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Headway Analysis using Automated Sensor Data under Indian Traffic Conditions

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Abstract

Headway is a microscopic parameter of traffic flow and is defined as the temporal or spatial distance between two consecutive vehicles. On a macroscopic level these headways translate to density and flow, which are two of the fundamental traffic flow parameters. Several studies were reported on headway patterns and the distribution followed by headways, mainly under the homogeneous and lane based traffic. Definition and measurement of these parameters under traffic condition as in India, with lack of lane discipline and heterogeneity in vehicle composition, is a challenging task. Measurement of these microscopic parameters is not easy and hence not many studies reported such analysis under Indian conditions. The present study reports such a statistical analysis of headways on a suburban arterial road in Chennai, using the data collected from a location based automated sensor. Analysis was carried out on the traffic as a whole as well on mode wise characteristics. Data were separated according to the class of leader and follower vehicle and statistical analysis was carried out separately for each class combination. It was found that the average headway of the stream as a whole was in the range of 2.2 to 3 sec. Headway is in the upper range, when heavy vehicles are involved in the leader follower pair. Log-likelihood method was employed to fit statistical distribution to the data. It was found that for all the categories, Weibull distribution is the best fit.

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Keywords: Time headway; Automated Sensors; Statistical Modelling; Heterogeneous Traffic

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1. Introduction and Literature Review

Headway is a microscopic parameter of traffic flow and is defined as the temporal or spatial distance between two consecutive vehicles. Headway can be either time headway, time that elapses between the arrival of a leading vehicle and the following vehicle at a point, measured in seconds, or space headway, which is the difference in position between the front of a leading vehicle and the front of the following vehicle measured in meters. On a macroscopic level, these headways translate to density and flow, which are two of the fundamental traffic flow parameters. Headway is one of the important parameters to be used in modeling and analysis of road traffic, especially in traffic simulation studies. Modeling of headway is important due to the fact that headway and their distribution can affect different flow parameters including capacity, level of service and safety (Arasan and Koshy, 2003). Headway varied with the traffic conditions; the more the flow of the traffic, the less the headway will be. Hence, it is important to understand headway to carry out traffic flow modeling, both theoretical and simulated. Headway is location specific since headway can be different for two different road types or stretches.

Several studies were reported on the distribution followed by headways, mainly under the homogeneous and lane based traffic. Al-Ghambi (2001) studied headway under three flow sates (low, medium and high) and observed headway at arterial sites follows gamma distribution and Erlang distribution at sites where the flow is high. Brackstone, Waterson and McDonald (2009) analyzed headways when traffic is congested and reported that headways are changing depending on the type of vehicle that follows. Pueboobpaphan, Park, Kim, and Choo (2012), analyzed the distribution of time headway of a traffic stream using probe vehicles and they found that the time headway follows negative exponential, if the volume of the probe vehicle is low irrespective of the general traffic volume. Ha, Aron and Cohen (2012) discussed about three types of probabilistic models namely single model, combined model and mixed model. Zhang, Wang, Wei and Chen (2007) did a comprehensive study on performance of typical headway distribution models on urban freeways. From Interstate Highway 5 in Seattle area in Washington, they collected time headway data using the Advanced Loop Event Data Analyzer (ALEDA) system. These headway data were used to calibrate and examine the performance of various headway models. They examined the goodness of fit for various distribution models using the collected headway. In order to evaluate the performance of these headway models, the Kolmogorov-Smirnov test and visualized comparison curves were used. Their test results showed that the Double Displaced Negative Exponential Distribution model provided the best fit to the urban freeway headway data, especially, for HOV lanes at wide ranging flow levels. The shifted lognormal distribution also fitted the general-purpose-lane headways. He, Guan and Ma (2007) analyzed the real traffic data from multiple sections of urban freeway and according to them time-headway distributions under different velocities fitted well with a class of distributions. The distribution is decomposed into an exponential distributed variable plus an independent Gaussian fluctuation. Li, Lu, Yu and Sui (2011) collected headway data from loop detectors on different sites of an urban arterial road in Beijing. Gamma and Erlang distribution were tried and based on K-S test, they found Gamma distribution as the best fit. Jang, Park, Kim, and Choi (2011) proposed a theoretical headway model using laser sensor-based traffic detector data. The headway data were divided into five flow states based on speed and concluded that Johnson SU model, Log logistic model and Lognormal were the best fits. Bham and Ancha (2011) proposed shifted lognormal and gamma distribution model for time headway in steady state car following and found out shifted lognormal distribution provided a better fit compared to the shifted gamma distribution. Yin, Li, Zhang, Yao, Su, and Li (2009) studied dependence of headway distributions on traffic status and concluded that in free-flow state, lognormal distribution as a better fit and log logistic model as the better fit in congested state.

