Jordan Journal of Civil Engineering, Volume **18**, No. **3**, **2024**
DOI: https://doi.org/10.14525/JJCE.v18i3.10

Jordan Journal of Civil Engineering

Journal homepage: https://jjce.just.edu.jo

Time Headway Using Computer Vision Integrated with Artificial Intelligence

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ARTICLE INFO

Article History:
Received: 29/3/2024
Accepted: 26/5/2024

ABSTRACT

Time headway between vehicles is considered as an important microscopic traffic flow parameter that affects the safety and capacity of highway facilities. This research work intends to provide a field study of vehicle time headway distribution on Petra multilane highway that connects Irbid and Ramtha cities in Jordan. The main objective of this study is to integrate the utilization of Computer Vision (CV) and Artificial Intelligence (AI) to extract time-headway data, as well as to investigate the suitability of the negative exponential distribution for the random headway state and the normal distribution for the constant headway state. Time headway data was videotaped for moving traffic over two different periods, one having medium traffic volume and the other representing the rush hour. Five hundred observations of time headway were extracted through an AI Python code developed specifically for this task and vehicle image detection. 50% of the observations represented the random headway state and the other 250 observations represented the constant headway state. The developed regression analysis model for the extracted time headway data *versus* their associated frequencies shows a tendency toward negative exponential distribution (R^2=0.98) for the random headway state, while showing a normal distribution relationship (R^2=0.99) with chi-square test at a level of significance of 0.01. This indicates the successful integration between Computer Vision (CV) and AI in investigating suitable models for headway distributions. This finding will open the door for the usage of AI and computer vision in numerous applications of traffic and transportation engineering disciplines.

Keywords: Computer vision (CV), Artificial intelligence (AI), Time headway.

INTRODUCTION

Time headway (h) refers to the time gap between when one vehicle reaches a point on the road and when the following vehicle arrives at that spot. It has a significant role in traffic flow analysis (Wu *et al.*, 2023). Typically, time headway is measured in seconds (Garber & Hole, 2018). This traffic parameter is considered one of the most essential microscopic traffic flow characteristics. Since the values of time headways and their distributions are closely related to traffic operation performance, such as road capacity and level of service, they have some implications regarding traffic safety simulation, safety measures and traffic conflict analysis. Therefore, it must be analyzed as precisely as possible based on actual driver behavior, which is now possible due to technological improvements. A minimum time headway must usually be considered to maintain safety on the road due to the sudden deceleration of lead vehicles.

As shown in Figure 1, the time headway consists of two components; the occupancy time which is the time required for the physical body of the vehicle to pass the point of observation and the time gap which represents the time between the rear of the lead vehicle and the front of the following vehicle (Garber & Hole, 2018).

