{4}$$

Where y is the probit of x; μ is the population mean; and σ is the standard deviation of the population. The transformation of cumulative percentage to probit can be obtained from a probit transformation table. This helps plot the data based on the transformation of the percentage of acceptance and gap size. Then the value of gap that produces probit of 5.0 can be identified by fitting a linear line on the chart. This value is defined as the median value of the stimulus, i.e., the critical gap.

The abovementioned methods are known as the statistical techniques for critical gap computation. However, most of these models require predefined functional form that may limit the prediction accuracy and, in some cases, can result in erroneous results. Moreover, the presence of outliers and missing values in the dataset can negatively influence these statistical models. The data mining models used in the gap acceptance analysis include but not limited to Decision Tree (DT), Random Forest (RF), Support

Vector Machine (SVM), and ANN [33]-[37]. According to the recent studies on modelling the gap acceptance behaviour of drivers, the data mining techniques proved to be more advantageous than statistical techniques because, first, they can resolve the outliers and missing values problem, and second they are non-parametric tools that do not need any predefined correlation between independent and target variables [33]. Pawar et al. [34] compared the SVM and binary logit models (BLM) to predict the critical gaps and they stated that SVM performed reasonably well in comparison with the BLM method.

There is a large body of literature focusing on the critical gap estimation with the application of both statistical and data mining techniques. Marczak et al. [38] used the logistic regression method to estimate the acceptance or rejection of a given gap. Devarasetty et al. [39] established a binary logit model to predict the probability of accepting and rejecting a given gap. Ashalatha and Chandra [12] utilized several techniques such as lag, Harder, logit, probit, modified Raff and Hewitt methods, to predict the critical gap at two T-intersections located in the southern part of India. Maze [22] calculated the critical gap using a logit model which closely approximates the probit model. Madanat et al. [18] suggested the queuing delay to be a new variable explaining the elapsed time between arriving at the intersection stop bar and joining the queue. Stop bar delay have also been considered in the proposed gap acceptance logit models. Gattis and Low [40] compared the critical lag and gap values that was estimated from Siegloch, Greenshields, Raff, acceptance curve, and logit methods. Zohdy et al. [41] evaluated the impact of wait time and rain intensity on the gap acceptance behavior of drivers using the logit method. Their study indicated that the critical gap decreases with increasing the wait time and increases with increasing the rain intensity. The drivers' aggressiveness at a priority unsignalized intersections was investigated by Kaysi and Abbany [14] and they developed a behavioral model that is incorporated into a simulation framework to predict the delay and conflict measures at unsignalized intersections. Bartin et al. [3] modelled and simulated the gap acceptance behavior of drivers in two unconventional roundabouts, located in New Jersey, using the binary probit model and the API of Paramics software based on ground truth data. They claimed that the default gap acceptance model of Paramics may not be suitable for some specific locations, thus the binary probit model performed better in Paramics in terms of predicting the gap acceptance decisions of drivers in these two unconventional traffic circles. In addition, Bartin [42] applied the same observed data used in [3] to reproduce the gap acceptance decision-making process in a stop-controlled intersection with the application of a Q-learning Reinforcement algorithm (RL). The study showed that the RL can be promising in terms of reproducing the drivers' gap acceptance decision in microscopic simulation with a high level of validation accuracy.

It should be noted that the estimated critical gap value may vary for each of these estimation approaches [43]- [46]. For instance, Amin et al [47] concluded that the clearing time method produces the most accurate results in heterogeneous traffic situations. They also claimed that the main assumption in most of these statistical models is that the traffic condition is consistent and heterogeneous, thus they are not suitable for mixed traffic conditions. Dutta and Ahmed [48] proved that the estimation of the critical gap at a three-legged unsignalized intersection performed better results in the logit method than in the clearing time method. In another study conducted by Maurya et al. [46], the value of the critical gap in the logit method was estimated to be roughly 0.2 s longer than that of Raff's method. Nagalla et al. [35] applied three machine learning models, SVM, RF, and DT to evaluate the gap-acceptance behavior of drivers in a left-turning manoeuvre in an unsignalized intersection. Their results indicated that both SVM and RF produced roughly similar performance, while the performance of the RF model was far better than the two others.

In addition to the critical gap calculation techniques, the selection and pre-processing of the collected data should be considered in estimating the critical gap value. Common issues that researchers should take into account in the processing of collected gap data include the inclusion or exclusion of large gaps, use of gaps and lags, use of maximum rejected gaps or all rejected gaps [43], [44], [49], [50]. The Highway Capacity Manual (HCM) [7] and the American Association of State Highway Transportation Officials (AASHTO) Green Book [51] consider critical gaps for different scenarios for roadway capacity analysis and design purposes. Generally, HCM proposes a base critical gap between 7.1 and 7.5 seconds for left turn from minor and between 6.2 and 6.9 seconds for right turn from minor. The Green Book suggests a base critical gap of 7.5 seconds for left turn from minor and of 6.5 seconds for right turn from minor with an additional 0.5 seconds for each additional lane on the main road. It is worth to note that not all gaps should be evaluated in the critical gap calculation process. As concluded by Kittelson and Vandehey [52], almost all gaps larger than 12 seconds are accepted and do not need to be included in the critical gap determination. In another research, which studied the gap acceptance at a roundabout, a time gap threshold is recommended, longer than which would not be relevant for the critical gap estimation and, therefore, for the capacity analysis [53].

Furthermore, the critical gap value may be influenced by several parameters. Hamed et al. [54] indicated that the traffic speed on the mainstream, age and gender of the driver, vehicle age, type of the trip (e.g. shopping, work), existence of a median, time of day, type of manoeuvre, time that the driver waited at the front of the queue, number of lanes, and flow of opposing-through traffic are the key variables in predicting left turn gap acceptance behaviours. Some studies have shown age-related declines in older drivers' gap acceptance perception, with this decline being a strong estimator of crash rate [55]- [57]. However, Kazazi et al. [58] proved no significant variation in the collision rates of younger and older age groups.

2.4 Artificial Neural Network (ANN)

There are nearly 10 billion to 500 billion neurons within the human brain. As indicated in Figure 7a, a cell body, an axon, and dendrites build a biological neuron system. The connections between the neurons are known as synapses, and each neuron is linked to 100 to 10,000 other neurons. The task of a neuron is very simple as it receives an output from neighbour or external sources, produces an output and transfers it to the other neurons linked to it via the synapses. A neural network is a kind of computational model which is constructed of a highly interconnected mesh of nonlinear elements and its structure is inspired based on the biological nervous system. Artificial neurons (also known as processing units) replicate the functions of biological neurons by receiving a series of input variables and calculating the total output using a transfer function (Figure 7b). Like the biological neurons, the artificial neuron also connects to other artificial neurons and the strength of the connections between units is called weight [59], [60].

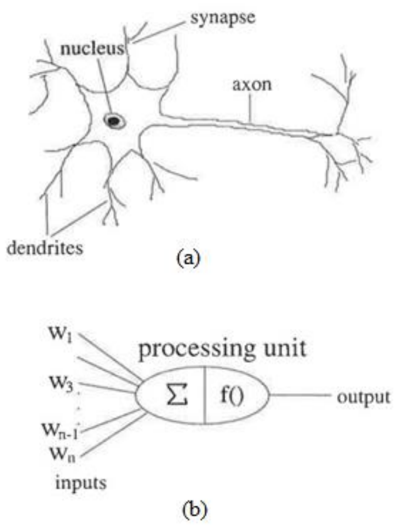

Figure 7: Schematic of (a) biological neuron, and (b) artificial neuron [61].

The Artificial Neural Network (ANN) is a system constructed of artificial neurons and artificial synapses used to simulate the functionalities of the biological neural network. Generally, the ANN can be defined as "a computing system made up of a number of simple, highly interconnected processing elements that process information by dynamic state response to external inputs" [62]. The structure of the ANN either can be single layer, of which all the processing elements take inputs from outside of the network and produce the outputs to the outside of network or can be multilayer. The axiom that can approximately calculate any reasonable function in an ANN is called architecture. The weights can be modified; the programming for modifying the weights is known as training, and the training impact is called learning. In fact, the learning process can be accomplished by being given weights that are calculated from a series of learning data or by tunning the weights automatically based on some criterion. In other words, an ANN receives training from the state-action pairs in the real data sets and develops state-action mapping rules to be used.

A feed-forward neural network and the associated backpropagation (BP) algorithm is one of the most successful paradigms of ANN. A feedforward neural network is a layered structure including an input layer, at least one hidden layer, and an output layer. The number of neurons in the input or output layer is exactly the number of variables in each layer. The units in the input layer are connected to the units in the hidden layer, which are linked, in turn, to the units in the output layer. Each of these units produces an output signal which is propagated to other units. Before communicating to other units, the output signal is transformed by an activation function. The regular activation functions used are sigmoid, ReLU (rectified linear units), tanh (hyperbolic tangent) functions. Moreover, all units in the network take a constant source of input from the bias. The BP algorithm is kind of supervised learning that acts as the state-action mapping rule. A BP neural network computes the residual between the estimated output and the real BP output, then propagates the residual back to each neuron in the network. The network weights are updated after each training episode. This process continues until the convergence of weight values and reaching a relatively small error propagation. The gradient decent algorithm is used for a BP neural network to gradually estimate the target values from the input data and target data [63].

In a BP neural network, the kth hidden-layer vector $s(k)$ is calculated from its upstream input-layer vector $s(k - 1)$. A weighted sum of input and bias is computed, and results are transformed by a transfer function:

$$\begin{bmatrix} S_{1,k} \\ S_{2,k} \\ . \\ . \\ S_{m,k} \\ . \end{bmatrix} = \begin{Bmatrix} h\left[\sum_{i=1}^{n_{k-1}} w_{i,1}^{k} s_{i,k-1} + b_{1}^{k}\right] \\ . \\ . \\ . \\ h\left[\sum_{i=1}^{n_{k-1}} w_{i,m}^{k} s_{i,k-1} + b_{m}^{k}\right] \\ . \end{Bmatrix} \tag{5}$$

Where $S_{m,k}$ is the value of the m^{th} hidden neuron, $h(.)$ is the transfer function, n_k is number of neurons in the k^{th} layer, $w^{k}_{i,m}$ is the weight connecting the i^{th} input and the m^{th} hidden neurons in the k^{th} layer, and b^{k}_{m} is the bias for the m^{th} hidden neuron in the k^{th} layer.

The nonlinear sigmoid activation function takes the value from the summation results and turns them into values between 0 and 1(equation (6)). The ReLU (rectified linear units) activation function is the most used activation function, and it returns 0 if it receives any negative input, but for any positive value z it returns that value back (equation (7)).

$$h(z) = \frac{1}{1 + e^{-z}} \tag{6}$$

$$h(z) = \max(0, z) \tag{7}$$

Similarly, the output layer vector $y(k)$ is computed as:

$$
\begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ y_l \\ . \end{bmatrix} = \begin{Bmatrix} h\left[\sum_{i=1}^{n_k} w_{i,1}^o s_{i,k-1} + b_1^o\right] \\ . \\ . \\ . \\ h\left[\sum_{i=1}^{n_k} w_{i,l}^o s_{i,k-1} + b_l^o\right] \\ . \end{Bmatrix} \tag{8}
$$

where $w^o_{i,l}$ is the weight connecting the i^{th} hidden and the l^{th} output neurons and b_l is bias for the l^{th} hidden neuron.

