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Traffic Analysis of Vehicular Ad-Hoc Networks of V2I Communication

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Abstract

Vehicular Ad-Hoc Network (VANET) has been emerged as a promising technology thanks to the recent advances in mechanics, networking, and information technologies. However, there is still a great deal of additional research required before it finally becomes a mature technology. This article concentrates on two factors which are holding back the development of VANETs. Firstly, there is a lack of traffic analysis & modeling for VANETs. Secondly, network optimization for VANETs needs more investigation. Among these two factors, the understanding regarding the traffic dynamics within VANETs provide a basis for further works on network optimization and anomaly detection for VANETs.

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Keywords: Quality of service (QoS); Roadside unit (RSU); Medium access control; VANET; Traffic analysis.

1. Introduction

With the advancement of technology, Ad-hoc Network is becoming a latest mode of communication with anywhere anytime service. To cope up with the demand the future wireless networks will combine high speed vehicles for communications with the present Internet infrastructure to communicate, access information, transact business, and provide entertainment. The demand of Internet connectivity is increasing exponentially, multiple services (like internet, multimedia applications) as well as better Quality of Service (QoS) are on high demand but the resources are limited. VANET is the technology of building a robust Ad-hoc network between Mobile Vehicles and each other, besides between mobile and Roadside Unit (RSU)[1–18].

The future of wireless ad-hoc network will face the challenge to combine high-speed mobile vehicular communications with the present Internet infrastructure to provide multiple services when they are moving. V2V and V2I communications allow the development of a large number of applications and can provide a wide range of information to drivers and travelers. Integrating on-board devices with the network interface, different types of sensors and GPS receivers grant vehicles the ability to collect process and disseminate information about itself and its environment to other vehicles in close proximity to it. That has led to enhancement of road safety and the provision of passenger comfort. Hence, traffic engineering is required to support different applications as they have different service requirements. For optimum performance, researchers and engineers must devise efficient techniques for mobility

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Table 1. Default parameter value for IEEE 802.11p between V2I interactions.

Parameter	Starting values
Scanning Mode	Passive
Beacon Interval	300 ms
Probe Delay	10 ms
Min Channel Time	20 ms
Max Channel Time	50 ms
Channel Time	300 ms

management and resource allocation to meet next generation demand. Mobility model analysis studies how vehicles move in the network. As the entities in VANETs are highly mobile vehicles, the fundamental characteristics of vehicular mobility, such as how vehicles rendezvous in terms of frequency and duration, how they visit a location and how wide they can cover a region of interest in both space and time dimensions, are therefore crucial to the design and ultimate performance of network protocols.

To achieve the goal of designing robust and reliable cellular wireless networks, understanding the characteristics of traffic and mobility prediction[14] plays a very critical role[9]. Empirical studies of measured traffic traces have led to the wide recognition of self-similarity in wired network traffic[2,3]. Multiclass Ethernet traffic exhibits dependencies over a long range of time scales[1,3]. This is to be contrasted with telephone traffic which is Poisson in its arrival and exponential in departure. In traditional Poisson traffic[16], the short-term fluctuations would average out, when it is integrated over a longer time domain and would come out with a constant mean value. Due to dynamic nature of VANETs many of the previous assumptions upon which ad-hoc systems have been built may no longer be valid in the presence of self-similarity[11]. To analyze the network performance and resource utilization, correct modeling of the network traffic is required. In this work, five different mobility file has been generated and tested. The collected data contains raw data of traffic events occurring among mobile vehicles and RSU. Various characteristics of this large collection of data were estimated to determine packet Inter-arrival time's distribution and time of connectivity of RSU with different vehicles distribution. The self-similar nature of the traffic is also tested. Based on these observations an analytical model for performance measures of a cellular wireless network is also proposed.

2. Simulation Setup

There are three main techniques to analyze the behavior of a system: Analytical Modeling, Computer Simulations and Real Time Physical Measurements. Analytical Modeling may be impossible for complex systems such as the one of this research and Real Time Physical Measurement would require a very long time to be performed and a considerable investment in equipment and resources. Computer Simulation is the only reasonable approach to the quantitative analysis of both traffic and computer networks for this research. The data analyzed in this work were simulated with the help of two simulators namely SUMO and ns2 respectively. The mobility of the vehicles were created with the help of SUMO. Once the mobility pattern is generated, then it is converted into the trace files readable by NS-2 for network traffic simulation. We have generated five different mobility for five different hours. A series of parameters has been fixed for both IEEE 802.11p physical layer (PHY) and medium access control layer (MAC) in order to ensure interoperability between OBU and RSU. The following table shows the default simulation values for IEEE 802.11p between V2I interactions (Table 1). Table 2 shows the trace data of five different simulation results for five different hours.