Definition and measurement of these parameters under traffic condition such as in India, with lack of lane discipline and heterogeneity in vehicle composition is a challenging task. Arasan and Koshy (2003) studied time headway distribution of urban heterogeneous traffic and the study showed that the headways of mixed traffic dominated by small vehicles like motorized two-wheelers can be modeled using negative exponential distribution. Dubey, Ponnu, Arkatkar (2012) proposed two distributions namely, Generalized Pareto (GP) and Generalized Extreme Value (GEV) along with other conventional distribution to model vehicular time gaps. They found from their study that GP distribution fits the time gap data well for low flow, and GEV fits the data well for the high flow levels. Kanagaraj, Asaithambi, Srinivasan and Sivanandan (2013) studied the headway distribution of heterogeneous traffic at aggregate level and across different leader-follower pair and they observed that truncated generalized extreme value distribution reasonably fitted the time gap for many classes and log normal fitted the following time headway. Dubey, Ponnu, Arkatkar (2013) proposed composite distribution model for heterogeneous traffic since non-composite probability distributions such as Weibull, Erlang, exponential, and lognormal distributions are not capable of modeling time gaps at higher flow rates. They tested different models for different flow rates and found the RMSE was the lowest for the Weibull+Lognormal among various combinations for different flow levels. Mukerjee, Rao, and Raichowdry (1988) evaluated negative and shifted exponential distribution to generate vehicles approaching an intersection and found that the shifted negative exponential distribution gave a close fit for the observed headways. Chandra and Kumar (2001) analysed exponential, log normal and hyperlang distribution for headway under mixed traffic condition and found hyperlang to be the best descriptor of headway under mixed traffic condition.

However, studies reported from India were mainly based on data collected manually, which has limitations, mainly in terms of sample size. With the availability of automated sensors, large amount of data is available making such analysis meaningful. The present paper reports such a statistical study, using data collected from a location based automated sensor. The location for the infrared sensor was in the Rajiv Gandhi Salai, at Perungudi, Chennai.

Nomenclature

Y	parameter of distribution
x_i	data observed or outcome

2. **Study site, Equipment, Data collection, Extraction and Preliminary Analysis**

2.1. Study Site

The time headway for the proposed analysis has been collected from the IT corridor near Perungdi, Chennai, which represents a typical urban road. The road is a six lane divided roadway and the sensor is fitted permanently at the selected location. The sensor collects traffic data for one direction of traffic movement. The collected data has been received through inbuilt GPRS modem in the sensor. The figure 1 shows the percentage composition of vehicles at the study site.

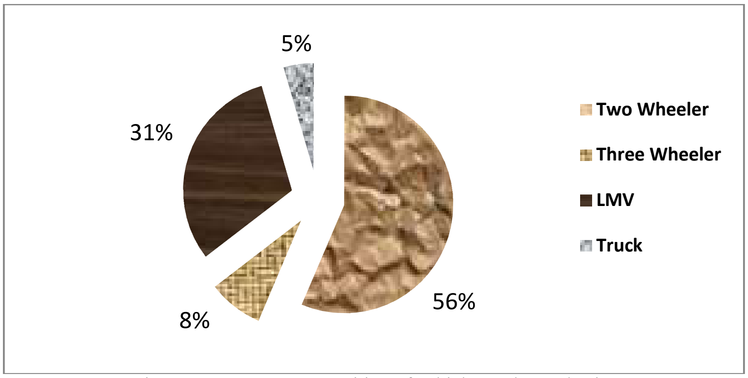

Fig. 1. Percentage composition of vehicles at the study site

2.2. Equipment Used

An infra red based traffic sensor called TIRTL, an acronym for The Infra Red Traffic Logger, is used for data collection. TIRTL consists of two units, a transmitter and a receiver, placed at both sides of the road, perpendicular to the traffic flow. The transmitter emits two infra-red beams and are received by the receiver placed opposite to it.

