anpet
brazilian association for transportation research and education
TRANSPORTES
ISSN: 2237-1346
anpet.org.br/transportes

Analysis of the effect of probabilistic response time at microsimulated intersections in AIMSUN

Análise do efeito do tempo de resposta probabilístico em interseções semaforizadas microssimuladas no AIMSUN

Wanderson Pedrosa[1], **Manoel Castro-Neto**[1], **Alessandro Araújo**[1]

[1]Universidade Federal do Ceará, Fortaleza, Ceará, Brasil

Contact: wanderson.pedrosa@det.ufc.br, (WP); manoel@det.ufc.br, (MN); alessandro.araujo@det.ufc.br, (AA)

Submitted:
20 November, 2024
Revised:
3 March, 2025
Accepted for publication:
10 March, 2025
Published:
5 June, 2025
Associate Editor:
Sara Ferreira, Universidade do Porto, Portugal

Keywords:
Response time.
Signalized intersections.
Microsimulation.
AIMSUN.

Palavras-chave:
Tempo de resposta.
Interseções semaforizadas.
Microssimulação.
AIMSUN.

DOI: 10.58922/transportes.v33.e3062

ABSTRACT
Signalized intersections are critical points in road infrastructure, often prone to congestion and accidents due to capacity limitations and traffic conflicts. Driver response time (RT), especially when prolonged, is a behavioral variable that affects traffic performance at these locations, contributing to increased delays and reduced road capacity. This study aimed to model and analyze the impact of drivers' RT on traffic flow at signalized intersections using the AIMSUN microsimulation software. The methodology involved collecting RT and headway data at an intersection in Fortaleza, modeling the RT probability distribution, and implementing it in the simulator. Different scenarios were simulated by varying vehicle demand and RT to assess their impacts on average delay, v/c ratio, saturation flow, and the capacity of signalized approaches. The results showed that the log-normal distribution was the best fit to the RT data. Probabilistic modeling of RT in AIMSUN showed that the RT of the first vehicle in the queue (RT1) was higher than that of the subsequent vehicles. Incorporating probabilistic RT modeling increased delays and reduced capacity compared to the default model. The study highlights that probabilistic RT modeling affects the flow of microsimulated signalized intersections, particularly under more saturated traffic conditions.

RESUMO
Interseções semaforizadas são pontos críticos da infraestrutura viária, frequentemente sujeitos a congestionamentos e acidentes devido às limitações de capacidade e aos conflitos de tráfego. O tempo de resposta (TR) dos motoristas, especialmente quando elevado, é uma variável comportamental que afeta o desempenho do tráfego nesses locais, contribuindo para o aumento dos atrasos e para a redução da capacidade viária. O objetivo deste trabalho foi modelar e analisar o impacto do TR dos motoristas na fluidez do tráfego de interseções semaforizadas, utilizando o software de microssimulação AIMSUN. O método empregado envolveu a coleta de dados de TR e de headways em uma interseção na cidade de Fortaleza, a modelagem da distribuição de probabilidade do TR e sua implementação no simulador. Diversos cenários foram simulados, variando a demanda de veículos, assim como a duração do TR, com o intuito de avaliar os seus impactos no atraso médio, na razão v/c, no fluxo de saturação e na capacidade de aproximações semaforizadas. Os resultados mostraram que a distribuição log-normal foi a que melhor se ajustou aos dados de TR. A modelagem probabilística do TR nos simuladores mostrou que o TR do primeiro veículo da fila (TR1) foi maior do que para os demais veículos em fila. A inserção da modelagem probabilística do TR aumentou os atrasos e reduziu a capacidade quando comparado ao modelo default. O estudo aponta que a modelagem probabilística do TR afeta a fluidez de interseções semafóricas microssimuladas especialmente em condições de tráfego mais saturado.

1. INTRODUCTION

Signalized intersections are critical components of urban traffic management, often characterized by high vehicle density and potential conflict points. These intersections play a crucial role in mobility, particularly in dense urban areas where traffic demand and system responsiveness are essential to prevent congestion and minimize accidents. Efficient intersection operations are influenced by various factors, including driver behavior.

The driver Response Time (RT) at signalized intersections is defined as the time a driver takes to start moving after the vehicle in front left. For the first vehicle in the queue, RT_1 is measured from the onset of the green signal.

Given the increasing demand for more realistic traffic modeling, one of the leading microsimulation software tools, AIMSUN, offers flexibility in modeling RT probabilistically. Thus, the primary objective of this article is to analyze the effects of probabilistic RT modeling on the traffic flow at a signalized intersection simulated in AIMSUN. The performance measures analyzed include discharge headways (s), saturation flow (veh/h), capacity (veh/h), average delay (s), and degree of saturation (v/c ratio, dimensionless). The analysis considered factors such as traffic demand and vehicle position in the queue.

2. LITERATURE REVIEW

Several transportation studies have explored physical road and traffic characteristics, but driver behavior remains a more complex challenge due to its variability in aspects such as gender, age, and reaction time (Xie, Zhu and Li, 2020). Response time (RT), defined as the interval between the green signal onset and the first vehicle's movement—or, for subsequent vehicles, the interval between the leading vehicle motion and the following vehicle's reaction—has been analyzed in different ways. Murat and Cetin (2019) demonstrated that RT significantly influences saturation flow. Other studies, such as those by Nourzad, Salvucci and Pradhan (2014) and Fitch et al. (2013), have employed cameras or eye-tracking sensors for RT analysis.