The learning process in BP algorithm is twofold, propagation and weight update. In the propagation phase, the training input is transferred forward through a neural network to produce the propagation's output activations. Next, to generate the gradient of all hidden neurons and output, BP of output activations is transferred towards a neural network using the target output. The weight update phase multiplies the input activation and output delta to obtain the gradient of weight. By subtracting a ratio from the weight learning rate, the weights are brought in the opposite direction of the gradient. Equation (9) illustrates one iteration of BP learning.

$$
W_{k+1} = W_k - \alpha_k g_k \tag{9}
$$

Where W_k is vector of current weights and biases, α_k is the learning rate, and g_k is the current gradient.

During the recent years, there has been an increasing interest in the application of ANN at a wide variety of problem-solving areas, specially the traffic and transportation domain [64]-[69]. The main popularity of ANN method is because of its capability to model complex scenarios and nonlinear problems such as heterogeneous vehicle characteristics with nonlinear and discontinuous interaction [70]. Kadali et al. [71] applied ANN model to evaluate the pedestrian's gap acceptance behavior under mixed traffic circumstances. The study showed that ANN model could accurately mimic the pedestrian's gap acceptance decision in heterogeneous traffic conditions. Zheng et al. [72] modelled driver lane-changing behavior using the ANN and multi-nominal (MNL) models. They reported that the ANN model performed better than the MNL model in predicting the vehicle's lane-changing decision. In another research, driver's car-following behavior was modelled with the application of ANN and an alternative model, Gazis-Herman-Rotery (GHR) model. The study concluded that the ANN model outperformed the GHR model in reproducing driver's car-following behavior [64]. Bagheri et al., [36] evaluated the feasibility of validating vehicles' gap acceptance decision in a stop-control intersection using the ANN model and microscopic traffic simulation programming in SUMO. The analysis results indicated that the ANN-based SUMO model produced superior results and led to significantly more realistic driving behavior in the major stream compared to the SUMO model with default gap acceptance parameters and the SUMO model with calibrated gap acceptance parameters.

2.5 Traffic Simulation

Simulation can be defined as the illustration of reality, often within a confined range. It is a system contains objects, elements, and components that are impacted by each other as well as the environment. These models could be explained and realized alone or in limited interactions by logical or mathematical analysis. However, in large and complicated scenarios, on which there are many interactions between entities and components, the simulation model is required. Simulation models are also beneficial in cases there is no other ways to investigate a dynamical problem or the cost of making the study in the field condition is too high [11].

There has been a wide variety of simulation models developed for predicting and estimating the safety, delay, capacity, queue and so on. Various simulation packages apply these models for traffic simulation that provide various analysis tools. These packages are categorized in two groups, stochastic and deterministic simulation models. Stochastic simulation models explain the traffic activities using an interval-based simulation. Deterministic simulation models correlate delay, capacity, queue, etc., with set of parameters using a series of equations [73]. There are three levels of simulation models depending on the stochastic or deterministic nature of simulation. These include macro-, meso- and microscopic models.

The macroscopic simulation model considers deterministic relationships of speed, density and flow in an aggregated scale and describes the activities and entities at the low level of detail. In this type of simulation, the traffic can be modelled on the network of transportation such as freeways, highways, rural highways, arterial parallels and surface-street grid networks to forecast the spatial congestion and extent that happens. The advantages of macroscopic models are their lower cost of development, maintenance, and execution as well as their less computation power requirement, while their accuracy might be less than a more detailed model [11], [74], [75].

In the microscopic simulation models, the traffic entities with its activities and interactions are simulated at a high level of detail. In other words, it allows to track the movements of individual vehicles and their interaction through the road network over a very small time interval, seconds or fraction of a second [11], [73].

The destination, vehicle type and driver are assigned for each vehicle upon network entry and its behaviour is determined based on simple car following, lane changing and gap acceptance models [75], [76]. The microscopic simulation models are more accurate than the macro- and mesoscopic models provided they are correctly calibrated. However, it is not an easy task because of the complexities of the model, data collection and large number of parameters to be defined in the model [11]. Furthermore, the simulation model at this level demands great computer capacity and the cost to develop, maintain and use is too high [11], [75].

In the mesoscopic models, the simulation level is between microscopic and macroscopic simulation and most entities are modelled at a large study area with a higher level of accuracy than macroscopic models [11], [75]. However, the interactions and activities among the vehicles are described on a much lower level of detail than that of microscopic model [75]. This type of modelling excludes the dynamic relationships and much of the travel movement are on aggregated basis [76].

In the simulation-based method, the analysis and modeling of complex traffic scenarios could be accomplished using off-the-shelf traffic simulation packages such as Paramics, MATSim, VISSIM, SUMO, etc. These tools provide invaluable capabilities to answer complex research questions and implement or evaluate various traffic management strategies and their impact at a network level, as it is impractical to examine operational alternatives in the real world. However, most of these simulation packages are based on empirical models, which are developed according to a particular traffic condition. Therefore, in some cases, it necessitates manipulating the default underlying models and constructing efficient models capable of simulating the local-specific driving behavior based on ground truth data. It is worth noting that the performance of a simulation model strongly depends on its ability to stochastically simulate the real-time traffic condition. The uncertainty in human-nature behavior, the random interaction between drivers and the highly nonlinear dynamics of traffic flow bring complexities and challenges into the simulation modeling task. Therefore, accurate replication of traffic behavior models, such as gap acceptance, car following, lane changing, and so on, necessitates performing an accurate calibration and validation process with the objective of minimizing the error between simulation and real-time outputs [77]. There is rich literature focusing on assessing the impact of various decision-making variables, design, and operational alternatives on real-world network efficiency and driving behavior using a precise calibration and validation of simulation models [3], [42], [78]- [82]. Leite et al. [9] examined the performance of a roundabout under various operational conditions such as changing the speed and acceleration within roundabouts as well as the minimum distance between vehicles utilizing the SUMO simulation software. The main conclusion drawn from this study is that a balance between minimum safe distance and adequate acceleration could be achieved through an accurate calibration of underlying simulation functions like the car-following or lane-changing models. Bartin et al. [3] modeled and simulated the gap acceptance behavior of drivers in two unconventional roundabouts, located in New Jersey, using the binary Probit model and the API of Paramics software based on ground truth data. They claimed that the default gap acceptance model of Paramics may not be suitable for some specific locations, thus the binary probit model performed better in Paramics in terms of predicting the gap acceptance decisions of drivers in these two unconventional traffic circles. In addition, Bartin [42] applied the same observed data used in [3] to reproduce the gap acceptance decision-making process in a stop-controlled intersection with the application of a Q-learning Reinforcement algorithm (RL). The study showed that the RL can be promising in terms of reproducing the drivers' gap acceptance decision in microscopic simulation with a high level of validation accuracy. Arafat et al. [84] used simulation modeling to investigate the performance of Signalized Left Turn Assist (SLTA) system, a connected vehicle (CV)-based application at signalized intersections. The calibration of the microscopic simulation model was accomplished according to real-world gap acceptance distribution to better assess real-world driver behaviors at permissive left-turn signals. The output revealed that the impact of SLTA could be beneficial, in terms of increasing the left-turn capacity, and safety as well as reducing the delay time, depending on the SLTA gap time parameter setting. Further, Arafat et al., [84] evaluated the impact of the Stop Sign Gap Assist (SSGA) system, which is a CV-based application at unsignalized intersections, on the mobility and safety performance of an intersection using well-calibrated microscopic simulation models. Their study demonstrated a clear trade-off between safety and capacity. This is to say the SSGA model holds the balance between capacity and safety by adjusting the time gap setting within the intersection; the smaller the time gap the higher capacity and the larger the time gap the higher safety. In short, simulation-based approaches are more beneficial than analytical methods because of the ability of simulation tools to reproduce the field data and examine various operational alternatives, which could be a strenuous task in the analytical method [12], [85]. As indicated by Dutta and Ahmed [48], both the clearing time method and logit method produced roughly similar critical gap values in the simulation-based method and analytical method.

Simulation of Urban Mobility, or SUMO for short is an open source (licensed under the GPL), highly portable, microscopic, and continuous road traffic simulation package designed by the DLR - Institute of Transportation Systems of DLR, the National Aeronautics and Space Research Center of the Federal Republic of Germany in Berlin. The software was developed in 2001 and became open source in 2002. Microscopic simulation, online interaction and the simulation of multimodal traffic has some of the features offered by the SUMO platform. Furthermore, the traffic light programs can be generated or imported automatically and there are no artificial constraints in the number of simulated vehicles and the network size. SUMO has its own file formats for traffic simulation; however, it has the ability to convert maps encoded in many public available sources like OpenStreetMap, VISUM, VISSIM and NavTeq. The programming language of SUMO is C++ and it uses only portable libraries. SUMO in fact comprises of various programs that should be used together for setting and running the simulation.

To start a simulation in SUMO, two types of information are required: a network topology and a traffic pattern demand. A SUMO network file (*.net.xml) is about the traffic-related part of a map, i.e., a network of roads, railways, pedestrian ways, aquatic routes or other means of moving cars, buses, trams, trucks, trains, boats or people, where the simulated vehicles run along or across. SUMO network is in fact a directed graph; nodes, usually called junctions that represent intersections, and edges, roads or streets. The next step after building a network is to create the traffic elements within the network and describe the traffic patterns in terms of vehicles. It could be possible by using the origin destination (OD) matrices and import them into route description. Traffic demand generation can be defined either as a trip or route. A trip is defined as a vehicle travelling from one point to another by the starting edge (street), the destination edge, and the departure time. A route is defined as an expanded trip that contains the start edge and the end edge as well as all the edges between them. In addition to the network topology and demand inputs, one can specify some additional files. The additional files are the add-ones for simulation and are optional inputs such as a background image, definition of various kinds of sensors installed in the network, POIs (Points Of Interest), like building names, or other landmark which could be included in the visualization of the simulation. Finally, a configuration file is required to be defined to run the simulation by unifying the inputs. All the parameters and options needed to start the application are included in a configuration file which can be defined in SUMO in an XML configuration file.

There are a sundry of research conducted with the application of SUMO trying to address a large variety of research questions [9], [86]-[88]. Krajzewicz et al. [87] applied SUMO to model modern traffic lights control systems. Their work indicated that, compared to the commercial simulation tools, the application of SUMO could be beneficial in terms of its cost when simulating a new road system. In another study, the pros and cons of SUMO and other traffic simulation tools, e.g., AIMSUN, PARAMICS Modeller, etc, have been compared [89]. The study concluded that despite SUMO being a free and open-source software, it is not easy to use. For instance, when creating the route file for the vehicular movement from OD matrices, SUMO requires creating an XML file with the detail pattern of OD matrices, while other commercial simulation tools like PARAMICS this task can be accomplished by simply editing an OD table. Leite et al. [9] simulated a multi-lane roundabout using SUMO. Bagheri et al. [36] utilized SUMO to evaluate the feasibility of an ANN-based gap acceptance model.