3. Statistical Tools

3.1 Self-similarity, long-range dependence and heavy-tailed distributions

In this paper, the determination of presence of Self-Similarity and long-range dependence in V2I traffic is stressed by estimating the Hurst Parameter and heavy-tailed ness of the traffic distributions[11]. The Hurst parameter[13] H is a measure of the level of self-similarity of a time series and its long-range dependence.

Table 2. Average trace data of 5 busiest hours.

Time	Total Packet Received by RSU	Average calls/sec
1st hour	30,185	0.41
2nd hour	25,267	0.36
3rd hour	24,117	0.33
4th hour	15,534	0.20
5th hour	17,453	0.23

Let $X = \{Xt : t = 0, 1, 2, 3, \dots\}$ represent the stochastic[18] stationary packet arrival process with mean $\mu = E(Xt)$, variance $\sigma 2 = \mathrm{Var}(Xt)$ and autocorrelation function (AFC).

$$R(k) = \frac{e[(X_t - \mu)(X_{t+k} - \mu)]}{\sigma^2} \tag{1}$$

where $k = 0, 1, 2, \dots$ and represents the time lag of the process. Xt represents the packet arrivals at the tth time slot of 10 ms each. If the whole sample size is divided into non-overlapping blocks of size $m = 1, 2, 3, \dots$, then the new stationary time series $X^{(m)} = \{X_k^{(m)} : k = 1, 2, 3, \dots\}$ can be obtained by averaging the original data series X. For each $m = 1, 2, 3, 4, \dots$, the series $X^{(m)}$ can be expressed as

$$X^{(m)} = \frac{1}{m}(X_{km-m+1} + \dots + X_{km}), k \geq 1 \tag{2}$$

This represents the same stationary stochastic process[17] as X with mean $\mu = E(X(m))$ and variance

$$\mathrm{Var}(X^{(m)}) = \frac{\sigma^2}{m} + \frac{2\sigma^2}{m^2}(m - k)R(k).$$

Now, both the series $X(m)$ and X will have the equal Self-Similar[11] nature when equations

$$\text{a) } R^{(m)}(k) = R(k) \quad \text{and} \quad \text{b) } \mathrm{var}(X^{(m)}) = \sigma^2 m^{-\beta}$$

are satisfied. For large m which is the case for network traffic analysis, the process is said to be asymptotically Self-Similar and is defined as $\mathrm{var}(X^{(m)}) = cm^{-\beta}$, where c is constant, $m \to \infty$. It shows that the variance of the sample mean decreases more slowly the reciprocal of the sample size m that implies $\sum R(k) = \infty$. The value of Hurst parameter can be calculated as $H = 1 - \beta/2$.

For a second-order stationary process to be Long-range dependence[13], the value of H should between 0.5 and 1. A value of ≤ 0.5 indicates the absence of self-similarity and the value closer to 1, the greater the degree of long-range dependence.

3.2 Goodness-of-fit test

In most network analysis, the knowledge of underlying distribution is required and mostly it is assumed based on prior evidences. When the underlying distribution is not known or not dependable, it is important to have some type of test that can establish the "Goodness-of-Fit" between the postulated distribution type of random variable X and the evidence contained in the experimental observations. Graphical methods are generally used to determine goodness of fit. We'll use analytical methods. In our case, X is a discrete random variable representing traffic data with unknown pmf given by $P\{X(i)\} = pi$. Now, we'll test the null hypothesis that X possesses a certain specific pmf given by $P_i P_o, 0 \leq I \leq k - 1$. Our goal then is to test $H0$ against $H1$, where: $H_o : P_i P_o, i = 0, 1, 2, \dots, k - 1$ and $H1$: not $H0$. Now, let we have n observations and Ni be the observed number of times (out of n) that the measured value of X takes the value i. Ni is clearly a binomial[17] random variable with parameters n and pi so that $E[Ni] = npi$ and $\mathrm{Var}[[Ni] = npi(1 - pi)$.