This literature review section discusses the RT's influence on traffic at signalized intersections and RT modeling in microsimulation software such as VISSIM and AIMSUN.

2.1. Response time and its influence on traffic at signalized intersections

Hurwitz et al. (2013) analyzed the impact of driver distraction on the start-up lost time at the beginning of signal phases at a signalized intersection, aiming to investigate whether the average headway of the first five vehicles in the queue changed when drivers were distracted compared to a control group without distraction. Analyzing 4,091 headways from the control group and 844 from distracted drivers, the study concluded that the average headway for distracted drivers was 0.4 seconds longer than for those who were not distracted.

In another study, Murat and Cetin (2019) sought to introduce a new perspective on estimating saturation flow by combining vehicular characteristics with human factors. Their findings indicated that RT was the most crucial factor for saturation flow and that reducing the average RT to below 0.8 seconds using new technologies could increase saturation flows to over 3,000 vehicles per hour.

Considering the statistical distributions found in studies over the past 20 years, Li and Prevedouros (2002) and Çalişkanelli and Tanyel (2018) analyzed the effect of type of turning movement on the response time of the first vehicle in the queue (RT_1). For vehicles moving through, the null hypothesis that RT_1 follows a normal distribution was not rejected. However, for turning vehicles, the only distribution that was not rejected for RT_1 was the log-normal distribution.

Li and Prevedouros (2002) conducted an analysis of RT at a signalized intersection in downtown Honolulu, Hawaii, using video recordings to track vehicle movements. The study focused on two types of movements: through and protected left turns, evaluating variables such as saturation headway, start-up lost time, and RT_1. The average RT was 1.76 seconds for the through vehicles and 1.42 seconds for the left-turning ones.

The difference in RT values was confirmed using the t-Student test, which indicated statistical significance between the mean RT of the two types of movement. These results align with the findings of Çalişkanelli and Tanyel (2018), who also observed shorter reaction times for turning.

Li and Prevedouros (2002) also noted that approximately 1% of drivers making left turns started moving before the green onset. Regarding RT distribution, the data presented strong positive skewness (skewness coefficient > 1.0), suggesting that the log-normal distribution might be appropriate. However, the Lilliefors test, a variation of the Kolmogorov-Smirnov test, rejected this goodness-of-fit.

In a similar study, Çalişkanelli and Tanyel (2018) investigated RT at intersections in a Turkish city, focusing on the influence of RT_1 on saturation flow and road performance. Nine intersections were selected based on criteria such as the absence of bus stops affecting vehicle movement, a longitudinal grade below 1%, and a parking ban along the analyzed section. Data collection covered 19 link approaches, with observations conducted during morning and/or afternoon peak hours, recording at least 25 cycles per approach.

The data collection involved installing a camera in a nearby building to capture images of the traffic signal and the first vehicle in the queue. In addition, an observer positioned next to the first vehicle manually recorded RT_1. Another observer collected data including vehicle type, lane width, movement direction, driver gender, and traffic signal timing, totaling 1,788 observations for the first vehicles in queue. The results showed that the RT of drivers performing turning movements (right or left) was significantly shorter than that of drivers going through.

To model the data, the authors applied the Anderson-Darling goodness-of-fit test to assess compatibility with different statistical distributions (log-normal, exponential, gamma, and Weibull). The results showed that the log-normal distribution best represented the data, being the only distribution that was not rejected. Subsequently, a linear regression model was developed to predict RT, suggesting that longer traffic signal cycles could increase driver distraction and, consequently, prolong RT.

Li et al. (2014) analyzed RT_1 at signalized intersections in Beijing, China, comparing scenarios with and without a countdown timer for the green phase. The study was conducted at three intersections—one with a countdown timer and two without—using cameras installed nearby to record four hours of data at each location. Data collection was assisted by an algorithm that detected both the start of the green phase and the beginning of vehicle movement. However, the algorithm had limitations and failed to record RT when pedestrians, cyclists, or objects obstructed the vehicle. The study gathered 150 RT observations for each scenario. The results indicated that the mean RT of drivers at the intersection with a countdown timer was lower than the mean RT at intersections without the device. This difference suggests that the presence of a countdown timer increases driver's attention and reduces distractions. To evaluate variance homogeneity between scenarios, the authors applied Levene's test, which rejected the null hypothesis of equal variances, indicating that RT variances differed significantly between the scenarios. Additionally, the Mann-Whitney U test confirmed a statistically significant difference in RT distributions between the two scenarios. The chi-square goodness-of-fit test indicated that RT for the first vehicle can be represented by the Weibull distribution in the scenario without a countdown timer and by the log-normal distribution in the scenario with the device.

2.2. RT Modeling in AIMSUN

AIMSUN (2024) allows users to specify both RT_1 and RT through values associated with probabilities. RT_1 can be modeled using the "reaction time at stop parameter. RT can be calibrated using the parameter "reaction time at traffic light", which represents the time a vehicle in a queue takes to react to the acceleration of the vehicle in front (AIMSUN, 2024).