CHAPTER III

METHODOLOGY

The methodology used to reach the study objectives is twofold. First, the ANN model is trained based on collected field data to model the vehicle's gap acceptance behavior when manoeuvring at each of the selected stop- and yield-control intersections within the circle. Then, the proposed ANN-based models were integrated in in the simulation with the application of SUMO API. The output of the ANN-based simulation model was compared with the outputs of the SUMO default model with calibrated gap acceptance Parameters. The selected output variables were the wait time of vehicles at the minor approach and the time headway of vehicles at the major approach.

3.1 Case Study

The intersection studied in this thesis work is Collingwood Roundabout in Wall Township, New Jersey. Collingwood Roundabout is at the intersection of Route 33, Route 34 and Asbury Road (County Route 547), as shown in Figure 8. Route 33 and route 34 are state highways with very high demand. Route 33 extends for 42 miles and traverses three counties—Mercer, Middlesex, and Monmouth—and most of it is a four-lane divided highway. Route 34 extends for 26.79 miles, from the intersection with Route 35 to the intersection with Route 9. It traverses two counties—Monmouth and Middlesex—and most of it is a four-lane divided highway.

Before 2006 Collingwood Roundabout was an operationally unconventional traffic roundabout where one stop control sign and three yield control signs forced the circulating flows to give way to traffic entering the roundabout. In 2006, construction changed to improve its performance and conform to standard right-of-way rules for roundabouts. In the one-way stop-controlled junction at location A, the traffic comes to a full stop to exit the circle into 547 SB. Particularly during the rush hours, when the flow on 33/34 EB is high, drivers waiting for acceptable gaps at location A form a queue, which then builds up and blocks the traffic flow to 33/34 WB). Figure 8 shows the old design of the Collingwood Circle, which contains one cross one-way stop-control intersection and four yield-control intersections, and its simulation model developed in SUMO. However, only three were chosen (Locations A, B, C) for validation, as they had a significant impact on the performance of the circle. Note that all links except movements 7, 10 and 11 in Figure 8 are two-lane roads.

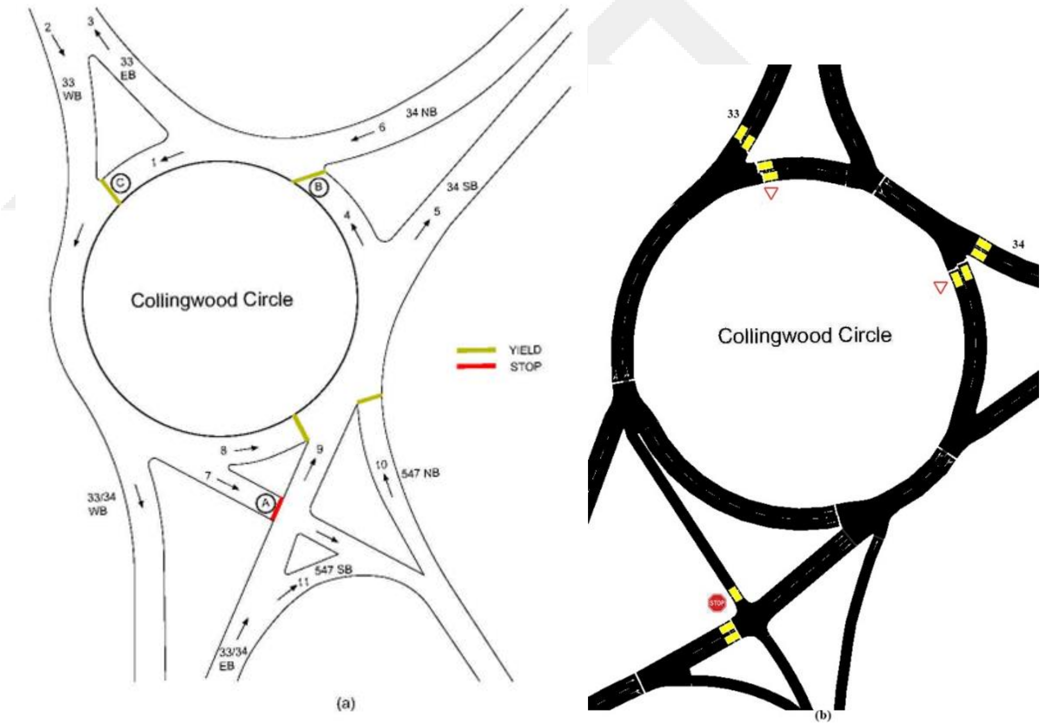

Figure 8: (a) Geometric and operational design of the Collingwood Circle (b) Simulation model in SUMO

In this study, the data is borrowed from Bartin et al. [3]. The Collingwood circle traffic data were originally collected on weekdays in 2003 and 2004 using a portable tower video surveillance system (POGO) that contains two dome cameras and two infrared cameras, a portable mast with a Sony camcorder and an omnidirectional camera, and two camcorders at circle approaches. The videos were captured for four hours, two in morning peak hours and two in afternoon peak hours. The recorded traffic data were then extracted in the Rutgers Intelligent Transportation Systems Laboratory. The time headway (gap) was defined as the difference between consecutive vehicles in major approach when crossing the intersection at each entry point. The cumulative wait time was calculated as the time difference when a minor approach vehicle arrives at and departs from the intersection. After a data preparation for the morning peak period, 7 AM to 9 AM, the following key variables were extracted: (i) vehicle counts with percentage composition of trucks and passenger cars, (ii) vehicle interarrival times at major road, (iii) vehicle wait times before stop/yield sign on minor road, (iv) the lane index of vehicles at major/minor road, and (v) gap acceptance/rejection times at the stop/yield sign.

3.2 Simulation Model Development

SUMO was used to implement and evaluate the ANN-based gap acceptance model within the selected traffic circle. SUMO is an open-source, multi-modal, portable, microscopic traffic simulation tool capable of simulating large traffic networks [90]. The API of SUMO, known as TraCI, provides users the control over the simulation objects, and the ability to adjust the object attributes, and implement improved user defined model in lieu of the default underlying models.

SUMO is able to use real-word map data, which either can be extracted from the OpenStreetMap website or imported from other source formats. Besides the accurate geometry, these maps include coded information for: type of street, which determines implicit speed limits and right of way rules, number of lanes and their directions, Junctions marked as nodes and their types valued as "signalized" or "unsignalized".

The studied area in this work is converted from a shape file to an XML file. Duration of simulation is two hours and 7 minutes, including 7 minutes of warm-up period and the two peak hours of the data.

3.3 Intersection model in SUMO

In the microscopic simulation of urban environments, the vehicles' behaviour while approaching and crossing an intersection is significantly important. Vehicles must prevent collision with any other vehicle that crosses their path. Therefore, various schemes should be considered for intersection control such as right-before-left rules, intersection priority rules and traffic lights. Unlike the car-following models where the behaviour of leader vehicle is independent of ego vehicle, a vehicle passing a junction considers that its presence on the junction can impact the behaviour of oncoming vehicles. Because of that, the intersection model in SUMO has more complexity than any of the car-following models.

During the SUMO evolution, the intersection model has seen an increasing growth in complexity. In the older model, the vehicle only decides whether to pass the intersection or not and if it decides to pass, it jumps to other side of intersection and continues driving. The current model takes into account the driving dynamics inside the junction as well, which includes the parameters corresponding to vehicle's car-following model. Generally, the vehicle enters the intersection provided that its expected time interval of intersection occupancy is distinct enough from the usage intervals of all other vehicles in the higher priority street. Furthermore, the acceptance of a safe gap for low priority drivers when crossing an intersection is another reason for growing complexity in the model. In the first version of the model, if the approaching vehicles do not adapt their speed, the other vehicles would not enter the intersection. In the new version, there is another degree of freedom that should be considered in the decision-making process. The impatience of vehicles is a parameter that represents the degree aggressiveness of drivers. This parameter is a real value between [0, 1] and is a function of vehicle's wait-time as well as a constant threshold related to the wait time. Vehicles with impatience of 1 will enter the intersection disregarding the approach of high priority stream, while the impatience of 0 implies that vehicles do not enter the intersection until they find an acceptable gap. In addition, some parameters used in the car-following model are also used in the intersection modeling in SUMO. Overall, a vehicle with the impatience of α will decide to enter the junction if it expects to leave the junction at time t. The equation for calculating the t is as follow:

$$t < (1 - \alpha) \times a_{min} + \alpha \times a_{max} \tag{10}$$

The parameters a_{min} and a_{max} respectively are the earliest and latest arrival time of vehicles in higher priority road to the intersection. these parameters are dependent on the acceleration/deceleration ability of vehicles and the speed limit at major approach.

The fluidity of traffic in simulation is greatly affected by the choice of α. For the low value of α, the traffic in low priority street may be blocked while the traffic in main road is heavy. As for the α with value near 1, the traffic in the prioritized road will be frequently disturbed in a way that does not replicate the field condition. To prevent these inconsistencies, the value of α is changing dynamically within the simulation. Therefore, the impatience factor or α implies something that increases with time. The value of α withing the simulation is defined dynamically as:

$$\alpha \coloneqq MAX(0, MIN\left(1, \alpha_c + \frac{waitingTime}{T}\right)) \tag{11}$$

Here, α_c is a constant specific to vehicle type which its default value is 0 and can be configured in the range [-1,1] to model the base level of driver impatience. The α_c with very higher and lower values results in constant values for α of 1 and 0, respectively. The value of T is a constant, configurable in the simulation, that is related to the time after which the vehicle will be removed from the simulation to prevent the deadlocks and is defaulting to 300 seconds. In fact, the T is the maximum wait time that a vehicle can tolerate within the simulation. Detailed information about intersection modelling and gap acceptance mechanism in SUMO is explained in Erdmann et al. [91]. Table 1 indicates the values of calibrated gap acceptance parameters.

Table 1: The values of calibrated gap acceptance parameters

	α_c	T	Acceleration	Deceleration
Stop-control	0.05	100	5.6	7.6
Yield-control	0.45	100	5.6	7.6

3.4 ANN Model Development

This study proposed an ANN model, which is developed based on a feedforward BP algorithm using the Keras library in Python. As mentioned before the input layer, hidden layers and output layers are the main skeletons of the ANN model. Each of these layers contains a set of neurons with predefined activation functions that are interconnected to each other via a weight value. In the training process the weights and bias are modified through an iteration of feeding forward the network, calculating the difference between estimated target and observed target and then propagate it back to each neuron until converging of connection weights and minimizing the error propagation. The gradient descent algorithm used as the learning rule during each training episode to gradually predict the drivers gap acceptance decision from the input and output data. The input layer contains number of neurons equal to the number of input variables. The bias and weighted inputs are summed to be the input of the activation function within the next (hidden) layer. The last layer is the output layer that depending on the nature of the classification problem can include one neuron (binary classification) or several neurons (multi-class classification). An extensive trial and error process is required to optimize the ANN structure (number of hidden layers and neurons) and hyperparameters with the main objective of maximizing validation accuracy and minimizing validation loss, taking into account the trade-off between bias and variance.