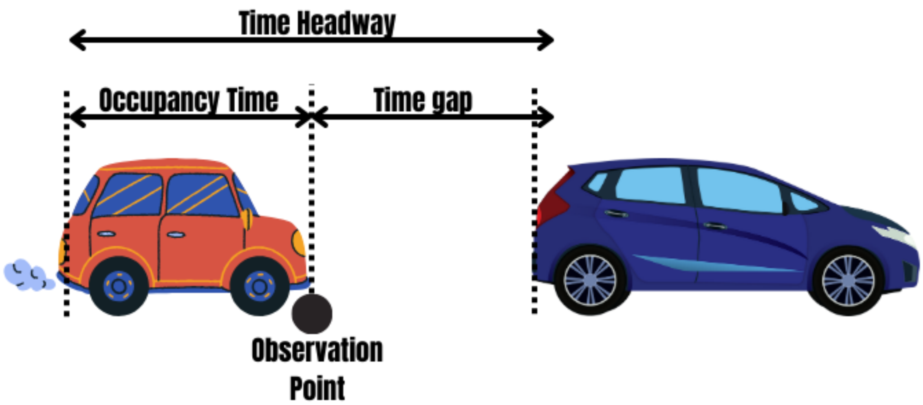

Figure (1): Time headway components

The headway between vehicles is influenced by many factors, such as the speed on the road, driver reaction time, road condition, traffic mix, traffic density, weather conditions and the time of driving (i.e., daytime and nighttime). Comprehending how drivers choose their desired headway enhances traffic planning and policy development across various traffic scenarios (Moridpour, 2014). The shape of time headway distribution varies as the traffic flow rate and vehicle interaction vary. There are three states for time headway distribution: random headway state, which happens under meager traffic conditions, where there is no interaction between vehicles, so the arrival of one vehicle does not affect the arrival time of another vehicle; this state follows the Poisson distribution and the interarrival time follows the negative exponential distribution. Constant headway state happens under heavy traffic conditions and the traffic flow is near capacity, where all vehicles interact; this state follows the uniform distribution and the time headway distribution follows the normal distribution. The intermediate headway state lies between the random headway and the constant headway states; in this state, some vehicles interact while others do not. This state can be modeled using two major approaches: the generalized mathematical approach and the composite model approach. In this study, a multi-lane highway, Petra highway, is taken and the study area was between Irbid Mall Grand and al-Sareeh signal. The area was investigated during two traffic flow levels: low traffic conditions and congested conditions. The study aims to test whether the collected time headway data followed the negative exponential distribution in the case of low flow levels (random headway state) and the normal distribution (constant headway state). Both cases will be tested using the chi-square test methodology, a statistical method used to assess whether the observed frequencies of categorical data differ from the expected frequencies.

Computer vision is often defined as a field of intelligence that aims to help computers understand and interpret data in their environment. This involves developing algorithms and structures that allow machines to derive meaning from images or videos to human vision. On the other hand, artificial intelligence refers to the progress of computer systems that can perform tasks usually linked with intelligence.

Integrating computer vision and artificial intelligence in modeling time headway represents a significant advancement in traffic management and analysis (Luo *et al*., 2023). The technologies used in this research have automated many routine data collection and analysis tasks. This integration has led to more accurate vehicle and lane detection, demonstrating the potential benefits of these technologies in traffic management.

This paper consists of six main sections: 1) Introduction section; 2) Literature review section that gives an overview of previous research related to time headway analysis and modeling and explains the deficiencies of these studies compared with this research; 3) Data collection section that provides information about data type, environmental condition and other details; 4) Methodology section explaining the research work; 5) Analysis and discussion section explaining research results and providing research limitations; and 6) Conclusions' section summarizing the research results.

LITERATURE REVIEW

Headway is the generalization of the time needed for the front of the first car to pass a specific point on the way and for the front of the next one to pass the same point (Michael *et al.,* 2000). Many studies have been conducted on the time headway distributions using different methods. Early investigations by Gazis *et al.* (1959) laid the groundwork by establishing fundamental distributions for time headways. Their work aimed at understanding traffic flow theory by applying exponential and gamma distributions to model time headways (Gazis *et al.,* 1959). Also, empirical studies utilizing real-world traffic data have further enriched our understanding of time headway distributions. Brackstone and McDonald (1999) analyzed time headway data collected from field observations, revealing the presence of heavy-tailed distributions, deviating from the assumptions of exponential or gamma distributions. Their findings suggested that the driver's behaviors, environmental factors and traffic conditions significantly influence time headway distributions (Brackstone & McDonald, 1999).

Nowadays, many models are suggested to represent the types of distribution of time headway. Some of these types are the exponential distribution (Cowan, 1975), the Erlang distribution (Salter & Hounsell, 1996), the lognormal distribution (Greenberg, 1966), the inverse Gaussian distribution (Sun & Benekohal, 2006), the gamma distribution (Luttinen, 1996), among others.

According to Brackstone *et al.* (2002 and 2009), the relationship between speed and headway has been investigated using a vehicle with radar rangefinder sensors to measure the distance between rear and front vehicles to determine the headway based on different flow levels, road types and type of lead vehicle. The study showed that flow level and road type do not affect headway choice, but the type of lead vehicle affects it (Brackstone *et al.,* 2002; Brackstone *et al.,* 2009).

Another study was conducted by Zhang *et al.* (2007) using one-day freeway traffic data with four different combinations of leading and following vehicles: car–truck, truck–car, truck–truck and car–car at different flow levels. The study showed that the vehicle combination has no effect on the time-headway distribution at low flow levels, but during congested conditions, there is a difference (Zhang *et al.,* 2007).