The specification of these parameters does not require programming; it is done through discrete values and their associated probabilities. One challenge is that inserting all probability values for both parameters becomes impractical due to the large number of possible combinations, with each combination corresponding to a separate entry line in the software interface. For example, if one specifies 100 probability values for the "reaction time when stationary" parameter (related to RT), he/she will need to input 100 lines in the software entry window for each value of the other parameter, RT_1. More details on this will be presented in the methodology section.

3. METHODOLOGY

The methodology of this study consists of four stages:

1. Data collection and processing.
2. Statistical modeling of RT.
3. Implementation of RT scenarios in Aimsun.
4. Analysis of the effects of RT on traffic microsimulation.

3.1. Data collection and processing

Data collection was conducted using drone footage, as these images provide an orthogonal aerial view, enhancing the accuracy of vehicle movement observations. The drone used was the Phantom 4 Pro+ V2.0, equipped with a 3-axis motorized stabilizer. Filming took place on May 31, 2023, lasting 60 minutes, during which the average traffic flow was 295 vehicles per hour. The recordings were captured during the day under favorable weather conditions, at an altitude of 30 meters, with a frame rate of 30 frames per second and Full HD video quality (1920 x 1080 pixels).

The selected location was the southbound approach of the intersection between Humberto Monte Avenue and Jovita Feitosa Avenue, in Fortaleza, Brazil. The recorded images allowed clear visualization of the stop line and the queue of vehicles (Figure 1). A low-volume motorcycle site was selected because they influence the RT of other vehicles, and assessing this effect was not within the scope of this study. The traffic signal was recorded using a tripod-mounted camera simultaneously with the drone footage to capture the exact moments of the green light onsets. The approach has three traffic lanes (each 2.6 meters wide) and a central median that segregates the opposite direction. Additionally, a designated waiting area for motorcycles (motobox) was present, as shown in Figure 1. Parking was prohibited on both sides of the road, and the maximum regulated speed was 60 km/h.

The software Road User Behaviour Analysis (RUBA) software, developed by Tonning et al. (2017), was used for data extraction from the videos. This software allows pausing, advancing, rewinding, and adjusting the playback speed to facilitate data collection. The tool includes clickable buttons for manually marking key moments of interest.

Figure 1. Signalized intersection approach used in this study.

The output file is a .csv that records the exact video timestamps when each key was pressed, with millisecond precision. A key was configured for each vehicle position in the queue, with data collected by lane. Observations were made using a slow playback speed of 5 frames per second (fps) to enhance accuracy. RT was recorded when the operator detected the vehicle's initial movement. Headway was recorded when the front tire of each vehicle crossed the stop line.

The total observed traffic volume was 295 vehicles, consisting of 282 (95.6%) cars, 11 (3.7%) trucks, and 2 (0.7%) buses. Traffic share across lanes was 19% in the right lane, 45% in the center lane, and 36% in the left lane. However, in this study, lane position was not considered a variable. The RT_1 sample included 69 (94.5%) cars, 3 (4.1%) trucks, and 1 (1.4%) bus. The RT sample included 213 (95.9%) cars, 8 (3.6%) trucks, and 1 (0.5%) bus. Due to the small sample sizes for trucks and buses, only cars were modeled in this study.

3.2. Statistical Modeling of RT

The estimation of probability distributions was based on the literature review. The normal, log-normal, gamma, and Weibull distributions were selected for both RT_1 and RT. RT includes all positions in the queue from the second position onward; thus, RTs were not differentiated beyond the second position, as recommended by Fontes, De Araújo and De Castro Neto (2022). The statistical goodness-of-fit tests used were the Kolmogorov-Smirnov, Chi-square, and Anderson-Darling tests. After selecting the most suitable probability models, they were implemented in the microsimulation software.

3.3. Implementation of the RT_{prob} Model in AIMSUN

To implement the Probabilistic Response Time (RT_{prob}), which is generated by the chosen probability distribution, in AIMSUN, the available parameters were used, namely: the "reaction time at stop" parameter for RT_1 and the “reaction time at traffic light” parameter for RT. As mentioned in Section 2.2, these parameters are input without requiring programming, using discrete RT values and their associated probabilities. One challenge is that the possible combinations of RT_1 and RT values can be extremely large, with each combination taking a separate entry line in the software interface, as shown in Figure 2. Therefore, in this study, RT_1 was fixed for scenarios in which RT varied.