In this study, three ANN models were developed for three different intersections (two yield-control and one stop-control) based on the observed data at each location. The specifics of each intersection is presented are the next subsection. The ANN model for any of these intersections comprise one input layer, three hidden layers, and one output layer. The input layer is comprised the following variables: (i) time headway (TH) of mainstream traffic, (ii) wait time at minor stream, (iii) the lane index of approaching vehicles at the major road, (iv) the lane index of vehicles at minor road for yield-controlled intersections, and (v) the type of vehicles at minor stream for stop-controlled intersection. Each hidden layer includes sixteen neurons with the Rectified Linear Unit (ReLU) activation function. The output layer includes one neuron with a sigmoid activation function. This function produces a probability output between 0 and 1 that predicts the probability of accepting a gap. The proportion of data for training the ANN model was 80% and for validating the ANN was 20%. The loss function used for this model is the Binary Cross-Entropy and the optimizer used is the Stochastic Gradient Descent with a learning rate of 0.05.

3.5 ANN Implementation in SUMO

Figure 9 demonstrates the flowchart of a simulation programming algorithm designed for testing the proposed ANN-based gap acceptance model in SUMO TraCI. The required input data to feed the simulation are network topology, traffic light programs and the demand elements distribution. Every simulation step (0.1 seconds), the simulation model requires a series of information from the incoming edges of three selected intersections at the selected circle. Basically, this command is called whenever there is a leading vehicle at the minor roads. For each approaching vehicle in the minor road, regarding its control sign (STOP/YIELD), the leading vehicle should stop or slow down before the intersection. If there are no vehicles at major road, the vehicle at minor road can proceed and cross the intersection. On the other hand, if the mainstream contains incoming vehicles, the simulation model retrieves and computes an array of variables for feeding the ANN model to predict the vehicle's gap-acceptance decision. This information includes the lane index of the major vehicle as well as its speed and distance from the intersection (to compute its arrival time), the lane index/ type of vehicle at minor approach, and its wait time. Next, the ANN model predicts 1 or 0, which means that the vehicle accepts or rejects the gap, respectively. If the gap is accepted vehicle is allowed to pass the intersection, otherwise, it should wait for the next vehicle's arrival time.

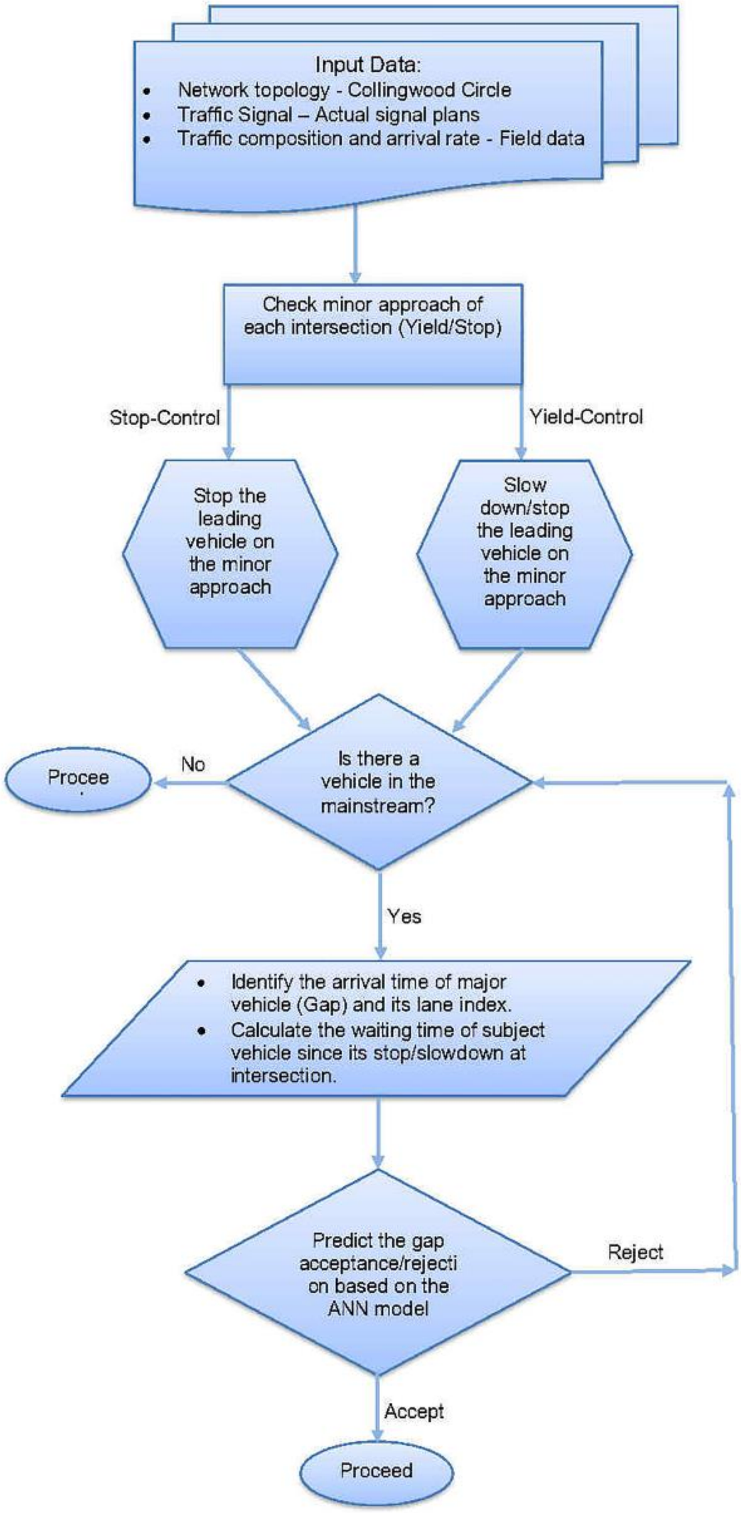

Figure 9: Simulation programming flowchart

CHAPTER IV

ANALYSIS RESULTS

The ANN models were run for 700 epochs. The performance of the developed models is presented in Table 2 for each intersection within the circle. As mentioned earlier, these models were incorporated in SUMO using TraCI.

Table 2: Performance of the ANN models

	Train		Validation	
	Accuracy (%)	Loss	Accuracy (%)	Loss
Location A	94.9	0.12	93.2	0.16
Location B	96.9	0.09	96.1	0.11
Location C	96.0	0.096	95.0	0.12

SUMO offers a wide range of parameters to be used for intersection modeling. These are (i) the minimum time gap when passing ahead of a prioritized vehicle, (ii) vehicles acceleration/deceleration ability in both approaches, (iii) speed limit in major approach and (iv) the impatience of vehicles in minor traffic stream. For example, the impatience of vehicles is a parameter that represents the drivers' degree of aggressiveness. This parameter is a real value between [0, 1] and is a function of vehicle's wait-time as well as a constant threshold related to the wait time. Vehicles with impatience of 1 will enter the intersection disregarding the approach of high priority stream, while the impatience of 0 implies that vehicles do not enter the intersection until they find an acceptable gap. In addition, some parameters used in the car-following model are also used in the intersection modeling in SUMO. Detailed information about intersection modelling and gap acceptance mechanism in SUMO is explained in Erdmann et al. [91]. These parameters can be customized in SUMO to calibrate the gap acceptance behavior in a traffic network.

Three output variables were used for validation. These are the (i) average wait time at the minor approach, (ii) traffic flow at the major and (iii) minor approaches. The simulation network was run iteratively based on the following formula [92]:

$$n^*(\gamma) = \min\left\{ i : \frac{t_{i-1,1-\alpha/2}\sqrt{S^2(i)/i}}{\left|\bar{X}(n)\right|} \le \gamma' \right\} \tag{12}$$

Where, $n^*(\gamma)$ minimum number of simulation runs is determined to obtain a relative error, γ, by iteratively increasing the number of simulation runs, i, by one until the proportion of the half-length of the confidence interval to the sample mean $\bar{\bar{X}}(n)$, i.e. this less than or equal to γ'. Here, γ is the relative error of the sample mean, calculated as $\gamma = |\bar{X}(n) - \mu|/|\mu|$ and $\gamma'$is the adjusted relative error, given as $\gamma' = \gamma/(1-\gamma)$. A relative error $\gamma' = 0.10$ and 95 percent confidence level were used in simulation analyses of this study. In other words, the simulation runs are iteratively increased until condition shown in equation (12) was satisfied for the three output variables simultaneously. It should be noted that 20 simulation runs were needed to satisfy this condition for the developed simulation model.

The observed and simulation system outputs for each selected location are shown in Table 3. The observed average wait time of vehicles at the minor approach and traffic flow at the major and minor approaches are compared with the corresponding values of the ANN-based and calibrated SUMO simulation models. Note that the queueing time was not considered when computing the wait time.

According to Table 3, the 95 percent confidence interval for the average wait time at Location B and C do not cover the corresponding field averages. However, such slight deviations should be expected considering the fact that these are yield-controlled intersections where most vehicles roll past the intersections, and that the output collection of SUMO and the analyst's data extraction methods from video recordings are never identical. Furthermore, Table 3 indicates that none of the simulated output values are substantially out of range. It can also be seen that the calibrated SUMO model produced similar results compared to ANN-based model as the observed average wait times are very close but outside the 95 percent confidence level. The results shown in Table 3 also show that the confidence interval for the number of vehicles processed at the major and minor approaches by the ANN-based and the calibrated SUMO models cover the observed values.

Table 3: Observed and Simulation Output at Morning Peak Hour (7 – 9 AM)

		Location A	Location B	Location C
Average Wait Time (s)	ANN TraCI	[7.52 - 8.12]	[5.93 - 6.18]	[2.66 - 2.75]
	SUMO Calibrated	[7.05 - 7.49]	[6.40 - 6.89]	[2.28 - 2.38]
	Observed	7.64	6.20	2.43
Traffic Flow at Major Road (vehicles)	ANN TraCI	[2,221 - 2,283]	[2,470 - 2,481]	[2,058 - 2,079]
	SUMO Calibrated	[2,227 - 2,290]	[2,463 - 2,496]	[2,058 - 2,091]
	Observed	2,240	2,476	2,070
Traffic Flow at Minor Road (vehicles)	ANN TraCI	[267 – 289]	[1,225 – 1,251]	[2,325 – 2,532]
	SUMO Calibrated	[271 – 293]	[1,238 – 1,270]	[2,493 – 2,538]
	Observed	282	1,243	2,503

In a recent work, using the same ANN-based approach Bagheri et al. [36] analyzed Location A in SUMO for the afternoon peak period, independently from the other intersections at the study circle. This study observed that in the calibrated SUMO model, 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 was due to the impatience parameter used by SUMO: as vehicles wait more than a certain threshold, they start ignoring the priority rules. In order to inspect this deceleration behavior, the speed and acceleration trajectories of vehicles on the major approach were generated for both simulation models, as shown in Figure 10 and Figure 11. These figures demonstrate the average speed and acceleration profiles of major vehicles within one standard deviation range when approaching the selected intersections at the circle. The positions of the intersections are shown by a vertical dashed line in the figures. The figures indicate that both simulation models show a consistent behavior regarding speed and acceleration, which means that the minor vehicle does not make a sudden decision to cross the intersection causing the major vehicles to decelerate or slow down.