Kong and Guo (2016) explored the optimal distribution for fitting various headway types that involved Car-Car (C-C), Car-Truck (C-T) and Truck-Truck (T-T) scenarios among the six usual models: lognormal, gamma, exponential, normal, inverse Gaussian and Erlang. Their results pointed out that the lognormal distribution was relevant to both C-C and T-T headways, while on the other hand, the inverse Gaussian distribution was fit for the C-T mode. Meanwhile, they noticed that several conditions, such as the percentage of vehicle flow, the percentage of trucks and road position, notably affected the performance of each model (Kong & Guo, 2016).

More research has been conducted to study the effect of lane position on time headway values and distribution. Abtahi *et al*. (2011) conducted one of these studies by investigating how the lane position affects the distribution that time headway values follow. The main finding of their research showed that the lane position model for a passing lane is different from that for the middle lane. Different driver behaviors for different lanes under various traffic conditions cause this lack of concordance. In the passing lane, many drivers choose negligent headways while giving way to other cars, which shows that their behavior is more prone to risk, leading to recognizable unbalance in capacities and probability density models of both lane sides (Abtahi *et al.,* 2011).

Another study on the effect of flow level and lane position was conducted by Al-Jameel and Al-Jumaili (2016). They studied the relationship between flow and headway and found that headway decreases as flow increases and that the outer lane always gives maximum value for R^2 of its relationship compared with other lanes (Al-Jameel & Al-Jumaili, 2016).

A recent research study by Alhamadany and Albayati (2022) was conducted in Baghdad, Iraq, for the time headway modeling of urban roads using the EasyFit 5.5 software to select the appropriate distributions for different flow rates. Research results indicated that GEV distribution also ranks high among the percentages of the actual distributions across the arteries, lanes and sections of the expressway. On the other hand, the problem with exponential distribution was found to be the unsuitability of its application, since this distribution only effectively depicted empirical distributions under conditions when the traffic was meager (Alhamadany & Albayati, 2022). The general extreme value (GEV) distribution refers to a group of continuous probability distributions developed by the extreme value theory. This distribution is considered to be the only possible limit distribution used to normalize the maxima of a sequence of independent random variables. The usage of this distribution provided a significant view of the limitations of previous distributions related to traffic flow levels as discussed in this research.

Despite extensive research on time headway modeling, it is still needed to bridge gaps in choosing the best distribution to describe the data, particularly in working on all vehicle types and different lane positions on multilane highways. Previous studies, such as Abtahi *et al*. (2011), have focused on lane position and its effect on distribution type, leaving the importance of vehicle types unexplored, which is significant because vehicles' dimensions and speeds have a vital role in the distribution of time headway on each lane of the highway. Additionally, methodological limitations in these previous studies, such as reliance on traditional techniques to collect and analyze data, have constrained the depth of insights into the application of new technologies in studying different traffic parameters.

Recognizing the limitations of traditional data collection and analysis methods, this research study proposes a novel approach by integrating computer vision and artificial intelligence. The research aims to revolutionize the way of collecting, extracting and utilizing time headway data. This innovative method promises not only to provide more accurate data, but also to open doors for new avenues of research and discovery in the field of traffic flow theory and advancing the current understanding in this field.

DATA COLLECTION

Field data was collected in December 2023 during the daytime under clear weather to have good visual conditions at the same site, but at two separate times of the day, to represent two levels of traffic flow. The data was collected by video recording at Petra highway between Irbid Mall Grand, Irbid-Jordan and al-Sareeh signal, as shown in Figure 2, during two periods; the first period was in the morning from 9:30 a.m. to 11:30 a.m. to represent the low traffic condition and the second period was from 2:30 p.m. to 4:30 p.m. to represent the congested condition. The studied section length was fifty meters. These locations at this section of the highway provide a clear vision without obstacles on the highway and the camera was hidden from drivers to get reliable data. According to Cochran (1977), the minimum sample size can be calculated using the equation:

$$n = \frac{z^2 \times p \times (1-p)}{E^2} \quad (1)$$

where

n: the required sample size.

z: z-score corresponding to the desired confidence level.

p: estimated proportion of the population with the characteristic of interest (if unknown, 0.5 is often used for maximum variability).

E: desired marginal error.

Using a confidence level of 99%, the z-score will be 2.58 and p=0.5 with a marginal error of 0.1 second. The desired sample size will be 167, less than the sample size used in each case, indicating that the sample size is sufficient.