The distortion in the beams caused by the wheels of the passing vehicles will be detected by the receiver. When the disturbance happens in the beam, two events will take place. Breaking of the beam is known as “Break Beam Event” while the re-establishment of the beam is called “Make Beam Event”. Time of these beam events occurrences will be recorded by the receiver. The time difference between the beam events is used to calculate speed of the vehicle. TIRTL is able to identify the vehicle classification using the wheel base length pre-defined by the user. Data collected by this detector included time of detection of vehicle, speed of the vehicle, distance of the vehicle from the sensor across the road width, etc. The sensor is able to give classification for a maximum of 15 types of vehicles.

2.3. Data collection, Extraction and Preliminary Analysis

Five days data collected from April 07, 2014 to April 11, 2014 were considered for analysis in this study. Using the time of detection reported by the sensor for consecutive vehicles, time headways were calculated. In this study, headway is considered only if the following vehicle exactly follows the leading vehicle or there is an overlap between leader and follower, in terms of space. In other words, if the leading vehicle has any influence on the following vehicle's movements, that vehicle pair is considered for headway calculation. Also, headways bigger than selected threshold value, in this case 5 seconds, were not considered since they are far apart for any interaction to happen. Headways thus obtained are shown in Figure 2. From the figure 2, it can be seen that the headways started decreasing from 3 sec to 2.2 sec with increase in the flow of traffic. After 11:00 AM, the variation in the headway is not very prominent.

Based on the variations observed, the data were classified into three different categories depending upon the flow conditions; 6:30 am to 7:30 am, 7:30 am to 10:45 am and 10:45 am to the end of the day and analysed separately. In addition, analysis was carried out for class wise pairs. The classes considered were Two wheeler, Three Wheeler, Four Wheeler, and Trucks. Based on the leader-follower pairs various combinations are analysed and are listed in Table 1.

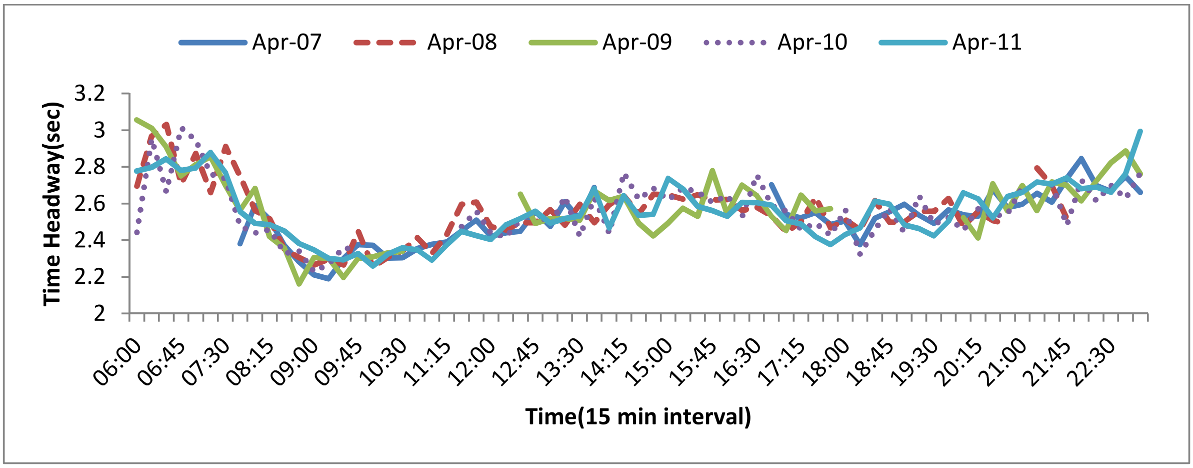

Fig. 2. Variation of time headway over time.

Table 1. Different leader follower pairs.

Leader Vehicle Type	Corresponding Pairs
2 Wheeler	2 Wheeler – 2 Wheeler
	2 Wheeler – 3 Wheeler
	2 Wheeler – 4 Wheeler
	2 Wheeler – Truck

3 Wheeler	3 Wheeler – 2 Wheeler
	3 Wheeler – 3 Wheeler
	3Wheeler – 4 Wheeler
	3 Wheeler – Truck
4 Wheeler	4 Wheeler – 2 Wheeler
	4 Wheeler – 3 Wheeler
	4 Wheeler – 4 Wheeler
	4 Wheeler – Truck
Truck	Truck – 2 Wheeler
	Truck – 3 Wheeler
	Truck – 4 Wheeler
	Truck – Truck

A preliminary statistical analysis of the headways of the above mentioned pairs were carried out separately. Figure 3 shows the comparison of mean headway values for various class wise pairs.