However, further visual verification of simulation runs revealed some vehicles at the yield-controlled approaches accepting unrealistically small gaps when moving in the inside circle lanes (e.g. movements 1 and 4 in Figure 8) when faced with major vehicles approaching in the outside lane of the major approaches (e.g. movements 2 and 6 in Figure 8). As their paths do not intersect in such circumstances, SUMO does not enforce deceleration for the major vehicles, as evidenced from Figure 10 and Figure 11. Further analysis of accepted gap values at the selected intersections was deemed necessary to understand what percent of minor vehicles exhibit such behavior. Figure 12 shows the frequency plots of accepted gaps from the ANN-based and the calibrated SUMO models compared with the observed values. The distributions of accepted gaps shown in these figures verify the findings of the visual verifications of the simulation runs. For instance, at Location B, the calibrated SUMO's results show that 22.4 percent of minor vehicles accepted gaps that are less than 2 seconds, compared to 7.2 percent in the field observations. When accepted gaps less than 6 seconds are considered, the cumulative percent of minor vehicles in the calibrated SUMO is 78.6 at Location B, while the observed cumulative percentage is at 57.4. Similarly, at Location C, the percent of minor vehicles accepting gaps that are less than 2 seconds is 24.3 in the calibrated SUMO results compared to 5.6 percent in the field observations. When gaps less than 6 seconds are examined, the cumulative percent of minor vehicles in the calibrated SUMO is 65.5 percent compared to 55.5 percent in the field data. Figure 12 indicates a better overall fit of accepted gaps by the ANN-based model. It can be concluded that the advantage of the ANN-based model lies not only in the accuracy of the selected output variables in comparison to the observed field values, but also in the realistic vehicle crossings at these uncontrolled junctions.

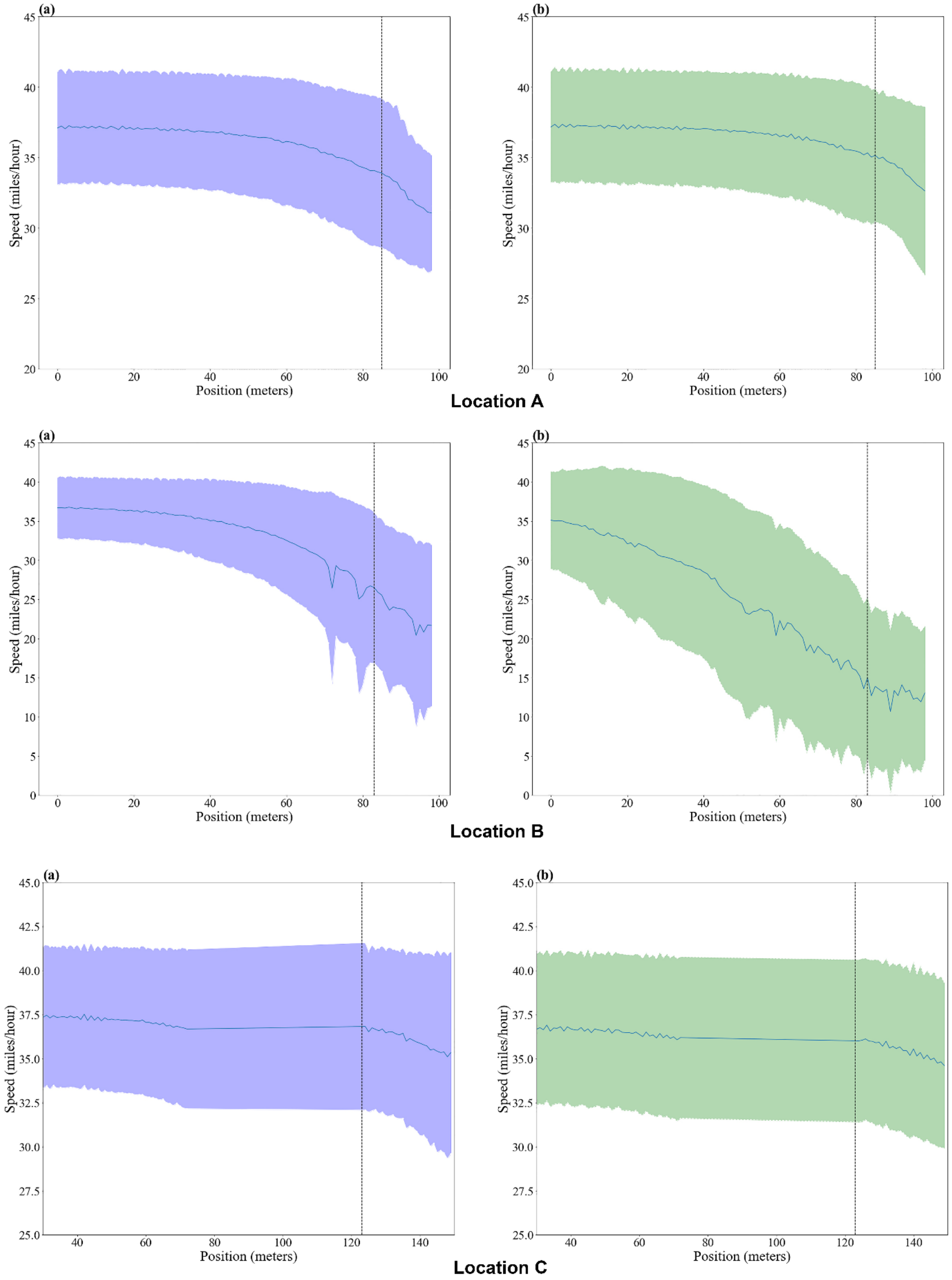

Figure 10: Speed trajectory at major approaches (a) ANN-based, (b) Calibrated models

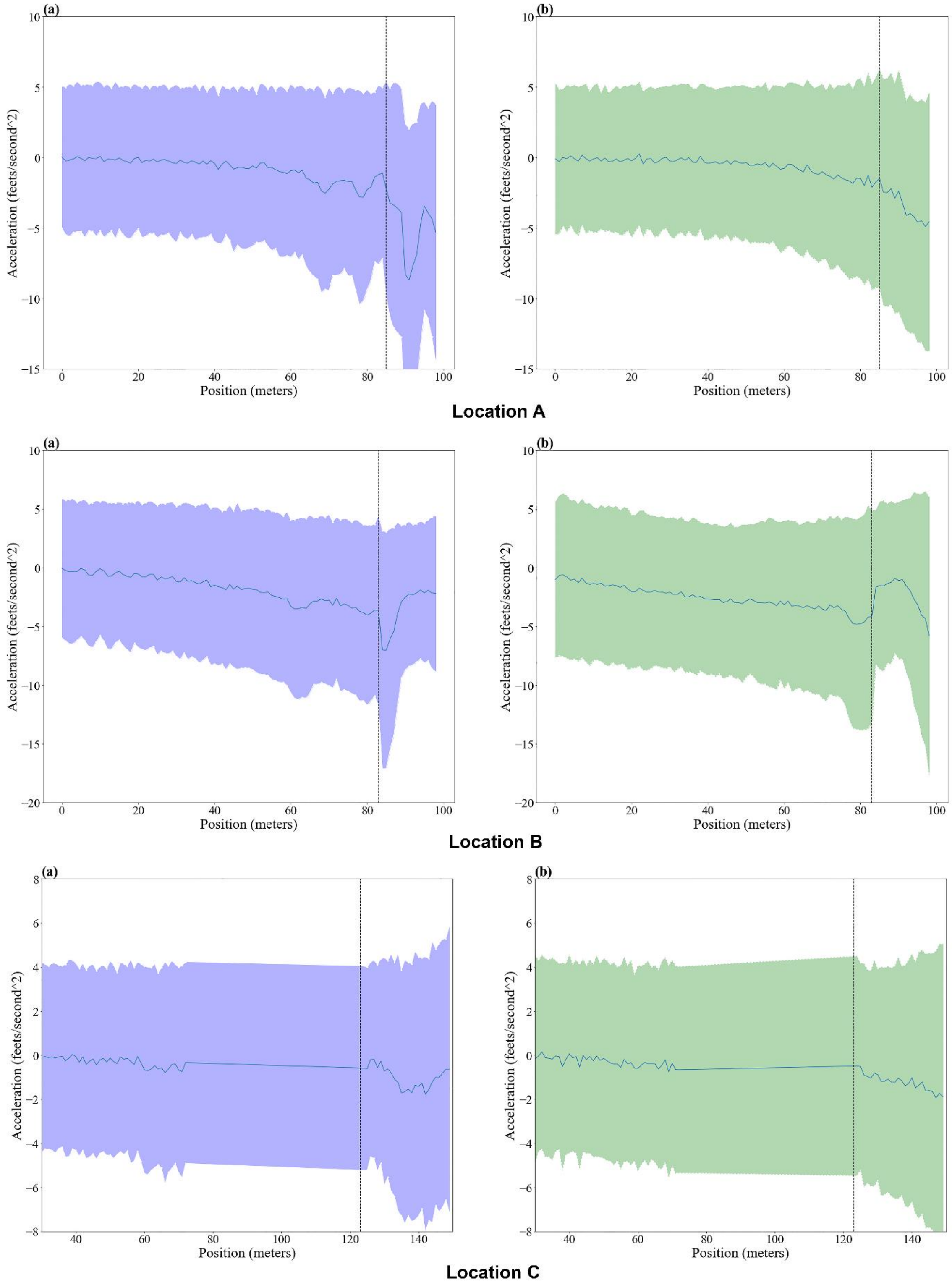

Figure 11: Acceleration trajectory at major approaches (a) ANN-based, (b) Calibrated models

