Traffic Condition Detection in Freeway by using Autocorrelation of Density and Flow

Hamid Torfehnejad[1], Ali Jalali[2]

Received: 13. 03. 2017 Accepted: 30. 07. 2017

Abstract

Traffic conditions vary over time, and therefore, traffic behavior should be modeled as a stochastic process. In this study, a probabilistic approach utilizing Autocorrelation is proposed to model the stochastic variation of traffic conditions, and subsequently, predict the traffic conditions. Using autocorrelation of the time series samples of density and flow which are collected from segments with predefined specifications is the main technique to detect the trend in flow and density changes if exist. A table of possibilities for flow and density changes in two sequential segments will help to detect congestion or any other abnormal traffic events.

In this study proposes a stochastic approach to predict the traffic situation in freeway. The dynamic changes of freeway traffic conditions are addressed with state transition probabilities. For sequence trends of density and flow change, using autocorrelation of speed and flow series will estimate the most likely sequence of traffic states. This is the novelty in this paper that introduces a robust method to recognize the traffic state in a segmented freeway. According to the model definitions 3-state traffic pattern prediction implemented as No Risk (NR), Risk (R) and High risk (HR). We evaluated the proposed method using different data sources of real traffic scenes from Tehran-Qom freeway, Iran. A total of 480 minutes, which corresponds to interstate highways, are chosen for testing. The number of passed vehicle and mean speed are collected by six traffic counter every 1 minute. The estimation rate of this model is 95% over a short time period for the month of **July 2014.**

Keywords: Flow, density, autocorrelation, traffic detection, prediction

Corresponding author E-mail: h_torfehnejad@sbu.ac.ir
[1] Ph.D Candidate, Department of Electrical Engineering , Shahid Beheshti University, Tehran, Iran
[2] Assistant Professor, Department of Electrical Engineering , Shahid Beheshti University

1. Introduction

Delays and congestion are two of the most important issues in traffic engineering studies. However, there is still congestion and delays for various reasons. Traffic events can be diagnosed by imaging cameras or by automatic incident detection algorithms (AID), which they have received their information from the several kinds of detectors. In classical approach the infrastructure plays the role of event detector like magnetic loops under road

Surface camera and other kinds of sensors on road side. Collected information is transmitted to traffic management centers and after processing data, information is provided to road users mainly using VMS and RDS-TMC.Active traffic management (ATM) is the ability to dynamically manage recurrent and non-recurrent congestion based on prevailing and predicted traffic conditions. Focusing on trip reliability, it maximizes the effectiveness and efficiency of the facility. It increases throughput and safety through the use of integrated systems with new technology, including the automation of dynamic deployment to optimize performance quickly and without delay that occurs when operators must deploy operational strategies manually. ATM approaches focus on influencing travel behavior with respect to lane/facility choices and operations. ATM strategies can be deployed singularly to address a specific need such as the utilizing adaptive ramp metering to control traffic flow or can be combined to meet system-wide needs of congestion management, traveler information, and safety resulting in synergistic performance gains [Kurzhanskiy and Varaiya, 2010].

Mathematical description of traffic flow has been a lively subject to research. The traffic flow theory is a science, which has addressed questions related to understanding traffic process and optimizing these processes through proper design and control [Hoogendoorn and Bovy, 2001]. During the past fifty years, a wide range of traffic flow theories and models have been developed. The models can be classified according to:

- Scales of the independent variables (continuous, discrete, semi-discrete).
- Representation of the processes (deterministic,stochastic).
- Level of detail (microscopic with high detail, mesoscopic with medium detail, macroscopic with low detail) [Yang and Sahli, n.d.]