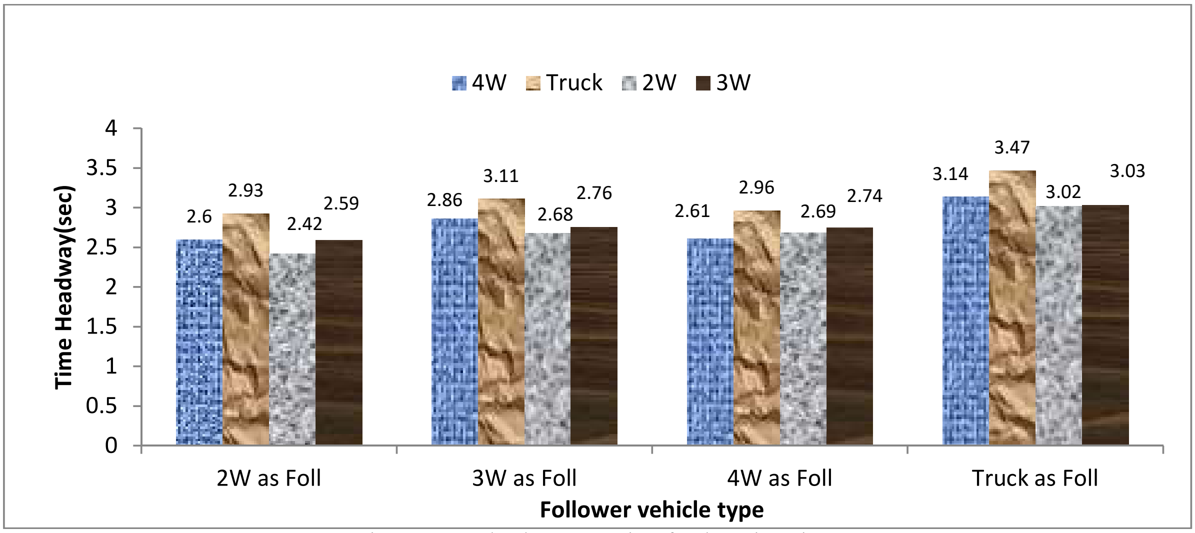

Fig. 3. Average headway comparison for class wise pairs.

It is can be clearly seen from the figure that the average headway for Truck-Truck (heavy vehicles) pair is the highest compared to the other pairs. It is also evident that the average headway is more when truck is involved as one of the vehicles in the leader-follower pair. The average headway of 2 Wheeler-2 Wheeler pair is the least among all these and came to be 2.42 sec.

3. Time Headway Modeling

In this section, the methodology to identify the best fitting distribution to the headway data is described. Log-likelihood values are used in this study to choose the best fit among various distributions attempted. Likelihood is a measure of fit which is similar to probability. The difference between probability and likelihood is, probability allow us to predict the outcome or event given a hypothesis, but likelihood measures the support that the data offer a specific model. The likelihood function can be written as the follows (Greene, 2008),

$$\mathrm{L}(\mathrm{Y}|\mathrm{x}) = \mathrm{P}(\mathrm{x}|\mathrm{Y}) \tag{1}$$

$$L(\mathrm{Y}|x_1, x_2, \ldots, x_\mathrm{n}) = P(x_1|\mathrm{Y}).P(x_2|\mathrm{Y}) \ldots P(x_\mathrm{n}|\mathrm{Y}) = \prod_{\mathrm{i}=1}^{\mathrm{n}} P(x_\mathrm{i}|\mathrm{Y}) \tag{2}$$

The above equations express that the likelihood of the parameter, Y, of a function or a distribution for the given data x_i is equal to the product of the probability of the outcome x_i given the parameter Y. Since the value of this likelihood function will be really small, mathematically it will be easy to work with the values if the logarithm is used on both sides. One more advantage of using logarithm (monotonically increasing function of its argument) is, it changes the product into sum as,

$$\ln L(\mathrm{Y}|x_1, x_2, \ldots, x_\mathrm{n}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \ln \mathrm{P}(x_\mathrm{i}|\mathrm{Y}), \tag{3}$$

The maximum likelihood estimate of Y, is the value that maximizes the above function given a model, say Normal, Exponential etc.. The likelihood value of all the assumed distributions will be compared and the distribution with maximum likelihood value will be chosen as the best fit.