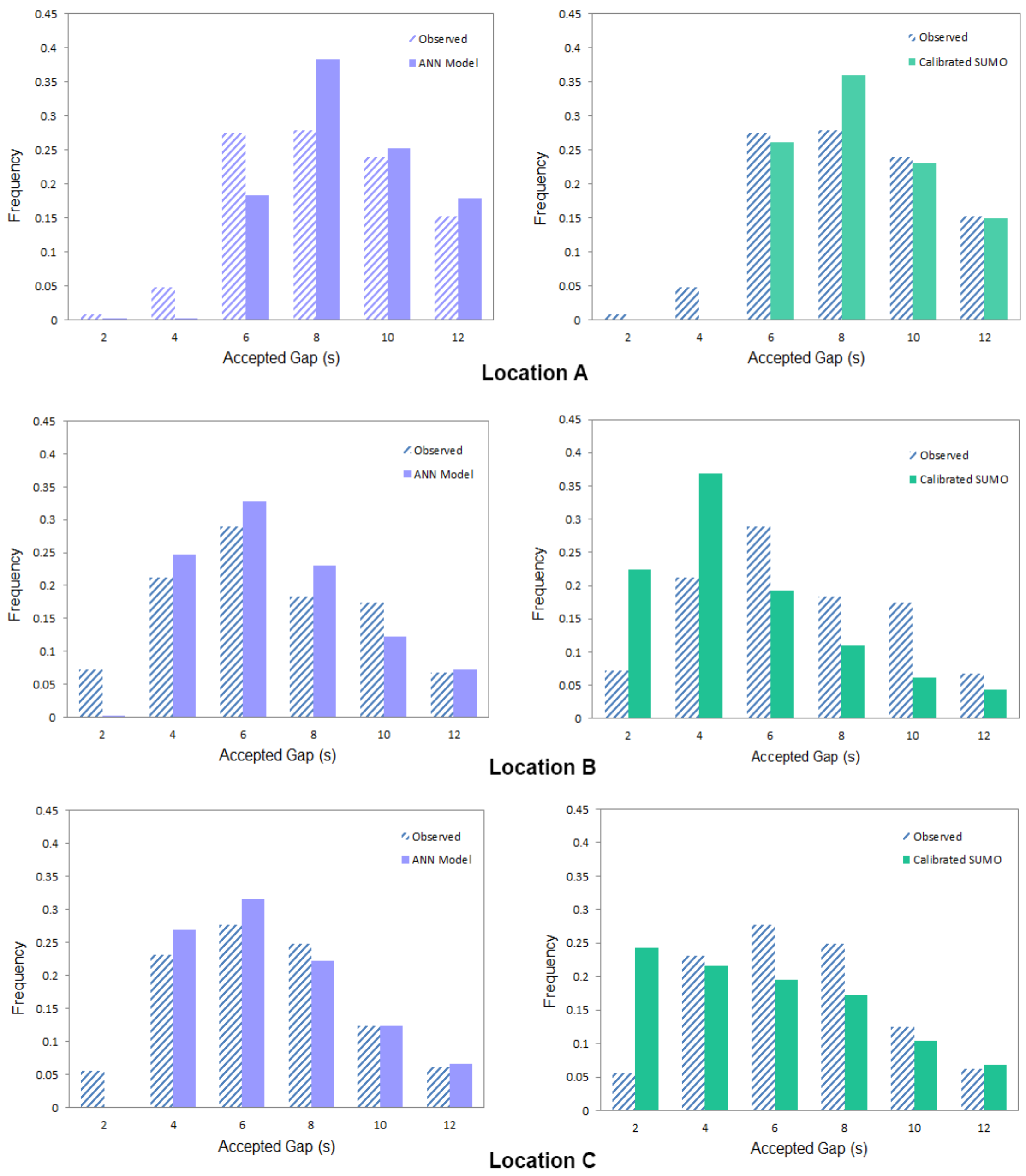

Figure 12: Comparison of accepted gap histograms (a) ANN-based, (b) Calibrated SUMO models

CHAPTER V

CONCLUSION

Intersections, specifically, roundabouts are important traffic facilities that can impact the overall performance of a traffic network. Gap acceptance is one of the influential driver decisions that impact the safety and operational performance of an intersection. Analytical and simulation-based methods are two ways of analyzing gap acceptance behavior at intersections. The simulation-based methods are more popular because of their benefits from computational power and time points of view. There is a wide range of simulation packages developed for the analysis and evaluation of various traffic scenarios. However, a valuable simulation model requires an extensive and accurate calibration and validation process to reproduce the real-world traffic condition. Most underlying models in the simulation may not be generalized to specific locations. Therefore, it is often necessary to adjust the underlying default models to match the location specific conditions data.

In this study, the feasibility of an ANN-based gap acceptance model was evaluated and compared with the default SUMO model with calibrated parameters based on the minor vehicles' wait time and traffic flow at the major and minor approaches. An ANN-based gap acceptance model was implemented in SUMO using its API capability. The Collingwood circle in New Jersey was used as a case study with the corresponding gap acceptance data to train the proposed ANN-model. Three intersections at the circle were chosen, two yield-control and one stop-control intersections, as they have critical impact on the performance of roundabout. These models were incorporated in SUMO using TraCI.

The analysis results showed that both the calibrated SUMO and the ANN-based model produced satisfactory results compared to those observed in the field. One exception was the unrealistically low accepted gaps at yield-controlled intersections in the calibrated SUMO, which was related to the way in which SUMO implements gap rejection decisions. That is, minor vehicles are allowed to cross the intersection when the paths of major and minor vehicles are not expected to cross. This is a similar case when a vehicle moving in the inside lane is faced with an approaching major vehicle moving in the outside lane. Field observations did not support this behavior as minor vehicles are wary of leaving the intersection even when the major vehicle is traveling in the outside lane. Between 22.4 and 24.3 percent of the vehicles at these intersections accepted gaps smaller than 2 seconds in the calibrated SUMO, compared to 5.6 and 7.2 percent observed in the field data. It should be noted that this behavior did not impact the overall wait time averages in the calibrated SUMO. Therefore, it can be concluded that a calibrated and validated SUMO model can be used to analyze various operational strategies at roundabout and circles. However, a more realistic gap acceptance model should be used when, for example, surrogate safety measures need to be extracted from the model for comparing different safety measures at these facilities.

APPENDIX A

ANN Implementation In SUMO via Traci, Interfaced with Python:

```
sumoBinary = "C:\\Program Files (x86)\\Eclipse\\Sumo\\bin\\sumo-gui.exe"
configfile =
"C:\\Users\\moham\\Desktop\\mohamad\\Ozu\\Transportation\\GapAcceptance\\Traci\\Circle_m
orning\\circle_morning.sumocfg"
sumoCmd_CollingWood_circle = [sumoBinary, "-c", configfile]
##################################
start = timeit.default_timer()
modell = "ANN_Model_Name"
traci.start(sumoCmd_CollingWood_circle)
t_s=0
runtime= 7600  # 2 hours (7200 s) running time and 100 s warmup period
Tw={}
Tc={}
D=0
stoplist=[]
resumelist=[]
TH_mj=[]
speed_mode_list=[]
E_1_list=[]
entered_E_1_list=[]
departID_33=[]
departID_34=[]
departID_stop=[]
approachID_33=[]
approachID_34=[]
approachID_stop=[]
mjID=[]
state=[]
time=[]
slowdownlist=[]
mn_mj_rjcted=[]
stop_list=[]
det_enter={}
mn_edge_list= ["2","4","7"]
lookup_list_33= pd.read_csv("lookup_list_Morning_33_v0.csv")
lookup_list_34= pd.read_csv("lookup_list_Morning_34_v0.csv")
lookup_list_stop= pd.read_csv("lookup_list_Morning_stop_v0.csv")
while t_s < runtime:              #simulation loop
    traci.simulationStep(t_s)        #run the simulation for t_s time
    if t_s>400:      #warmup period
        Gap_Extraction()     #collects data from SUMO
    for edge in mn_edge_list:  #search for each edge in every simulation step
        mnlist=traci.edge.getLastStepVehicleIDs(edge)[::-1]     #get the veh IDs)
        mjlist=[]
        if len(mnlist)>0:
            speed_mode_command(mnlist,32)
            if edge == "4":
```

```
            mnlist_0=traci.lane.getLastStepVehicleIDs("4_0")[::-1]
            mnlist_1=traci.lane.getLastStepVehicleIDs("4_1")[::-1]
            mn_lane="4_0"
            agent="yield"
            distance_mn=10
            speed=10
            color=(0, 255, 0)
            lookup_list= lookup_list_33
            if len(traci.edge.getLastStepVehicleIDs("10"))>0:
                distance_mj=traci.lane.getLength("10_1")
                mjlist= traci.edge.getLastStepVehicleIDs("10")[::-1]
            elif len(traci.edge.getLastStepVehicleIDs("10"))==0 and
len(traci.edge.getLastStepVehicleIDs("29.150"))>0:
                distance_mj=traci.lane.getLength("29.150_1")+traci.lane.getLength("10_1")
                mjlist= traci.edge.getLastStepVehicleIDs("29.150")[::-1]
        elif edge == "2":
            mnlist_0=traci.lane.getLastStepVehicleIDs("2_0")[::-1]
            mnlist_1=traci.lane.getLastStepVehicleIDs("2_1")[::-1]
            mn_lane="2_0"
            agent="yield"
            distance_mn=20
            speed=10
            color=(0, 0, 255)
            lookup_list= lookup_list_34
            if len(traci.edge.getLastStepVehicleIDs("13"))>0:
                distance_mj=traci.lane.getLength("13_1")
                mjlist= traci.edge.getLastStepVehicleIDs("13")[::-1]
            elif len(traci.edge.getLastStepVehicleIDs("13"))==0 and
len(traci.edge.getLastStepVehicleIDs("-E7"))>0:
                distance_mj=traci.lane.getLength("-E7_1")+traci.lane.getLength("13_1")
                mjlist= traci.edge.getLastStepVehicleIDs("-E7")[::-1]
        elif edge== "7":
            mnlist_0=traci.lane.getLastStepVehicleIDs("7_0")[::-1]
            mnlist_1=[]
            mn_lane="7_0"
            agent="stop"
            distance_mn=1
            speed=0
            color=(0, 255, 255)
            lookup_list= lookup_list_stop
            if len(traci.edge.getLastStepVehicleIDs("19"))==0 and
(len(traci.lane.getLastStepVehicleIDs(":14_1_0"))>0 or
len(traci.lane.getLastStepVehicleIDs(":14_1_1"))>0):
                distance_mj=traci.lane.getLength("19_1")+traci.lane.getLength(":14_1_0")
                mjlist= traci.lane.getLastStepVehicleIDs(":14_1_0")[::-
1]+traci.lane.getLastStepVehicleIDs(":14_1_1")[::-1]
            elif len(traci.edge.getLastStepVehicleIDs("19"))>0:
                distance_mj=traci.lane.getLength("19_1")
                mjlist= traci.edge.getLastStepVehicleIDs("19")[::-1]
            elif len(traci.edge.getLastStepVehicleIDs("19"))==0 and
len(traci.lane.getLastStepVehicleIDs(":14_1_0"))==0 and
len(traci.lane.getLastStepVehicleIDs(":14_1_1"))==0 and
len(traci.edge.getLastStepVehicleIDs("15"))>0:
                    distance_mj=traci.lane.getLength("15_1")+traci.lane.getLength("19_1")+traci.l
        ane.getLength(":14_1_0")
```

```
                mjlist= traci.edge.getLastStepVehicleIDs("15")[::-1]
            elif len(traci.edge.getLastStepVehicleIDs("19"))==0 and
len(traci.lane.getLastStepVehicleIDs(":14_1_0"))==0 and
len(traci.lane.getLastStepVehicleIDs(":14_1_1"))==0 and
len(traci.edge.getLastStepVehicleIDs("15"))==0 and
len(traci.edge.getLastStepVehicleIDs("1700"))>0:
                distance_mj=traci.lane.getLength("15_1")+traci.lane.getLength("19_1")+traci.l
                ane.getLength(":14_1_0")+traci.lane.getLength("1700_1")
                mjlist= traci.edge.getLastStepVehicleIDs("1700")[::-1]
        L=[]
        if len(mnlist_0)>0:
            L.append(mnlist_0[0])
        if len(mnlist_1)>0:
            L.append(mnlist_1[0])
        for v in L:
            if traci.lane.getLength(mn_lane)-traci.vehicle.getLanePosition(v)<distance_mn:
                if agent =="stop" and (v not in stop_list):
                    traci.vehicle.setSpeed(v, speed)
                    stop_list.append(v)
                traci.vehicle.setColor(v, color)
                if len(mjlist) > 0:
                    mj_approach=find_approach_veh(mjlist)
                    speed_mode_command(mjlist,32)
                    if traci.vehicle.getSpeed(mj_approach)>2:
                        T = ((distance_mj - traci.vehicle.getLanePosition(mj_approach)) /
(traci.vehicle.getSpeed(mj_approach)))
                    else:
                        if agent=="stop":
                            T=15
                        else:
                            T=0.0001
                    if T > 2 and T < 9 and ((v, mj_approach) not in mn_mj_rjcted):
                        if v not in det_enter:
                            det_enter[v]= traci.simulation.getTime()
                            tw= traci.simulation.getTime() - det_enter[v]
                        if tw>80:
                            tw=80
                        if agent=="yield":
                            l_i_mn=Lane_index(v)
                            l_i_mj=Lane_index(mj_approach)
                            decision = lookup(lookup_list, l_i_mn, l_i_mj,
round(round(T,1)*100),round(round(tw,1)*100))
                        elif agent=="stop":
                            l_i_mj=Lane_index(mj_approach)
                            decision = lookup(lookup_list, vclass (v), l_i_mj, round(round(T,1)*100),
round(round(tw,1)*100))
                        if decision[decision.index[0]] == 0:
                            if traci.lane.getLength(mn_lane)-traci.vehicle.getLanePosition(v)<1:
                                traci.vehicle.setSpeed(v, 0)
                                mn_mj_rjcted.append((v,mj_approach))
                            else:
                                traci.vehicle.setSpeed(v, 5)
                        else:
                            if traci.vehicle.getSpeed(v)<6:
                                traci.vehicle.setSpeed(v, -1)
```

```
                                traci.vehicle.setSpeedMode(v, 32)
                    elif T<2 and (v, mj_approach) not in mn_mj_rjcted:
                        if traci.lane.getLength(mn_lane)-traci.vehicle.getLanePosition(v) < 1:
                            traci.vehicle.setSpeed(v, 0)
                            mn_mj_rjcted.append((v,mj_approach))
                        elif traci.lane.getLength(mn_lane)-traci.vehicle.getLanePosition(v) >1:
                            traci.vehicle.setSpeed(v, 5)
                    elif T>9:
                        if traci.vehicle.getSpeed(v)<6:
                            traci.vehicle.setSpeed(v, -1)
                else:
                    if len(mnlist_0)>0 and traci.vehicle.getSpeed(mnlist_0[0])<6:
                                traci.vehicle.setSpeed(mnlist_0[0],-1)
                                traci.vehicle.setSpeedMode(mnlist_0[0], 32)
                    if len(mnlist_1)>0 and traci.vehicle.getSpeed(mnlist_1[0])<6:
                                traci.vehicle.setSpeed(mnlist_1[0],-1)
                                traci.vehicle.setSpeedMode(mnlist_1[0], 32)
    t_s+=0.1
traci.close(False)
stop = timeit.default_timer()
print('Time: ', stop) - sta
```