The data was captured using an Oppo A74 cellular phone camera. This camera, equipped with a 48MP primary lens and 8MP wide-angle lens with an aperture of f/2.2. The camera has high-quality imaging capabilities. The selected resolution was set to 6000 x 8000 pixels to ensure detailed images. Videos were recorded at a frame rate of 30 fps, providing smooth and detailed footage for analysis. These specific settings were carefully chosen to ensure the accuracy of the data. Table 1 presents the camera coordinates for the two periods, further demonstrating the meticulous approach to data collection.

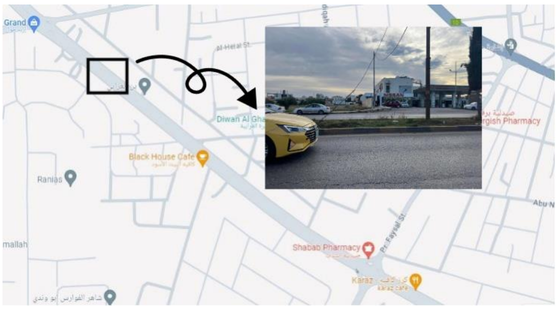

Figure (2): Site of data collection

Table 1. Camera coordinates

Camera	Location Coordinates	
	N	E
9:30 a.m.-11:30 a.m.	32°31'44.33"	35°53'32.68"
2:30 p.m.-4:30 p.m.	32°31'45.91"	35°53'34.15"

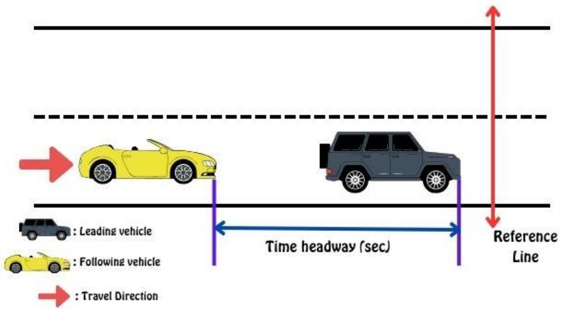

Figure (3): Measurement of time headway

An electric pole was utilized as a fixed reference point to ensure consistent measurements across different data collection periods. The pole was chosen for its permanent position and easily identifiable characteristics, which facilitated the precise alignment of the camera setup during data collection and being readily detected with AI. Data was collected for the passing lane (inner lane) and the number of observations was 250 observations for each case. The data collected in the video was extracted by Artificial Intelligence (AI) using a Python code to make sure that the data was accurate. This code defines a function to calculate the time headway between vehicles based on frame-by-frame analysis of the taped video, car detection and extracting the time headway between the detected vehicles.

The study considers the vehicle mixes to represent more accurate data. Figure 3 shows how time headway can be calculated between two successive vehicles.

Flow rate is the number of vehicles passing through a point on a road within a given time. It is calculated using the formula:

$$flow\ rate = \frac{3600}{h_{avg}} \tag{2}$$

where h_{avg} is the average headway in seconds in the lane.

The extracted data included the time headways; their frequency is shown in Figure 4 and Figure 5.