Therefore, the statistics $q = \sum_{i=0}^{k-1} N_i - np_i^2$ is chi-squire distribution[17] with $(k-1)$ degree of freedom and can be written as

$$X_{k-1}^2 = \sum_{i=0}^{k-1} \text{observed} - \text{expected}^2 \tag{3}$$

Here, X is a continuous random variable and the hypothesis test for the distribution of X is

$$H_o : \text{for all } x,\ F_x(x)F_o(x) \text{ against}$$
$$H_1 : \text{there exists} x \text{ such that } F_x(x) \neq F_o(x)$$

The chi-squire test was applied here but image of X has to be divided into a finite number of categories and hence there will be a loss of power of the test. Therefore, Kolmogorov-Smirnov test is preferred for continuous population distribution. In this test, the random samples are first arranged in order of magnitude so that the values are assumed to satisfy $x1 \leq x2 \leq x3 \cdots \leq xn$. Then the empirical distribution function $\Psi n(x)$ is defined as:

$$\psi_n(x) = \begin{Bmatrix} 0, x \prec x_1 \\ i/n, x_i \leq x \leq x_{+1} \\ 1, x_n \leq x \end{Bmatrix} \tag{4}$$

The alternative definition of $\Psi n(x)$ is:

$$\psi_n(x) = \frac{\text{number of values } \varepsilon \text{ the sample that } \leq x}{n} \tag{5}$$

A natural measure of deviation of the empirical distribution function from $F0(x)$ is the absolute value of the difference:

$$d_n(x) = |\psi_n(x) - F_0(x)| \tag{6}$$

Since $F0(x)$ is known, the deviation $dn(x)$ can be calculated for each value of x. The largest of these values, as x varies over its full range, is an indicator of how well $\Psi n(x)$ approximates $F0(x)$. As $\Psi n(x)$ is a step function with n steps and $F0(n)$ is continuous and non-decreasing, it suffices to evaluate $dn(x)$ at the left and right end points of the intervals $[xi, xi + 1]$. Then, the maximum value of the $dn(x)$ is the value of the Kolmogorov-Smirnov (K-S) estimator defined by: $|\psi_n(x) - F_0(x)|$.

We reject the null hypothesis at a level of significance α if the observed value of the statistic dn exceeds the critical value dn; α, otherwise we rejects alternative hypothesis $H1$.

4. Analysis and Results

The traced data for packet inter-arrival times and connectivity times of different vehicles with RSU were analyzed. The Kolmogorov-Smirnov test were performed to determine the best fit distribution for each trace of packet inter-arrival times and connectivity times of different vehicles with RSU. Normal distribution, exponential, weibull, lognormal, gamma distributions were considered to determine the goodness-of-fit test.

The parameters are estimated for packet inter-arrival times with the maximum likelihood method[17] and are given in Table 3. $h = 1$ indicates that the null hypothesis test is rejected when the Kolmogorov-Smirnov test parameter d is greater than critical value. $h = 0$ means the hypothesis for the distribution is accepted.

Tests are performed with 90% confidence. p-value or descriptive level of a test is defined as the probability of getting a result as extreme as, or more extreme than, the observed result under null hypothesis i.e. the p-value of a test $H0$ is the smallest level of significance α at which the observed test result would be declared significant or would declared indicative of rejection of $H0$. We also calculated the autocorrelation function, tested self-similarity and Long-range dependency of the traced traffic data.

Table 3. K-S test results for packet inter-arrival times.

Distributions	Parameters	1st Hour	2nd Hour	3rd Hour	4th Hour	5th Hour
	h	1	1	1	1	1
Normal	p	0.0049	0.0048	0.0045	0.0037	0.0035
	d	0.0253	0.0356	0.0254	0.0156	0.0210
	h	1	1	1	0	0
Exponential	p	0.053	0.047	0.042	0.038	0.032
	d	0.0251	0.0280	0.0296	0.0312	0.0288
	h	0	0	0	0	0
Weibull	p	0.421	0.400	0.381	0.325	0.314
	d	0.0151	0.0142	0.0138	0.0132	0.0128
	h	0	0	0	0	0
Gamma	p	0.483	0.435	0.401	0.379	0.375
	d	0.0161	0.0148	0.0136	0.0129	0.0119
	h	1	1	1	1	1
Lognormal	p	2.35e-20	1.89e-20	1.74e-20	1.58e-20	1.54e-20
	d	0.0801	0.0823	0.0834	0.0858	0.0848

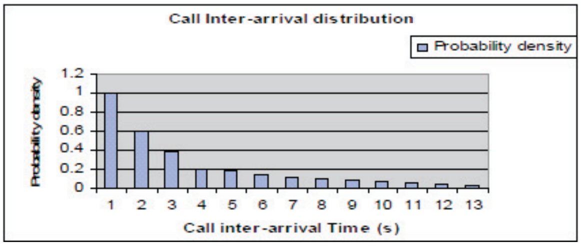

Fig. 1. Packet inter-arrival distribution.