The description of traffic dynamics and the level of detail differ in each family of traffic models. In the first order models of macroscopic family, fundamental diagrams specify the static function that exists between the density and the realized flow, which results in a static speed-density relationship. As a result, the resulting density dynamics might result in large speed variations as drivers travel along the freeway, especially in the locations with shocks. Higher order models capture the fact that drivers cannot respond to speed changes instantaneously. These models augment the conservation equations with the dynamics of the space-mean speeds to provide better descriptions of the traffic dynamics. The Cell Transmission Model (CTM) was extended to simulate traffic dynamics in a network with a more general topology, by introducing models for merging and diverging flows. This model was also further adapted to accommodate non-uniform cell lengths and other continuous, piecewise differentiable fundamental diagram [Daganzo, 1995]. The detection of traffic conditions using microscopic models and macroscopic models and the integration of different data received three defined phases by Boris Kerner intended and normal traffic

Definitions (Free Flow), heavy (Synchronized Flow) and dense (Wide Moving Jam) as they are.[Kerner, 2013] In this research a simplified model will be used with no on-ramps and off-ramps or road junctions. This is a valid assumption for a freeway stretch between two road junctions or for an inter-urban freeway with small in and out traffic along its length. If this assumption does not hold, additional measures, such as ramp metering, may be necessary.

2. Literature Review and Traffic Models

So many researchers had studied the problem of reliable incident detection on freeway and had developed a number of automatic detection systems using different equipment live loop detectors, camera, or IntelliDrive-based probe vehicles. [Willsky et al. and Qiu et al. 2010]. Some other researchers have developed different algorithms to predict the traffic flow or other algorithms for dynamic speed management in segmented freeways. [Torfehnejad, 2011] develoed a realistic and practical method of dynamic speed limit control based on an operational macroscopic traffic flow simulation model which requires relatively less data collection efforts.. Such a solution reduces the cost of communication and the on-line computational load, and increases the modularity and scalability of the system. An accurate prediction of traffic parameters can help improve the transportation system functions with respect to real-time control strategies, advance warning in monitoring systems, as well as reduction of congestion, delay, and energy consumption. [Porikli and Li, 2004] Predictive information is essential to both transportation system users and providers for better decision making that could improve the productivity of the transportation system and reduce the direct and indirect cost of both the system users and providers. In this study, a probabilistic approach utilizing autocorrelation of speed and flow time series is proposed to model the stochastic variation of traffic conditions, and subsequently, predict the traffic conditions. Since the early 1970s, there has been increasing interest in the traffic engineering research community in developing better freeway incident detection algorithms. Examples of these algorithms include the comparative algorithm, time series algorithm, McMaster algorithm [Aultman- Hall et al. 1991], artificial intelligence (AI) algorithm, macroscopic algorithm and wavelet algorithm. According to the comparative algorithms, incidents are detected by comparing a pair of traffic measurements (primarily occupancy) obtained from contiguous upstream and downstream detectors. Examples of these algorithms are the California algorithm [Payne and Tignor, 1978], the low-pass filtering algorithm [Stephanedes and Chassiakos, 1993], the Bayesian algorithm [Levin and Krause, 1978], and the shock wave analysis algorithm [Lin, 1995]. Among these comparative algorithms, the California algorithm is the one that was first developed. The low-pass filtering algorithm was developed based on the California algorithm. The study by Lin (1995) provided a theoretical proof for the approach taken by the comparative algorithms. The time series algorithms are characterized by application of the time series modeling techniques to freeway incident detection. These algorithms include the moving average (MA) algorithm [Whitson et al., 1969], the double exponential MA algorithm [Cook and Cleveland, 1974], the standard normalized deviation algorithm [Dudek and Messer, 1974], and the autoregressive integrated MA algorithm [Ahmed, 1983]. It can be seen from the time series methods that were employed in these algorithms, the sophistication of these time series methods increases with time. AI algorithms are distinguished from other algorithms by adopting techniques developed in the field of AI. The AI techniques that are applied to incident detection include the artificial neural networks (ANN) [Abdulhai and Ritchie, 1999; Ishak and Al-Deek, 1999], the fuzzy logic [Chang and Wang, 1995], and the combined fuzzy logic and ANN [Hsiao et al. 1994]. It can be seen from the listed references above that most of the neural network models have been tested in the studies for incident detection. In macroscopic algorithms, macroscopic traffic variables are used in incident detection. These algorithms include the multiple model algorithm [Willsky et al. 1980] and the generalized likelihood ratio algorithm [Willsky et al. 1980]. Wavelet algorithms are the recent developments in freeway incident detection algorithms. In [Adeli and Karim 2000], wavelet transform was used with a fuzzy data clustering method for feature extraction. This feature extraction was integrated with the radial basis function neural network (RBFNN) for incident detection. In general, the wavelet was viewed as a means to denoise the traffic measurements in these studies.