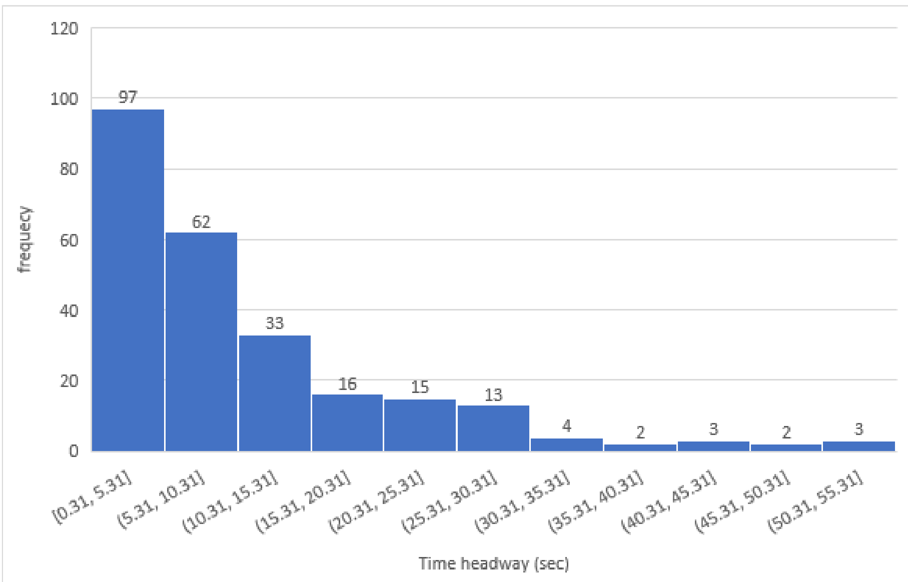

Figure (4): Time headway distribution during low traffic

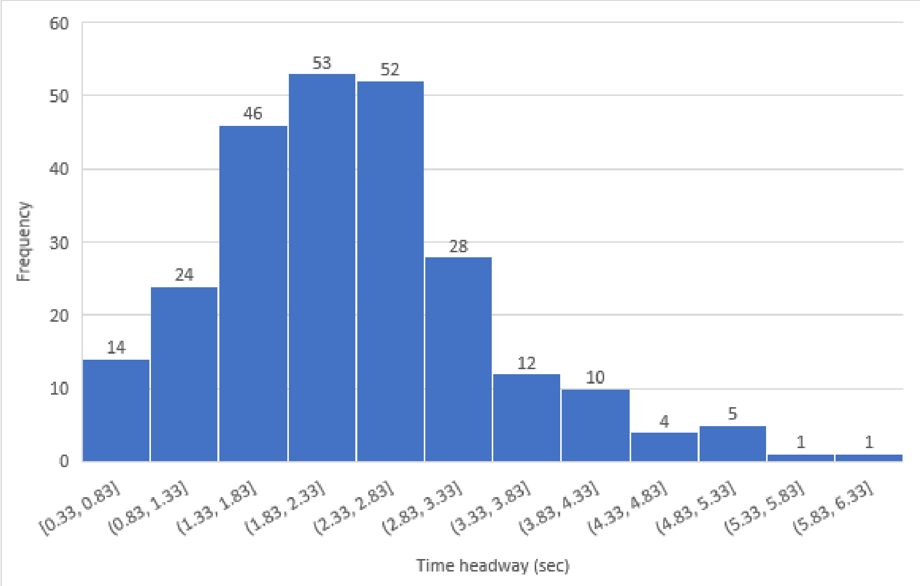

Figure (5): Time headway distribution during heavy traffic

METHODOLOGY

The research aims to test the usage of CV integrated with AI to collect and analyze time headway data. A camera was installed away from drivers' vision with no obstacles in front of it. A video was taped using this camera during two different periods of time for the passing lane on the highway.

To extract data from the taped videos, CV and AI used a Python code written using two main libraries: Numerical Python (NumPy) and Open-source Computer Vision (OpenCV), using PyCharm and Visual Studio code programs. A pre-trained car detection model was uploaded to the program and then by OpenCV library, the vehicles were detected on the lane by defining the video frame by frame. Each frame is then converted into grayscale form to detect the vehicles in frames quickly. After vehicle detection, an imaginary reference line was drawn by Python code at the location of the electric pole to extract time headway data by drawing a rectangular frame around detected vehicles, measuring the time at which each vehicle passed through the reference line and then calculating the difference in time between the leading and the following vehicles. Then, the iteration was repeated for the following vehicle to get the time headway between the two successive vehicles.

The YOLOv3; i.e. you only look once, algorithm was employed for the object detection tasks in the study which has good potential in deep convolutional neural networks in object detection (Naqvi *et al.*, 2022). It was chosen for its efficiency and accuracy with a confidence threshold of 0.5 to reduce the likelihood of false positives by considering the detections with a high probability. An intersection over the union threshold of 0.4 non-maximum suppression was used to minimize the possible overlapping between boundary boxes. On the other hand, for time headway calculation, a fixed time interval of 0.1 second was set between consecutive frames to capture the frames accurately.

After data extraction and collection, statistical models should be used to fit the data in order to find an appropriate model for headway distribution. Since the highway was under light and heavy traffic conditions, the negative exponential distribution was applied for light traffic (Adams, 1937; Greenshields *et al.*, 1946) and the normal distribution was applied for heavy traffic (May, 1990) in this study. Table 2 shows the equations and parameters used for those two distributions.