BIBLIOGRAPH

[1] Federal Highway Administration. Safety – Unsignalized Intersections. https://safety.fhwa.dot.gov/intersection/about/index.cfm (Accessed November 7, 2021)

[2] Maheshwari, P., Khaddar, R., Kachroo, P. *et al.* "Dynamic Modeling of Performance Indices for Planning of Sustainable Transportation Systems". *Netw Spat Econ* **16,** 371–393 (2016). https://doi.org/10.1007/s11067-014-9238-6

[3] Bartin, Bekir, Kaan Ozbay, Ozlem Yanmaz-Tuzel, and George List. "Modeling and Simulation of Unconventional Traffic Circles." Transportation Research Record 1965, no. 1 (January 2006): 201–9. https://doi.org/10.1177/0361198106196500121.

[4] Dutta, M., Ahmed, M.A. "Gap acceptance behavior of drivers at uncontrolled T-intersections under mixed traffic conditions". *J. Mod. Transport.* **26,** 119–132 (2018). https://doi.org/10.1007/s40534-017-0151-9

[5] Elefteriadou L. 'An introduction to traffic flow theory'. *Springer*; 2014. https://doi.org/10.1007/978-1-4614-8435-6

[6] FHWA, Roundabout. Technical Summary. Washington: *Federal Highway Administration US. Department of Transportation*, 2010.

[7] Manual, H.C. HCM2010. *Transportation Research Board, National Research Council, Washington, DC*, *1207*, 2010.

[8] Shaaban, K. and Hamad, H. "Group gap acceptance: a new method to analyze driver behavior and estimate the critical gap at multilane roundabouts". *Journal of Advanced Transportation*, *2018*.

[9] Leite, B., Azevedo, P., Leixo, R. and Rossetti, R.J. December. "Simulating a three-lane roundabout using SUMO". In *International Conference on Intelligent Transport Systems*, pp. 18-31, 2019.

[10] Guo, R., Liu, L. and Wang, W. "Review of roundabout capacity based on gap acceptance". *Journal of Advanced Transportation*, 2019.

[11] Federal Highway Administration. traffic flow theory. US dept of transport, USA. 2009.

[12] Ashalatha, R. and Chandra, S. "Critical gap through clearing behavior of drivers at unsignalised intersections". *KSCE Journal of Civil Engineering*, *15*(8), pp.1427-1434, 2011.

[13] Patil, G.R. and Sangole, J.P. "Behavior of two-wheelers at limited priority uncontrolled T-intersections". *IATSS Research*, *40*(1), pp.7-18, 2016.

[14] Kaysi, I.A. and Abbany, A.S. "Modeling aggressive driver behavior at unsignalized intersections". *Accident Analysis & Prevention*, *39*(4), pp.671-678, 2007.

[15] Yan, X., Radwan, E. and Guo, D. "Effects of major-road vehicle speed and driver age and gender on left-turn gap acceptance". *Accident Analysis & Prevention*, *39*(4), pp.843-852, 2007.

[16] Rakha, H., Sadek, S. and Zohdy, I. "Modeling differences in driver left-turn gap acceptance behavior using bayesian and bootstrap approaches". *Procedia-Social and Behavioral Sciences*, *16*, pp.739-750, 2011.

[17] Polus, A., Shiftan, Y. and Shmueli-Lazar, S. ""Evaluation of the waiting-time

effect on critical gaps at roundabouts by a logit model". *European Journal of Transport and Infrastructure Research*, *5*(1), 2005.

[18] Madanat, S.M., Cassidy, M.J. and Wang, M.H. "Probabilistic delay model at stop-controlled intersection". *Journal of Transportation Engineering*, *120*(1), pp.21-36, 1994.

[19] Lieu, H., "Revised monograph on traffic flow theory". *Federal Highway Administration*, 2003.

[20] Brilon, W., Koenig, R. and Troutbeck, R.J. "Useful estimation procedures for critical gaps". *Transportation Research Part A: Policy and Practice*, *33*(3-4), pp.161-186, 1999.

[21] Mohan, M., and S. Chandra. "Review and Assessment of Techniques for Estimating Critical Gap at Two-Way StopControlled Intersections". *European Transport*, Vol. 61, No. 61, pp. 1–18, 2016.

[22] Maze, T.H. "A probabilistic model of gap acceptance behavior". *Transportation research record*, *795*, pp.8-13, 1981.

[23] Greenshields, B.D., Schapiro, D. and Ericksen, E.L. *Traffic Performance at Urban Street Intersections*, 1946 (No. Tech Rpt 1).

[24] Fitzpatrick, K. "Gaps accepted at stop-controlled intersections". *Transportation Research Record*, *1303*(11), pp.103-112, 1991.

[25] Raff MS. "A New Study of Urban Stop Signs: A Volume Warrant". *Traffic Quarterly*; 4(1), 1950.

[26] Radwan, A.E., Sinha, K.C. and Michael, H.L. "Development and Use of a Computer Simulation Model for the Evaluation of Design and Control Alternatives for Intersections of Minor Road with Multi-Lane Rural Highways: Field Studies and Model Validation: Interim Report". 1979.

[27] Solberg, P. and Oppenlander, J.C. "Lag and gap acceptances at stop-controlled intersections" 1964.

[28] Neter, J., Kutner, M.H., Nachtsheim, C.J. and Wasserman, W. *Applied linear statistical models*, 1996.

[29] Troutbeck, R. "Estimating the Critical Assessment Gap From Traffic Movements". *Research Report*, (92-5), 1992.

[30] McGowen, P. and Stanley, L. "Alternative methodology for determining gap acceptance for two-way stop-controlled intersections". *Journal of transportation engineering*, *138*(5), pp.495-501, 2012.

[31] Wu, N. "A new model for estimating critical gap and its distribution at unsignalized intersections based on the equilibrium of probabilities". *In Proceeding of the 5th international symposium on highway capacity and quality of service. Yokohama, Japan*, July 2006.

[32] Gerlough, D. L., and Huber, M. J. ''Traffic flow theory.'' *Transportation Research Board, National Research Council, Washington, D.C.* Spec. Rep. No. 165, 1975.

[33] Mafi, S., Abdelrazig, Y. and Doczy, R. "Analysis of gap acceptance behavior for unprotected right and left turning maneuvers at signalized intersections using data mining methods: a driving simulation approach". *Transportation research record*, *2672*(38), pp.160-170, 2018.

[34] Pawar, D.S., Patil, G.R., Chandrasekharan, A. and Upadhyaya, S. "Classification of gaps at uncontrolled intersections and midblock crossings using support vector

machines”. *Transportation research record*, *2515*(1), pp.26-33, 2015.

[35] Nagalla, R., Pothuganti, P. and Pawar, D.S. “Analyzing gap acceptance behavior at unsignalized intersections using support vector machines, decision tree and random forests”. *Procedia Computer Science*, *109*, pp.474-481, 2017.

[36] Bagheri, M., Bartin, B. and Ozbay, K. “Simulation of Vehicles’ Gap Acceptance Decision at Unsignalized Intersections Using SUMO”. *Procedia Computer Science*, *201*, pp.321-329, 2022.

[37] Pant, P.D. and Balakrishnan, P. “Neural network for gap acceptance at stop-controlled intersections”. *Journal of transportation engineering*, *120*(3), pp.432-446, 1994.

[38] Marczak, F., Daamen, W. and Buisson, C. “Merging behaviour: Empirical comparison between two sites and new theory development”. *Transportation Research Part C: Emerging Technologies*, *36*, pp.530-546, 2013.

[39] Devarasetty, P.C., Zhang, Y. and Fitzpatrick, K. “Differentiating between left-turn gap and lag acceptance at unsignalized intersections as a function of the site characteristics”. *Journal of transportation engineering*, *138*(5), pp.580-588, 2012.

[40] Gattis, J.L. and Low, S.T. “Gap acceptance at atypical stop-controlled intersections”. *Journal of Transportation Engineering*, 125(3), pp.201-207, 1999.

[41] Zohdy, I., Sadek, S. and Rakha, H.A. “Empirical analysis of effects of wait time and rain intensity on driver left-turn gap acceptance behavior”. *Transportation research record*, *2173*(1), pp.1-10, 2010.