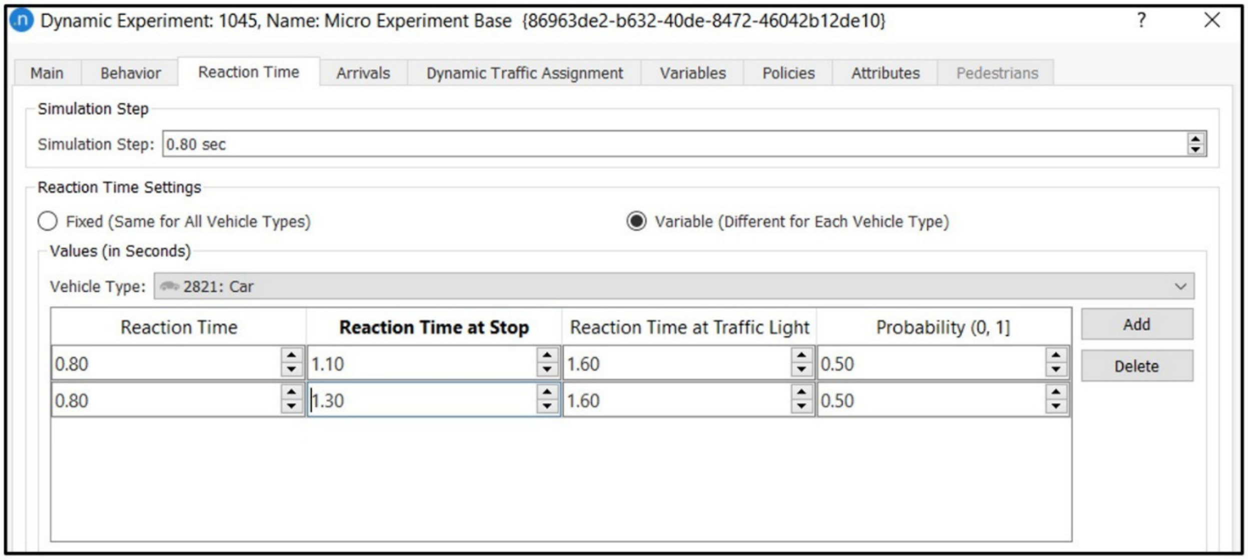

Figure 2. User interface for entering RT_1 and RT values in AIMSUN.

To focus on the analysis on RT, a simple two-lane road was created and lane changing was prohibited. This configuration ensured more uniform vehicle discharge during the green phase, facilitating the analysis of RT effects. Four simulation scenarios were created, as shown in Table 1. The mean RT_1 in Scenario 2 (1.9 S) and the mean RT in Scenario 3 (1.5 S) were obtained from field data. Scenario 4 was designed to assess the effects of an RT increase of 0.5 S, to achieve the fourth objective of the study.

Table 1: Simulation Scenarios in AIMSUN.

Scenarios	RT_1	RT
1	Default (1.6 S)	Default (1.2 S)
2	RT_{1prob} (mean = 1.9 S)	Default (1.2 S)
3	Default (1.6 S)	RT_{prob} (mean = 1.5 S)
4	Default (1.6 S)	RT_{prob} (mean = 2.0 S)

The traffic signal timing had a cycle of 80 seconds, with 57 seconds of green, 3 seconds of yellow, and 20 seconds of red. The desired speed was set according to the collected data at 60 km/h. Three vehicle demand scenarios (1,380, 1,780, and 2,180 pcu/hour) were simulated to analyze scenarios 1 to 5 at different volume/capacity (V/C) ratios: 0.50, 0.65, and 0.80, using the V/C ratio of scenario 3 as a reference. For each scenario, 30 replications of 15 minutes were conducted, plus a 100-second network warm-up period, using the same set of random seeds across the four scenarios. For each replication, the output variables obtained were average delay, saturation flow, and capacity. The network is represented in Figure 3.

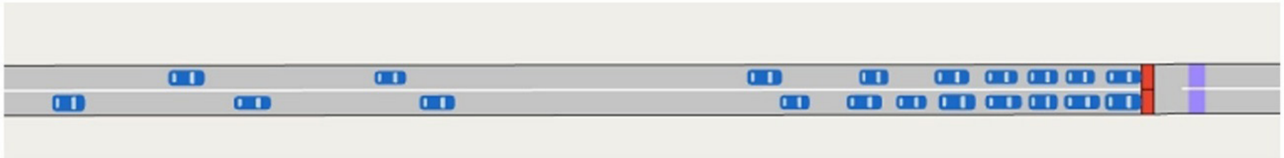

Figure 3. Study Simulation Network.

3.4. Analysis of RT effects on microsimulated traffic flow

To evaluate the effects of modeling RT_{prob} on headway, capacity, and saturation flow, a saturated demand of 10,000 vehicles/hour was applied in all proposed scenarios. A total of 30 replications of 15 minutes were conducted, each with a 100-second network warm-up period. A vehicle detector placed immediately after the traffic signal collected flow in both lanes. This demand was extrapolated to 10,000 vehicles/hour to generate sufficiently long queues in the simulation, allowing for the observation of saturation flow and approach capacity in each scenario.

Saturation headway data in AIMSUN were obtained from a .txt output file for each lane and replication, containing headway values for each vehicle, separated by position and traffic signal cycle. Saturation flow was calculated as the inverse of the average saturation headway. Average delays and capacity were estimated directly from the software outputs. Scenario analyses were based on line and bar graphs, as well as t-Student 5%-significance tests for the three demand levels.

All parameters of the driving behavior models (car-following, lane-change, gap-acceptance, speed-acceleration curves etc.) were kept at their default values for all four evaluated scenarios, except for the reaction time which is the studied parameter. This decision was made because the study did not focus on a specific location, so the default software settings were maintained.

4. RESULTS AND DISCUSSIONS

4.1. Data collection of RTobs and Headway

As previously mentioned, data collection was conducted through drone footage recorded at the intersection of Jovita Feitosa Avenue and Humberto Monte Avenue. The recordings occurred between 9:00 AM and 10:30 AM, divided into eight video takes, totaling one hour of footage. A total of 28 signal cycles were analyzed, with 289 observed vehicles, including 11 trucks (3.8%), 2 buses (0.6%), and 276 passenger cars (95.5%).