Table 2. Equations and parameters of distributions

Distribution	Equations	Parameters
Negative exponential distribution	$P(h \geq t) = e^{\frac{-t}{\bar{t}}}$	t: selected time interval (sec.) $\bar{t}$: time headway means
Normal distribution	$\propto = \bar{t} - 2s$ $z = \lvert \bar{t} - t \rvert$	$\propto$: $shift\ parameter$

In this form, given the meantime headway, the analysts can select various time intervals t, such as 0,1,2,3,... and P (h≥ 0,1,2,3, …). In this study, Δt = 5 seconds has been selected for negative exponential distribution and Δt=0.5 second for normal distribution (May, 1990).

Then, the probability for headways between (t) and (t+Δt) can be calculated as presented in the following formula:

$$P(t \leq h < t + \Delta t) = P(h \geq t) - P(h \geq t + \Delta t). \quad (3)$$

As a last step, the probabilities are then converted into frequencies using the following formula:

$$F(t \leq h < t + \Delta t) = P(t \leq h < t + \Delta t) * N \quad (4)$$

where:

$F(t \leq h < t + \Delta t)$: is the predicted number of time headways in the time headway group (t ≤h <t+Δt).

N: is the total number of observed headways.

After finishing the previous steps, the used distributions should be tested to determine whether they are appropriate to fit the extracted data. The chi-square test has been used with a significance level of 0.01.

A hypothesis has been set to test the significance of the tests. It states no difference between a measured time headway distribution and a specific mathematical distribution. So, suppose that the outcome of the test accepts the hypothesis. In that case, the conclusion statement is “There is no evidence of a statistical difference between the measured time headway and the selected mathematical distribution and the distribution is good to express the data.”. Otherwise, if the outcome of the test rejects the hypothesis, the conclusion statement is “There is evidence of a statistical difference between the measured time headway and the selected mathematical distribution and the distribution is not good enough to express the data”.

The equation used in the chi-square test is:

$$X^2_{calc} = \sum_{i=1}^{I} \frac{(f_0 - f_t)^2}{f_t} \quad (5)$$

where:

X^2_{calc}: calculated chi-square value.

f_0 : observed number or frequency of observations in time headway interval i.

f_t: theoretical (or other observed) number or frequency of expected observations in time headway interval i.

i: any time headway interval.

I: number of time headway intervals.

The conclusions from the hypothesis are summarized as follows:

H_0: $if\ X^2_{calc} \leq X^2_{table}$; the hypothesis is accepted.

H_1: $if\ X^2_{calc} > X^2_{table}$; the hypothesis is rejected.

To get the value of X^2_{table} , the number of degrees of freedom should be calculated from the equation:

$$n = (I - 1) - p \quad (6)$$

where:

n: number of degrees of freedom.

I: number of time headway intervals being compared.

1: constant.

p: number of parameters estimated in defining the mathematical distribution (for negative exponential distribution, p=1 and for normal distribution, p=2).

DATA ANALYSIS AND DISCUSSION

The total number of observations extracted was for 500 vehicles; 250 for the period from 9:30 to 11:30 a.m. and the other 250 for the period from 2:30 to 4:30 p.m. The statistical characteristics of the data are shown in Table 3 and Table 4, respectively.

Table 3. Data summarization during random arrival

Number of headway observations	**250**
Flow rate (veh/hr/lane)	335.44
Maximum time headway (sec.)	52.9
Minimum time headway (sec.)	0.31
Mean of headways (sec.)	10.73
Mode of headways (sec.)	7.1
The median of headways (sec.)	7.12
Standard deviation	10.71

The minimum time headway during random and constant arrivals is 0.31 second and 0.33 second, respectively, while the maximum time headway is 52.9 seconds and 5.94 seconds for both random and constant arrivals, respectively. Individual headways reach over 10 seconds in the case of random arrival due to the low flow rate which was 335.44 veh/hr/lane. The mean, median and mode in case of constant arrival state indicate that the data may follow the normal distribution, because they almost had the same values. However, in the case of random arrival, the mean is greater than the median and the median is greater than the mode, indicating that the data may follow the negative exponential distribution (Singh and Santhakumar, 2022).