[42] Bartın, B.O. “Simulation of vehicles’ gap acceptance decisions using reinforcement learning”. *Uludağ Üniversitesi Mühendislik Fakültesi Dergisi*, *22*(2), pp.161-178, 2017.

[43] Miller, A.J. “Nine estimators of gap-acceptance parameters”. *Publication of: Traffic Flow and Transportation*, 1971.

[44] Tupper, S.M. “Safety and operational assessment of gap acceptance through large-scale field evaluation”. 2011.

[45] Akçelik, R. “A review of gap-acceptance capacity models”. In *Conference of Australian Institutes of Transport Research (Caitr), 29th, Adelaide, South Australia, Australia.* Dec. 2007.

[46] Maurya, A.K., Amin, H.J. and Kumar, A. “Estimation of Critical Gap for through Movement at Four Leg Uncontrolled Intersection”. *Transportation Research Procedia*, *17*, pp.203-212, 2016.

[47] Amin, H.J. and Maurya, A.K. “A review of critical gap estimation approaches at uncontrolled intersection in case of heterogeneous traffic conditions”. *Journal of Transport Literature*, *9*, pp.5-9, 2015.

[48] Dutta, M. and Ahmed, M.A. “December. Critical gaps at three-legged unsignalised intersections using microsimulation”. In *Proceedings of the Institution of Civil Engineers-Transport* (pp. 1-10). Thomas Telford Ltd, 2020,

[49] Ragland, D. R., S. Arroyo, S. E. Shladover, J. A. Misener, and C. Y. Chan. Gap Acceptance for Vehicles Turning Left across On-Coming Traffic: Implications for Intersection Decision Support Design. *Presented at 85th Annual Meeting of the Transportation Research Board, Washington, D.C*. 2006,

[50] Zhong, X., Zhu, X., Zhang, Y. and Liu, X. “Left-turn gap acceptance behavior of tee type of unsignalized intersection”. In *International Conference on Transportation Engineering 2007* (pp. 2975-2980) , 2007.

[51] AASHTO. A Policy on Geometric Design of Highways and Streets. American Association of State Highway and Transportation Officials, Washington, D.C., 2010.

[52] Kittelson, W.K. and Vandehey, M.A., 1991. *Delay effects on driver gap acceptance characteristics at two-way stop-controlled intersections* (No. 1320).

[53] Polus, A. and Lazar, S.S. Entry capacity at roundabouts and impact of waiting times. *Road & Transport Research*, *8*(3), p.43, 1999.

[54] Hamed, M.M., Easa, S.M. and Batayneh, R.R. “Disaggregate gap-acceptance model for unsignalized T-intersections”. *Journal of Transportation Engineering*, *123*(1), pp.36-42, 1997.

[55] Ball, K. and Owsley, C. “Identifying correlates of accident involvement for the older driver”. *Human Factors*, *33*(5), pp.583-595, 1991.

[56] Ball, K., Owsley, C., Sloane, M.E., Roenker, D.L. and Bruni, J.R. “Visual attention problems as a predictor of vehicle crashes in older drivers”. *Investigative ophthalmology & visual science*, *34*(11), pp.3110-3123, 1993.

[57] Owsley, C., McGwin Jr, G. and Ball, K. “Vision impairment, eye disease, and injurious motor vehicle crashes in the elderly”. *Ophthalmic Epidemiology*, *5*(2), pp.101-113, 1998.

[58] Kazazi, J., Winkler, S. and Vollrath, M. “The influence of attention allocation and age on intersection accidents”. *Transportation Research Part F: Traffic Psychology and Behaviour*, *43*, pp.1-14, 2016.

[59] R. Hecht-Nielsen. “Neurocomputing”. *Addison-Wesley Publishing Company, Inc., Reading, Mass*, 1990.

[60] P . K. Simpson. “Artificial Neural System”. *Pergamon Press, Inc., New York , N.Y.* , 1990.

[61] Faghri, A. and Hua, J. “Evaluation of artificial neural network applications in transportation engineering”. *Transportation Research Record*, *1358*, p.71, 1992.

[62] Caudill, M. “Neural networks primer”, part I. *AI expert*, *2*(12), pp.46-52, 1987.

[63] Chong, L., Abbas, M.M. and Medina, A. “Simulation of driver behavior with agent-based back-propagation neural network”. *Transportation Research Record*, *2249*(1), pp.44-51, 2011.

[64] Kalyoncuoglu, S.F. and Tigdemir, M. “An alternative approach for modelling and simulation of traffic data: artificial neural networks”. *Simulation Modelling Practice and Theory*, *12*(5), pp.351-362, 2004.

[65] Hunt, J.G. and Lyons, G.D. “Modelling dual carriageway lane changing using neural networks”. *Transportation Research Part C: Emerging Technologies*, *2*(4), pp.231-245, 1994.

[66] Karlaftis, M.G. and Vlahogianni, E.I. “Statistical methods versus neural networks in transportation research: Differences, similarities and some insights”. *Transportation Research Part C: Emerging Technologies*, *19*(3), pp.387-399, 2011.

[67] Dia, H. “An object-oriented neural network approach to short-term traffic forecasting”. *European Journal of Operational Research*, *131*(2), pp.253-261, 2001.

[68] Dia, H. “An agent-based approach to modelling driver route choice behaviour under the influence of real-time information”. *Transportation Research Part C:*

Emerging Technologies, *10*(5-6), pp.331-349, 2002.

[69] Reggiani, A., Romanelli, R., Tritapepe, T. and Nijkamp, P. “Neural networks: an overview and applications in the space economy”. *Neural Networks in Transport Applications*, pp.21-54, 2019.

[70] Bonabeau, E. “Agent-based modeling: Methods and techniques for simulating human systems”. *Proceedings of the National Academy of Sciences*, *99*(suppl_3), pp.7280-7287, 2002.

[71] Kadali, B.R., Rathi, N. and Perumal, V. “Evaluation of pedestrian mid-block road crossing behaviour using artificial neural network”. *Journal of Traffic and Transportation Engineering (English edition)*, *1*(2), pp.111-119, 2014.

[72] Zheng, J., Suzuki, K. and Fujita, M. “Predicting driver’s lane-changing decisions using a neural network model”. *Simulation Modelling Practice and Theory*, *42*, pp.73-83, 2014.

[73] Gallelli, V. and Vaiana, R. “Roundabout intersections: evaluation of geometric and behavioural features with VISSIM”. In *Proceedings of TRB National Roundabout Conference. Kansas City, Missouri, USA*, May 2008.

[74] Walsh, D., Stewart, D., Luk, J. and Tay, J. “The use and application of microsimulation traffic models”, 2006.

[75] Federal Highway Administration (2004a). *Traffic Analysis Toolbox Volume I: Traffic Analysis Tools Primer. US dept of transport, USA*.2014

[76] Olstam, J. “A model for simulation and generation of surrounding vehicles in driving simulators”, PhD dissertation, Institutionen för teknik och naturvetenskap, 2005.

[77] Bartin, B., Ozbay, K., Gao, J. and Kurkcu, A. “Calibration and validation of large-scale traffic simulation networks: a case study”. *Procedia computer science*, *130*, pp.844-849, 2018.

[78] Lord-Attivor, R. and Jha, M.K. “Modeling gap acceptance and driver behavior at stop controlled (priority) intersections in developing countries”. In *Proceedings of the 6th WSEAS international conference on Computer Engineering and Applications, and Proceedings of the 2012 American conference on Applied Mathematics, World Scientific and Engineering Academy and Society (WSEAS)*, Jan, 2012.

[79] Rossi, R., Meneguzzer, C., Orsini, F. and Gastaldi, M. “Gap-acceptance behavior at roundabouts: Validation of a driving simulator environment using field observations”. *Transportation research procedia*, *47*, pp.27-34, 2020.

[80] Barton, R.R. and Schruben, L.W. “Resampling methods for input modelling”. In *Proceeding of the 2001 Winter Simulation Conference (Cat. No. 01CH37304)* (Vol. 1, pp. 372-378). IEEE, Dec 2001.

[81] Dowling, R., Skabardonis, A. and Alexiadis, V. “Traffic analysis toolbox, volume III: Guidelines for applying traffic microsimulation modeling software” (No. FHWA-HRT-04-040). *United States. Federal Highway Administration. Office of Operations*, 2004.

[82] Iyer, S., Ozbay, K. and Bartin, B. “Ex post evaluation of calibrated simulation models of significantly different future systems”. *Transportation research record*, *2161*(1), pp.49-56, 2010.

[83] Arafat, M., Hadi, M., Raihan, M.A., Iqbal, M.S. and Tariq, M.T. “Benefits of connected vehicle signalized left-turn assist: Simulation-based study”. *Transportation Engineering*, *4*, p.100065, 2021.

[84] Arafat, M., Hadi, M., Hunsanon, T. and Amine, K. “Stop sign gap assist application in a connected vehicle simulation environment”. *Transportation Research Record*, *2675*(9), pp.1127-1135, 2021.

[85] Mohan, M. and Chandra, S. “Critical gap estimation at two-way stop-controlled intersections based on occupancy time data”. *Transportmetrica A: Transport Science*, *14*(4), pp.316-329, 2018.

[86] Leksono, C.Y. and Andriyana, T. “Roundabout Microsimulation using SUMO: A Case Study in Idrottsparken RoundaboutNorrköping”, Sweden, 2012.

[87] Krajzewicz, D., Brockfeld, E., Mikat, J., Ringel, J., Rössel, C., Tuchscheerer, W., Wagner, P. and Wösler, R. “Simulation of modern traffic lights control systems using the open source traffic simulation SUMO”. In *Proceedings of the 3rd Industrial Simulation Conference* (pp. 299-302). EUROSIS-ETI, June 2005.

[88] Singh, S., Saraswat, A. and Yadav, S. “Traffic simulation integration using SUMO simulator”. *International Journal of Scientific Research and Review*, *7*(2), pp.22-26, 2019.

[89] Kotusevski, G. and Hawick, K.A. “A review of traffic simulation software” , 2009.

[90] SUMO User Documentation. Accessed address: https://sumo.dlr.de/docs/index.html [Accessed August 31, 2022]

[91] Erdmann, J. and Krajzewicz, D. “SUMO’s road intersection model”. *In Simulation of Urban MObility User Conference (pp. 3-17). Springer, Berlin, Heidelberg*, May 2013.

[92] Law, A. M. and Kelton, W. D. *Simulation Modeling and Analysis*, 2nd Edition, McGraw-Hill, Inc., 1991.

VITA

Mohammad Bagheri finished his first Master's degree in Geotechnical Engineering at Azarbaijan Shahid Madani University, Tabriz, Iran. In his first Master's Program, he conducted an experimental study to investigate the durability and strength of problematic soils improved with a novel polymeric stabilizer, considering the economic and environmental constraints. His work was accompanied by two papers published in well-known journal articles. In his current Master's program, his research interests lie in the field of transportation engineering, integrating machine learning techniques and traffic simulation programming. He modeled driver's gap acceptance decision using the Artificial Neural Network models and tested the models' feasibility in a microscopic traffic simulation software. As the results of this study, one conference paper is published in Elsevier, and one is submitted to the Transportation Research Board.