4.2. Statistical Modeling of RT

To analyze probability distributions, the R software was used, utilizing the libraries “readxl,” “fitdistrplus,” “goftest,” “tseries,” and “nortest.” The Chi-square (χ^2), Kolmogorov-Smirnov (KS), and Anderson-Darling (AD) tests were performed to assess the goodness-of-fit of the normal, log-normal, gamma, and Weibull distributions to the RT_1 data (a) and RT data (b) (Figure 4). For RT_1, only the log-normal distribution was not rejected in any of the tests (all p-values > 5%) (Table 2). For RT, none of the distributions were rejected (all p-values >5%) (Table 3).

Table 2: Goodness-of-Fit Tests for Probability Distributions for RT_1.

Distribution	χ^2 Test	p-value	KS Test	p-value	AD Test	p-value
Normal	317.6	0.00	0.10	0.02	4.85	0.00
Log-normal	13.3	0.15	0.07	0.24	1.02	0.35
Gamma	25.2	0.00	0.07	0.23	0.89	0.42
Weibull	46.3	0.00	0.07	0.25	1.58	0.16

Table 3: Goodness-of-Fit Tests for Probability Distributions for RT.

Distribution	χ^2 Test	p-value	KS Test	p-value	AD Test	p-value
Normal	7.3	0.29	0.07	0.83	0.45	0.80
Log-normal	1.7	0.95	0.1007	0.53	0.49	0.75
Gamma	2.4	0.88	0.08	0.82	0.29	0.94
Weibull	6.2	0.40	0.07	0.85	0.40	0.85

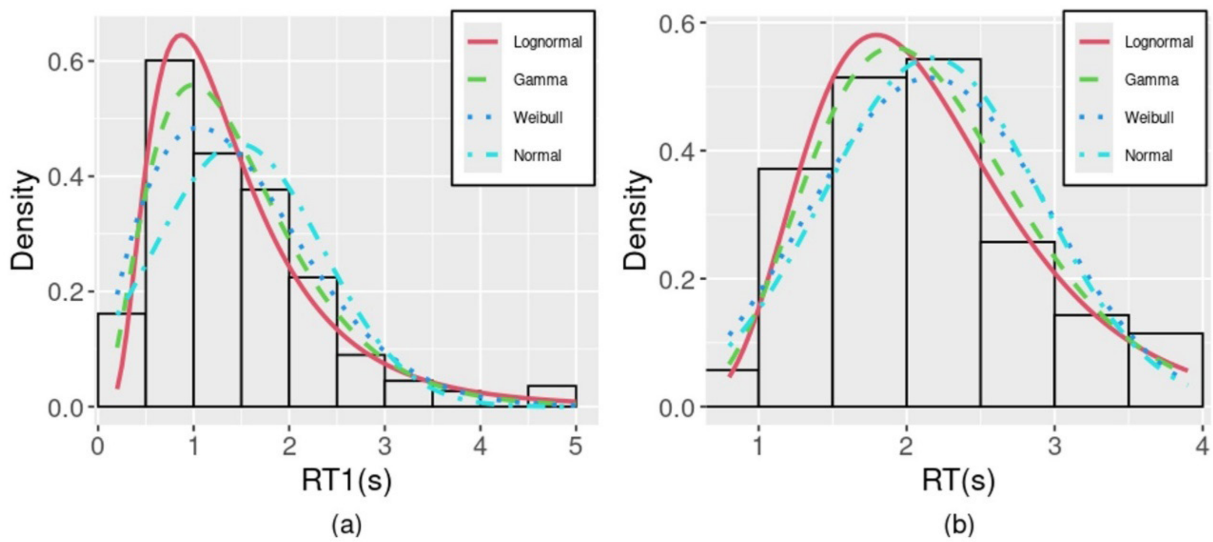

Figure 4. Goodness-of-Fit Analysis of the Statistical Distributions for RT_1.

Given these results, in the subsequent steps, probabilistic modeling of RT_1 and RT was implemented in Aimsun using the log-normal distribution, the only one not rejected in any of the tests. Furthermore, previous studies have supported its applicability to this parameter, as demonstrated in the literature review.

4.3. Analysis of RT effects on microsimulated traffic

This section presents the results of the analysis of the effects of incorporating probabilistic RT modeling into the simulations. The impacts on average delay, capacity, saturation flow, and simulated discharge headway were evaluated for different levels of saturation and average RT, as defined in section 3.

A summary of the delay and saturation degree results by demand level for the proposed AIMSUN scenarios is shown in Figure 5. The letter following each scenario indicates the demand level. The range of values along the delay curve (red) connects the limits of the 95% confidence intervals for each scenario.