These distributions were analyzed to investigate whether the negative exponential distribution would fit the extracted measurements during random arrival and the normal distribution would fit the extracted measurements during constant arrival. The application was done as shown in the methodology and Figures 6 and 7 show the plotted relations for the test. Regression analysis indicated distinct distributions for each group, as summarized in Table 5.

Table 4. Data summarization during constant arrival

Number of headway observations	**250**
Flow rate (veh/hr/lane)	1563.77
Maximum time headway (sec.)	5.94
Minimum time headway (sec.)	0.33
Mean of headways (sec.)	2.302
Mode of headways (sec.)	2.21
The median of headways (sec.)	2.21
Standard deviation	1.015

Table 5. Equations of the curves and R^2 values

Distribution Type	**Regression Equation**	**R^2**
Negative Exp. Dist.	$y = 107.85e^{-0.398x}$	0.9775
Normal Dist.	$y = 0.0915x^6 - 2.0504x^5 + 16.996x^4 - 62.311x^3 + 88.246x^2 - 14.397x + 11.141$	0.9935

These equations related the frequency of time headway to its values. In the case of random arrival, the equation has the shape of a negative exponential function with a coefficient of correlation of 0.98, which means that this model explained 98% of variations in frequency. Based on Figure 6, the model perfectly fits when time headway values are higher. However, the equation of the constant arrival data has the shape of a polynomial of sixth degree with a strong coefficient of determination of 0.99, which means that this model explained 99% of variations in frequency and based on Figure 7, the model perfectly fits when time headway values are smaller.

According to the chi-square test, conducted at 0.01 level of significance, the results showed that for random arrival $\chi^2_{calc} = 11.31 < \chi^2_{table} = 21.7$ and for constant arrival $\chi^2_{calc} = 19.61 < \chi^2_{table} = 21.7$. Since $\chi^2_{calc} < \chi^2_{table}$ in both cases, the hypothesis is accepted and we can say that "there is no evidence of a statistical difference between the measured time headway and the selected mathematical distribution and the distribution is good to express the data." Therefore, the negative exponential distribution is suitable for the random arrival state and the normal distribution is suitable for the constant arrival state.

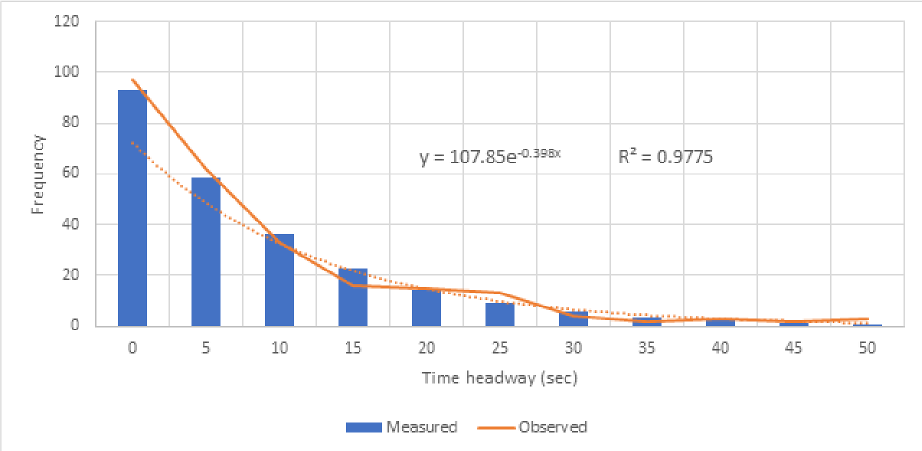

Figure (6): Time headway frequency and negative exponential distribution for random arrival