Based upon the literature review and the preliminary statistical analysis, seven distributions were attempted for the headway data, namely, Normal, Log Normal, Exponential, Weibull, Gamma, Chi Square and Logistic. The statistical parameters for all the seven distributions were estimated using MLE (Maximum Likelihood Estimation) using R software. The estimated parameters were used in the corresponding distributions and the log-likelihood values were estimated for each distribution for each category. Table 2 shows the log-likelihood values obtained for the distributions.

Table 2. Log likelihood values of the assumed distributions

Categories	Normal	Chi Square	Weibull	Logistic	Exponential	Lognormal	Gamma
4w_4w	-56006.5	-63046.68	-54646.9	-57390	-68677	-56312.3	-55083.4
4w_3w	-6273.27	-7189.41	-6221.61	-6430.23	-7922.31	-6712.24	-6414.96
4w_2w	-37387.1	-40961.12	-36520.7	-38350.5	-44226.2	-38231	-37067.4
4W-Truck	-7421.09	-9308.198	-7351.39	-7614.43	-10599.5	-7826.29	-7585.02
Truck-Truck	-1587.04	-2262.141	-1575.05	-1623.4	-2651.07	-1735.04	-1656.59
Truck-2W	-7356.21	-8877.976	-7271.49	-7551.26	-9953.7	-7630.76	-7402.5
Truck-3W	-1709.28	-2181.209	-1692.49	-1756.16	-2489.29	-1779.49	-1733.58
Truck-4W	-5990.2	-7458.456	-5911.79	-6155.93	-8431.39	-6019.96	-5939.25
2W-4W	-49481.2	-54931.55	-48576.2	-50778.5	-59720.4	-51161.9	-49508.5
2W-3W	-16021.9	-17604.83	-15787.1	-16435.3	-19024.1	-16870.5	-16172
2W-2W	-33519.2	-34776.69	-32496.2	-34370.4	-36537.3	-34427.3	-33016.3
2W-Truck	-12612.2	-15119.47	-12486.1	-12943.1	-16987.9	-13282.5	-12859.2
3W-Truck	-2107.54	-2536.197	-2082.89	-2164.18	-2856.53	-2189.92	-2132.93
3W-2W	-11370.6	-12492.67	-11126	-11655	-13481.3	-11713.6	-11313.3
3W-3W	-3995.02	-4469.936	-3939.41	-4101.25	-4881.81	-4195.03	-4033.13
3W-4W	-5578.65	-6273.578	-5486.8	-5725.89	-6865.26	-5788.64	-5594.8

Whole day	-213519	-234572.2	-208069	-218435	-252022	-217836	-210776
6:30 to 7:30 am	-3688.61	-4202.716	-3655.43	-3785.87	-4610.97	-3997.66	-3760.82
7:30 to 10:45 am	-66922	-71826.22	-64869.8	-68298.4	-75869.7	-70680.3	-65793
10:45 am to end of the day	-141660	-157601.7	-139567	-144956	-169638	-155269	-142847

The distribution with the maximum log-likelihood value is considered as the best fit. From the table, it can be seen that, under all categories, Weibull distribution has the maximum likelihood and hence was selected. Table 3 shows the statistical parameters for the selected distribution for each set of data. The last column of the table shows the parameters of the Weibull distribution for that category.

Table 3. Time headway distribution analysis

Categories	Mean	Standard Deviation	Variance	Fitted Distribution and parameters
4w_4w	2.6	1.26	1.6	Weibull - shape = 2.359768119 ,scale = 2.956457789
4w_3w	2.86	1.23	1.51	Weibull - shape = 2.53515918,scale =3.22864910
4w_2w	2.61	1.2	1.43	Weibull - shape =2.199127708 ,scale = 2.942023607
4W-Truck	3.14	1.09	1.18	Weibull - shape = 3.27237814,scale = 3.50628361
Truck-Truck	3.47	0.92	0.85	Weibull - shape = 4.33389048,scale = 3.81120602
Truck-2W	2.93	1.12	1.26	Weibull - shape =2.88372162 ,scale = 3.29101574
Truck-3W	3.11	1.05	1.11	Weibull - shape = 3.35159032 ,scale = 3.48062992
Truck-4W	2.96	1.05	1.11	Weibull - shape = 3.07973142 ,scale = 3.31816189
2W-4W	2.69	1.06	1.13	Weibull - shape = 2.300395833,scale = 3.040325052
2W-3W	2.68	1.26	1.58	Weibull - shape = 2.21173938 ,scale = 3.02494991
2W-2W	2.42	1.29	1.66	Weibull - shape = 1.81991938 ,scale = 2.72331063
2W-Truck	3.02	1.36	1.86	Weibull - shape =2.92218163 ,scale = 3.39442074
3W-Truck	3.03	1.15	1.33	Weibull - shape = 2.95280080,scale = 3.40321479
3W-2W	2.59	1.15	1.31	Weibull - shape = 2.20240017,scale = 2.93474055
3W-3W	2.76	1.26	1.59	Weibull - shape =2.36405536 ,scale = 3.12354401
3W-4W	2.74	1.24	1.53	Weibull - shape = 2.39822727,scale =