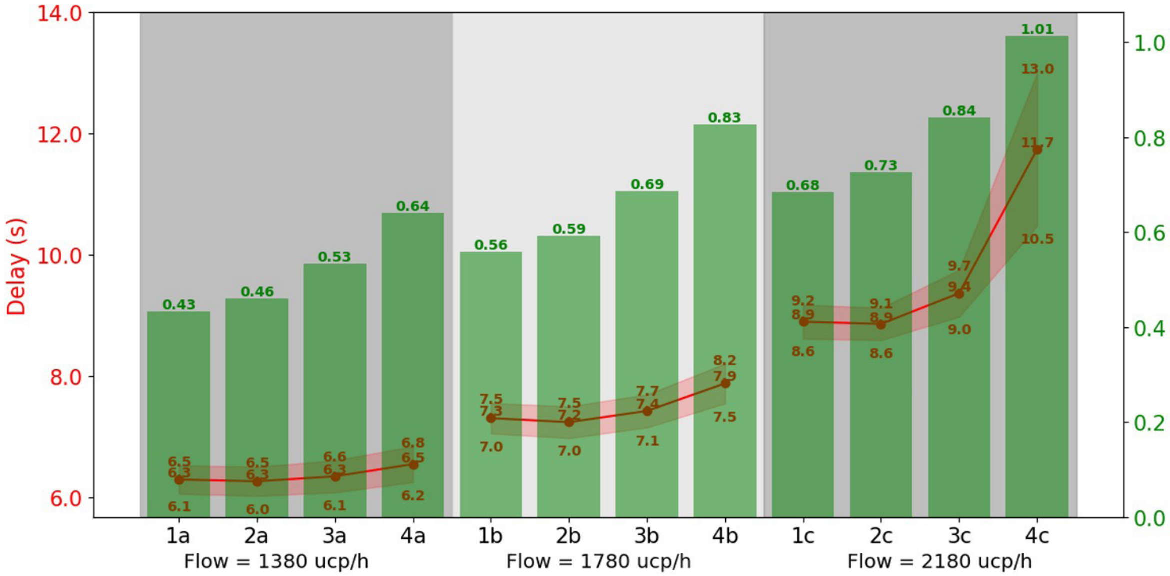

Figure 5. Delay and V/C Simulation Results for Each RT and Flow Scenario.

Significant differences in the v/c ratio can be observed among the four scenarios for the same demand level, except for the first two scenarios. **Regarding delay, differences only emerged in Scenario 4, particularly at higher flow levels. Paired t-tests were conducted to determine whether there were significant differences in the average delay, capacity, and saturation flow among scenarios. The results, along with the absolute percentage differences between their values, are presented in** Table 4. Cells marked with (*) indicate comparisons where the t-test found no statistically significant difference between the means. The calculation in each cell was as follows (Equation 1):

$$Percentage\,Difference = \frac{Column\,Mean - Row\,Mean}{Row\,Mean} \times 100 \quad (1)$$

Thus, in Table 4, for example, the value of 4% in the first row and fourth column means that the delay in scenario 4a was 4% higher than the delay in scenario 1a.

As observed, scenarios 1, 2, and 3 presented no statistically significant differences, except in the case with a demand of 2,180 vehicles/h, where there was 6% increase in delay from scenario 2c to 3c, and 5% reduction from scenario 3c to 1c, indicating some impact. However, the differences between the default scenario and the scenario with an RT increase of up to 0.5 S reached over 32%. These high delay values, reflected in a v/c ratio greater than 1, indicate a strong sensitivity of AIMSUN to RT modeling.

Particular attention is given to the comparison between scenarios 1 and 3, as scenario 1 represents the default software values, while scenario 3 includes probability distributions estimated from field-observed RT data. The results show that using probabilistic RT did not cause delay differences in lower and medium demand scenarios; in the higher demand scenario, probabilistic modeling increased the average delay by 5%.

Table 4: Comparison of Delays Between Simulated Scenarios.

Flow	Scenarios	1a	2a	3a	4a
1,380 ucp/hour	1a	-	0%*	1%*	4%
	2a	0%*	-	1%*	5%
	3a	-1%*	-1%*	-	3%
	4a	-4%	-4%	-3%	-
1,780 ucp/hour	1b	-	-1%*	2%*	8%
	2b	1%*	-	3%*	9%
	3b	-2%*	-3%*	-	6%
	4b	-7%	-8%	-6%	-
2,180 ucp/hour	1c	-	0%*	5%	32%
	2c	0%*	-	6%	33%
	3c	-5%	-5%	-	25%
	4c	-24%	-25%	-20%	-

For the analysis of capacity and saturation flow, as with delay, a graph was generated with the values per scenario (Figure 6). Additionally, the percentage differences between scenarios are presented in Table 5.