4.1 Packet inter-arrival times

To determine the distribution of packet inter-arrival pattern, Normal, exponential, Weibull, gamma, lognormal distribution were considered and found that except normal, other four distributions namely exponential, Weibull, gamma, lognormal fit the data better but only Weibull and Gamma distribution pass the significance test with 90% confidence for all hourly traces where as exponential pass hypothesis test only for two hourly traces. The higher p-values of Weibull and Gamma distribution show better fit than exponential distribution. Non Poisson and different distribution is also reported by Rajaratnam *et al.*[18].

The autocorrelation[17] coefficients of the packet inter-arrival times with different lags from the hourly traces are also determined with 95% and 99% confidence levels and they are shown in Table 4. This shows non-negligible correlation among packet inter-arrival times. The traces of packet inter-arrival times were also tested for long-range dependence by estimating the Hurst parameter. Estimates of H for hourly traces are shown in Table 3. For all the traces H is found to be greater than 0.5. This shows that packet inter-arrival times exhibit long-range dependency and self-similarity.

4.2 Service times

We compare the distribution of the connectivity times with the same procedure that were followed for the packet inter-arrival times. None of the considered distributions namely Normal, exponential, weibull, gamma, lognormal, passes the test when the traces are tested with 10% and 5% significance levels. Therefore, randomly chosen sub-traces of length 1,000 extracted from each hourly trace were used to test with a significance level α of 1%. This time only lognormal distribution passes the test for very few sub-traces.

When sub-traces of length 500 are tested with the same significance level, the lognormal distribution exhibits the best fit. It passes the Kolmogorov-Smirnov (K-S) test for almost all 1000-sample sub-traces of all hourly traces. The

Table 4. (a) H Value for call inter-arrival times; (b) Autocorrelation coeff of packet inter-arrival times.

Hour	Value of H
1	0.934
2	0.911
3	0.853
4	0.801
5	0.844

(a)

Lag	Coeff.
10	0.040
20	0.028
30	0.020
40	0.017
50	0.008
60	0.0
70	0.011
80	0.001
90	−0.012
100	−0.016

(b)

Table 5. (a) Value of H for hourly traces of call holding times; (b) Autocorrelation coefficients of call holding times.

Hour	Value of H
1	0.482
2	0.471
3	0.463
4	0.457
5	0.464

(a)

Lag	Coeff.
10	−0.035
20	0.018
30	0.042
40	0.030
50	−0.045
60	0.025
70	−0.030
80	−0.035
90	0.03
100	−0.033

(b)

test rejects the null hypothesis when those sub-traces are compared with the other four candidate distributions namely normal, exponential, Weibull, and gamma. Non Poisson and different distribution is also reported by Rajaratnam *et al.*[18].

The autocorrelation coefficient of the connectivity times of different OBU and RSU from the hourly traces were determined as shown in Table 5 and found that there are no significant correlations for non-zero lags because all but a few autocorrelation coefficients are within the 95% and 99% confidence intervals. The long-range dependence in the call holding times is also investigated by calculating the Hurst parameter H as shown in Table 5. For all traces $H < 0.5$ showing that connectivity time or service times are not long-range dependent.

4.3 Performance measures

4.3.1 Modeling arrival and departure process

Let us consider a vehicular ad-hoc network with N no of mobile vehicles as the sources of multiclass traffic that can be broadly categorized as elastic traffic[15] and non-elastic traffic[15]. We have found that, in the presence of multiclass traffic, neither inter-arrival times nor service times are exponentially distributed[18]. Therefore, to analyse the performance of a vehicular ad-hoc network we'll generalize the arrival process by removing the restriction of the exponential interevent times. If Xi be the time between the ith and the $(i-1)$th packet arrivals, then $\{Xi|i = 1, 2, 3, \dots\}$ will represent the sequence of independent identically distributed random variables and hence the process will constitute a renewal process[17]. Here, Xi represents a continuous random variable and let us assume that the underlying distribution of this renewal process is $F(x)$. If Sk represents the time from the beginning till the kth packet arrival, then

$$Sk = X1 + X2 + X3 + X4 + \cdots + Xk \tag{7}$$

and if $F(k)(t)$ denote the distribution function of Sk, clearly, $F(k)$ is the k-fold convolution of F with itself. For notional convenience, we define

$$F^{(0)}(t) = \begin{Bmatrix} 1, & t \geq 0 \\ 0, & t < 0 \end{Bmatrix} \tag{8}$$