				3.10721643
Whole day	2.5	1.23	1.51	Weibull - shape = 2.170418529,scale = 2.832040956
6:30 to 7:30 am	2.8	1.23	1.51	Weibull - shape =2.46296549 ,scale = 3.16210427
7:30 to 10:45 am	2.34	1.24	1.53	Weibull - shape =1.971762669 ,scale = 2.637180808
Rest of the day	2.56	1.22	1.5	Weibull - shape =2.20795 ,scale =2.888868

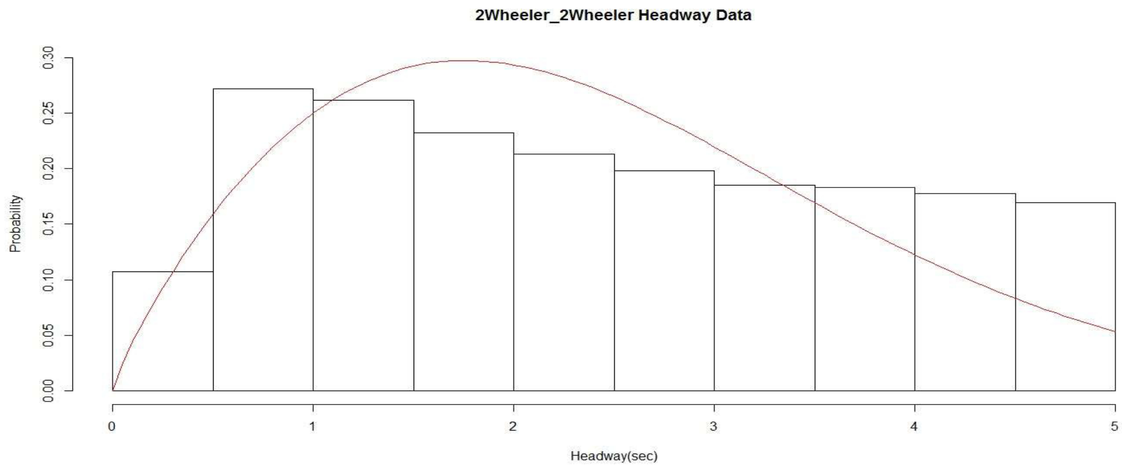

Fig. 4. Fitted Weibull distribution curve to the 2w_2w headway data

The above figure shows the Weibull distribution function, with the parameters estimated using Maximum Likelihood Estimation, fitted on the two wheeler-two wheeler pair headway data. The data was separated into bins of size 0.5 sec and the Weibull probability distribution curve is fitted over the histogram.

4. Summary and Conclusions

The present study analysed time headway data acquired using an automated sensor, under Indian conditions. The location of the headway data collected was at Rajiv Gandhi salai, Perungudi, Chennai. Five days data were collected using an automated sensor called TIRTL. From the sensor output file headway is extracted using a computer program. Headway is considered only if the following vehicle exactly follows the leading vehicle or there is an overlap between leader and follower, in terms of space. A threshold of 5 sec is used and any headway more than 5 sec were not considered, since the vehicles are far apart for any interaction to happen. The whole data were separated into different categories and time headway in each category is then modeled. Log likelihood method is used to identify the best fit from the list of probability distribution. The average time headway is found to be between 2.2 to 3 sec. The average time headway is found to be more when one of the leader-follower vehicle is a heavy vehicle. The results shows that among all the distribution tried, Weibull distribution fits the data, of all the categories, better than the other distributions. It should be noted that these distributions and the corresponding parameters are limited to this particular road stretch where the time headway data were collected.

5. Acknowledgements

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