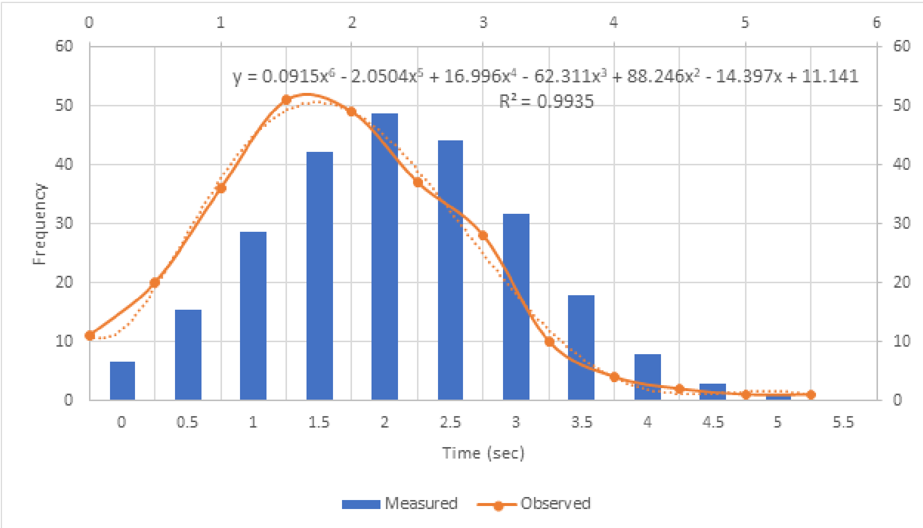

Figure (7): Time headway frequency and normal distribution for constant arrival

The random (negative exponential) distribution has the inherent characteristics that the smallest headways are most likely to occur and the probabilities consistently decrease as time headway increases. Also, the two distributions mostly have the best comparison under low flow levels. However, the normal distribution has the inherent characteristics of being mostly symmetrical about the mean, having a bell-shaped distribution and having the best comparison under the highest flow levels. However, the normal distribution fits regular and high-traffic flows, while the negative exponential distribution fits low-traffic flows due to its skewness and long tail.

Comparing our results with those of existing studies shows consistency with Zhang *et al.* (2009), who also reported that time headway values depend on flow levels. Also, the findings align with Al-Jameel and Al-Jumaili's (2016) findings regarding the influence of lane position on headways. However, the approach of integrating CV with AI provides more accurate results by automating routine traffic parameter studies. This method enhances traffic management, operation and safety in a more efficient and cost-effective manner than conventional methods. On the other hand, the findings of Abtahi *et al*. (2011) showed that the appropriate models for headway distribution are different in the passing and middle lanes under congested conditions. They found that the lognormal model with 0.24-second shift was selected as the appropriate model for headway and for the middle lane, the gamma model with 0.69-second shift was selected as the most appropriate model. This is because the different behavioral operations of drivers are affected by specific conditions of each lane. These results show a discrepancy with this research results; this might be due to different sample size, used and the traffic flow on tested highways, indicating the importance of testing different situations to generalize research results.

The study was limited to a small sample size of 500 vehicles during two different time periods, which may not fully represent the variation in traffic flow patterns during the same day or during the weekdays, which may not account for temporal variations in traffic flow. Additionally, the study relied on a specific technical setup, noting that the usage of a more improved camera and changing the positions of data collection may have direct effects on the results. Moreover, the study was applied on one lane of one section of the highway, which could limit the generalizability of the findings to different lanes and sections. Furthermore, the chi-square test was conducted at 0.01 confidence level and the distributions were said to be fitted, but at higher levels of confidence, the test failed and the hypothesis was rejected, suggesting the need for a larger sample size in future research.

Despite these limitations, the study provides valuable insights into the distribution and characteristics of time headways under different traffic conditions, laying a foundation for future research to build upon and refine this-research findings.

CONCLUSIONS

In light of the results, the study reached the following conclusions:

1) The usage of computer vision integrated with artificial intelligence gives a higher level of accuracy in analyzing time headway data, which is clear in regression analysis models.
2) Regression analysis models were developed for the relationship between time headway data *versus* associated frequencies. These models were: the negative exponential distribution (R^2=0.98) for the random headway state and the normal distribution relationship for the constant headway state (R^2=0.99) with chi-square test at a level of confidence of 0.01.
3) The flow rate and the selection of inner or outer lanes would affect the headway data and the modeling distributions.
4) Mixed vehicle flow gives more accurate headway data for modeling purposes.
5) The fundamental statistics for the collected data followed the general characteristics of the time headway distribution: a) in case of negative exponential distribution, the mean is always higher than the median, which is always higher than the mode; and b) in case of normal distribution, the mean, the median and the mode are almost equal.

Future research should explore the integration of AI and CV in other traffic parameters to validate and extend the current study's results. Interdisciplinary approaches combining insights from traffic engineering, data science and urban planning could provide a more comprehensive understanding of traffic management and safety studies.

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