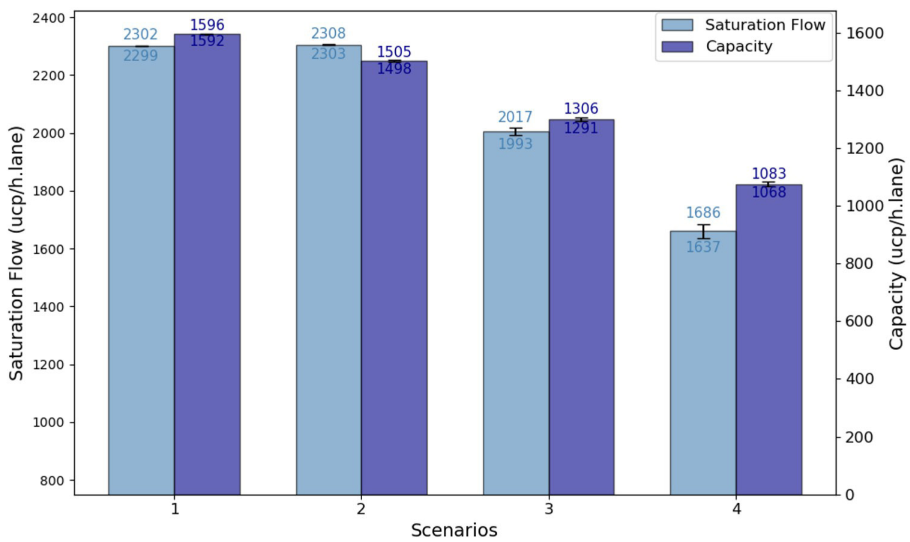

Figure 6. Capacity and Saturation Flow by Simulation Scenario.

Table 5: Differences in Capacities Among the Simulated Scenarios.

Scenarios	1	2	3	4
1	-	-6%	-19%	-33%
2	6%	-	-13%	-28%
3	23%	16%	-	-17%
4	48%	40%	21%	-

For these analyses, it is important to recall the differences among scenarios. Scenarios 1 and 2 differ due to the probabilistic modeling of RT_1 in Scenario 2, whereas Scenario 1 maintains all values on default. Additionally, Scenarios 3 and 4 in AIMSUN model only RT probabilistically, while keeping RT_1 fixed at its default value.

In the results presented in Table 5, probabilistic modeling of RT led to a significant reduction in capacity, with Scenario 3 diverging from the default (Scenario 1) by 19% and showing a 13% difference between Scenarios 2 and 3. These differences are statistically significant, as shown by the 95% confidence intervals in Figure 6, which do not overlap. The significant difference between Scenarios 1 and 2 suggests that modeling RT_1 probabilistically, with a more realistic field-measured mean value of 1.9 S, resulted in a reduction in roadway capacity in AIMSUN. The even greater difference in Scenarios 3 and 4 compared to Scenario 1 indicates that modifications to RT had more relevant effects on roadway capacity.

The results on saturation flow (Table 6) show that the probabilistic modeling of RT_1 had no significant impact, whereas RT_{prob} had – especially when its mean value was increased. This is because the calculation of saturation flow considers only vehicles from the fifth position. Cells marked with (*) indicate comparisons where the t-test found no statistically significant difference between the means. The calculation in each cell was performed according to Equation 1.

Table 6: Differences in Road Capacities among the Simulated Scenarios.

Scenarios	1	2	3	4
1	-	0%*	-13%	-28%
2	0%*	-	-13%	-28%
3	15%	15%	-	-17%
4	39%	39%	21%	-

To evaluate the behavior of the average discharge headway by vehicle position in the queue, a graph was created showing the mean headway values per position for each simulated scenario, along with field-obtained data (Figure 7).

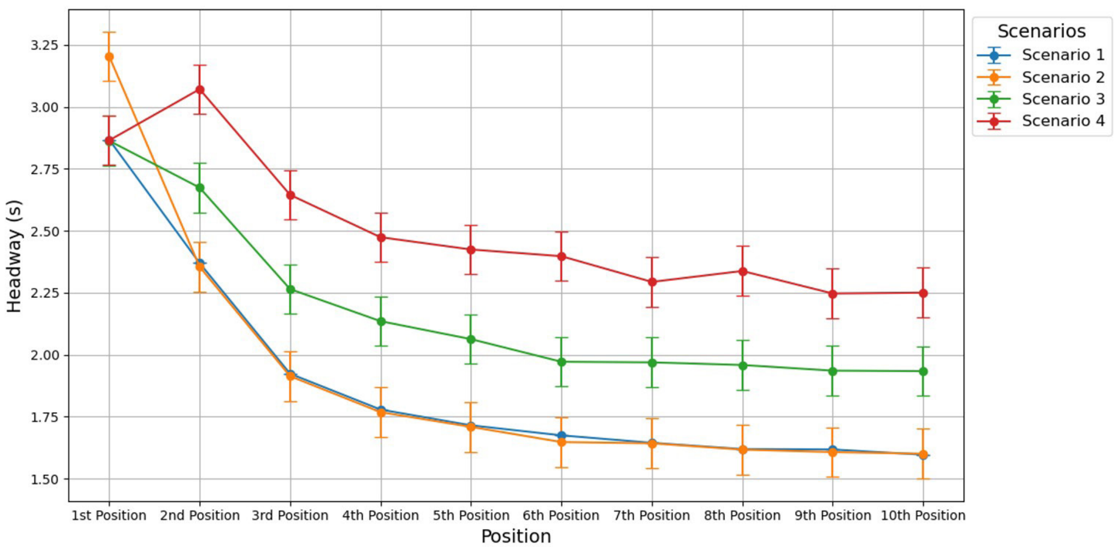

Figure 7. Average Headway by Vehicle Position in the Queue, for Each Simulation Scenario.

Figure 7 shows that, for the 1st position, the highest headway was from Scenario 2, while for all other scenarios it was practically identical. This is because the RT_1 adopted in Scenario 2 was the probabilistic RT_1 (RT_1prob) with a mean of 1.9 S, whereas in all other scenarios, the default value of 1.6 S was used.