Our primary objective here is to determine the number of packets received $N(t)$ in the interval $(0, t)$. $N(t)$ is a discrete parameter called renewal random variable here. Then, the process $\{N(t)|t \geq 0\}$ is a discrete-state, continuous-time renewal counting process[15]. Now, it can be observed that $N(t) = n$ if and only if $Sn \leq t \leq Sn + 1$. Then,

$$P[N(t) = n] = P(S_n \leq t \leq S_{n+1}) \tag{9}$$

$$P(S_n \leq t) - P(S_{n+1} \leq t) \tag{10}$$

$$F^{(n)}(t) - F^{(n+1)}(t) \tag{11}$$

If $M(t)$ be the average number of packet arrivals in the interval $(0, t)$, then

$$M(t) = E[N(t)] = \sum_{n=0}^{\infty} nP[N(t) = n] \tag{12}$$

$$\sum_{n=0}^{\infty} nF^{(n)}(t) - \sum_{n=0}^{\infty} nF^{(n+1)}(t), \quad \sum_{n=0}^{\infty} nF^{(n)}(t) - \sum_{n=1}^{\infty}(n-1)F^{(n)}(t) \tag{13}$$

$$F(t) + \sum_{n=1}^{\infty} F^{(n+1)}(t)$$

It can be noted that $F(n + 1)$ is the convolution of $F(n)$ and F. Assuming f be the density function of F, it can be written as

$$F(^{(n+1)})(t) = \int_0^t F(^{(n)})(t - x)f(x)dx \tag{14}$$

Therefore,

$$F(t) + \sum_{n=1}^{\infty} \int_0^t F^{(n)}(t - x)f(x)dx.$$

The rate of average packet arrivals $m(t)$ can be defined to be the derivative of $M(t)$, i.e.

$$m(t) = \frac{dM(t)}{dt} \tag{15}$$

For small h, $m(t)h$ denotes the probability of a packet arrival in the interval $(t, t + h)$. Thus for Poisson process, $m(t)$ equals the Possion rate λ. To determine $m(t)$, taking Laplace transform[17] on both sides and using convolution property of the transform, equation (15) can be rewritten as

$$L(m(t)) = L(f(t)) + L(m(t))L(f(t)) \tag{16}$$

$$\text{Therefore } L(m(t)) = \frac{L(f(t))}{1 - L(f(t))}$$

$$\text{and } L(f(t)) = \frac{L(m(t))}{1 - L(m(t))}$$

i.e. if either $f(t)$ or $m(t)$ is known, the other can be determined.

Now, Let us assume that service times are not exponential and are independent general random variables with common distribution function G. If $X(t)$ is number of packets received in the system at time t and $N(t)$ is the total number of packets arrivals in the interval (0,1). The number of departures of vehicles $D(t) = N(t) - X(t)$.

It is known that for $n \geq 1$ occurred arrivals in the interval $(0, t)$, the conditional joint pdf of the arrival times $T1, T2, T3, \ldots, Tn$ is given by[17]

$$f(t_1, t_2, t_3, \ldots, t_n \vee N(t) = n) = \frac{n!}{t^n} \tag{17}$$

When a packets arrive at time $0 \leq y \leq t$, from equation (11), the time of arrival of the packets is independently distributed on $(0, t)$, i.e.

$$f_Y(y) = \frac{1}{t}, 0 < y < t.$$

The probability that this connectivity is still undergoing service at time t given that it arrived at time y is $1 - G(t - y)$. Then the unconditional probability that the packet is undergoing service at time t is

$$\int_0^t [1 - G(t - y)] f_Y(y) dy$$

$$\int_0^t \frac{1 - G(t - y)}{t} dy$$

$$\int_0^t \frac{1 - G(x)}{t} dx \tag{18}$$

If n packets have arrived and each has the probability p of independently not completing by time t, then a sequence of n Bernoulli[17] trials is obtained.

Thus, the number of packets in service in the system at the time t has the Poisson distribution with parameter

$$\lambda' = \lambda t p = \lambda \int_0^t [1 - G(x)] dx \tag{19}$$

when connectivity times are exponentially distributed with parameter μ then $G(x) = 1 - e^{-\mu x}$

$$\int_0^t [1 - G(x)] dx = \frac{1}{\mu} - \frac{e^{-\mu t}}{\mu} \tag{20}$$

hence, $t \to \alpha$, $\lambda' = \frac{\lambda}{\mu}$. Now, if the number of channels in a vehicular ad-hoc network system is C.

5. Conclusion

In this paper, we analyze the traffic data traced from simulation. Our observation shows that packet inter-arrival time distribution can be best modeled by both gamma (Erlang) and weibull distributions instead of exponential distribution. It also shows self-similarity and long-range dependency. Connectivity times or service time distribution can be best expressed by lognormal distributions without showing long-range dependency.

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