5. CONCLUDING REMARKS

Although the literature presents various studies on driver response time (RT), especially of the first vehicle in the queue (RT_1), there are significant gaps regarding the effect of this variable at signalized intersections, particularly in the context of traffic flow. This study aimed to fill this one gap, by modeling and analyzing the impact of drivers' RT at signalized intersections, microsimulated in AIMSUN.

To achieve this objective, RT and headway data were collected at an intersection in Fortaleza, the probability distribution of RT was modeled, and it was implemented by AIMSUN . The data collection was conducted in Fortaleza, where the RTs of drivers in different traffic lanes were recorded and analyzed. Goodness-of-fit tests were used to identify the probability distributions that best represent field RTs, and the log-normal distribution was the most suitable.

Regarding the results, the probabilistic implementation of RT in the microsimulator marginally increased average delay, increased the v/c ratio, and reduced capacity and saturation flow at the intersection. Furthermore, it was possible to separately verify the impacts of RT_1 and RT modeling, with the latter having a greater effect on delay, capacity, and saturation flow.

Given the results, this study reinforces the importance of traffic managers and analysts in properly modeling RT to obtain more realistic performance predictions at signalized intersections. It is important to note that the observed effect sizes of RT modeling on the traffic variables –delay, capacity, saturation flow, and headways–are limited to the studied intersection. However, the results illustrate how more realistic modeling of RT can cause significant differences in the estimation of these variables, potentially leading to incorrect conclusions and decision-making.

Among the main limitations of this study, two are highlighted: the consideration of only one intersection, and the limited observations of other vehicle types, such as buses and trucks. Therefore, future research should consider different traffic conditions, including various vehicle types and service levels, to better understand the effects of RT on traffic modeling. Finally, future studies could conduct similar analyses using other microsimulation software packages.

AUTHORS' CONTRIBUTIONS

WP: Writing – original draft; MN: Supervision, Data curation; AA: Data collection.

CONFLICTS OF INTEREST STATEMENT

The authors declare that there is no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence tools were used in the research reported here or in the preparation of this article.

ACKNOWLEDGEMENTS

This research was supported by the Coordination for the Improvement of Higher Education Personnel (CAPES) – Brazil – Funding Code 001 and the National Council for Scientific and Technological Development (CNPq).

REFERENCES

AIMSUN (2024). AIMSUN Next Users Manual, AIMSUN Next Version 24.0.1. Available at: <https://docs.AIMSUN.com/next/24.0.1/> (accessed 11/20/2024).

Çalişkanelli, P. and S. Tanyel (2018) Investigating the driver's response time at signalized intersections, *Transport*, v. *33*, n. 2, p. 380-388. DOI: 10.3846/16484142.2016.1250106.

Fitch, G.M.; S.A. Soccolich; F. Guo et al. (2013) *The impact of hand-held and hands-free cell phone use on driving performance and safety-critical event risk. (Report No. DOT HS 811 757).* Washington, DC: National Highway Traffic Safety Administration.

Fontes, D.B.; A.M. De Araújo and M.M. De Castro Neto (2022) Modelagem probabilística do tempo de resposta de motoristas em interseções semaforizadas no VISSIM, *Transportes*, v. *30*, n. 1, p. 2501-2501. DOI: 10.14295/transportes.v30i1.2501.

Hurwitz, D.S.; K.P. Heaslip; S.D. Schrock et al. (2013) Implications of distracted driving on start-up lost time for dual left-turn lanes, *Journal of Transportation Engineering*, v. *139*, n. 9, p. 923-30. DOI: 10.1061/(ASCE)TE.1943-5436.0000569.

Li, Z.; J. Zhang; J. Rong et al. (2014) Measurement and comparative analysis of driver's perception–reaction time to green phase at the intersections with and without a countdown timer, *Transportation Research Part F: Traffic Psychology and Behaviour*, v. *22*, p. 50-62. DOI: 10.1016/j.trf.2013.10.012.

Li, H. and P.D. Prevedouros (2002) Detailed observations of saturation headways and start-up lost times, *Transportation Research Record: Journal of the Transportation Research Board*, v. *1802*, n. 1, p. 44-53. DOI: 10.3141/1802-06.

Nourzad, S.H.H.; D.D. Salvucci and A. Pradhan (2014) Computational modeling of driver distraction by integrating cognitive and agent-based traffic simulation models, *Computing in Civil and Building Engineering*, v. *2014*, p. 1885-92. DOI: 10.1061/9780784413616.234.

Murat, Y.S. and M. Cetin (2019) A new perspective for saturation flows at signalized intersections, *Periodica Polytechnica. Civil Engineering*, v. *63*, n. 1, p. 296-307. DOI: 10.3311/PPci.11344.

Tonning, C.; T.K.O. Madsen; C.H. Bahnsen et al. (2017) Road user behavior analyzes based on video detections: Status and best practice examples from the RUBA software. In *Proceedings of the 24th ITS World Congress (Los Angeles, CA)*. Dubai: ITS World, p. 1-10.

Xie, D.-F.; T.-L. Zhu and Q. Li (2020) Capturing driving behavior Heterogeneity based on trajectory data, *International Journal of Modeling, Simulation, and Scientific Computing*, v. *11*, n. 03, p. 2050023. DOI: 10.1142/S1793962320500233.