In microscopic models, individual vehicles are modeled along with their interaction with other vehicles and the road network. These individual vehicles adjust their speeds and lanes and the interaction of all vehicles models the resulting traffic in the network. Macroscopic models ignore these individual vehicle interactions and represent the aggregate dynamic properties of a group of vehicles, usually represented as a continuum. Most macroscopic models represent traffic as a compressible fluid, and describe the density, flow and speed evolution using dynamic equations. Many different traffic flow models have been developed since the first attempts in 1930. Mesoscopic models imply an aggregation level halfway between the microscopic and macroscopic families. The Lighthill Whitham Richards model, commonly known as the LWR model, is a first order model described by the vehicle conservation equation. The Cell Transmission Model (CTM) as a first order discrete dynamic model which is consistent with the hydrodynamic theory of the LWR model [Daganzo, 1995]. The CTM can be interpreted as the discretization of the LWR model with a time step of Ts and uniform sections with length L, according to $L = Tsvf$, where vf is the free-flow speed. The uniform sections are known as cells, and they are increasingly numbered from upstream to downstream. The main assumption in the first order models is the existence of a static density flow relationship, which also implies a static speed-density relationship. Greenshields was the first to propose a parabolic fundamental diagram from observations of traffic along a two lane highway. [Golob et al. 2007] used Autocorrelations, the correlation of a variable at one 30-s interval with the value of the same variable in the previous 30-s interval, for all adjacent time intervals in the 20-min period of traffic condition as one of the parameters to evaluate highway safety performance. The right aim in this research is using autocorrelation function to evaluate the condition of trend changes in flow and density. In fact we use autocorrelation factor to detect the direction of changes in time series of flow and density in order to detect the traffic condition in each segment in a segmented freeway.

3. Methodology

3.1 Definitions

In previous paper we introduced a simple and applicable approach with considering macroscopic model and stochastic discrete variables to detection of freeway abnormal traffic flow like incident, classified congestion, exit of congestion, and so on. [Torfehnejad and Adamnejad, 2014] proposed a stochastic approach, Hidden Markov Model (HMM), for freeway traffic prediction. The dynamic changes of freeway traffic conditions are addressed with state transition probabilities. For a sequence of density and flow change trends, HMMs estimate the most likely sequence of traffic states.

In this scenario we assume that the minimum local equipment is present to collect the required data. As it shows in Figure 1, we have just a couple of loop detectors per lane or any other traffic counter system at the start point of each segment, so we can collect the time mean speed $v_i(k)$ and the number of passed vehicles$m_i(k)$, related to each segment in each time interval(τ) .

The following equations are defined:

L = Segment length, T =Time period of the algorithm,

τ=Data acquisition time interval (time step)

$m_i(k)$Total number of passed vehicles in all lanes at segment i in kth time step.

$u_i(k)$=$\frac{1}{m_i(k)}\sum_{n=1}^{m_i} u_n$ Time mean speed of all vehicles at segment i in kth time step

$u_n =$ Speed of nth vehicle passed in segment i in kth time step

$v_i(k)$=$\frac{1}{\frac{1}{m_i(k)}\sum_{n=1}^{m_i(k)} t_n(k)}$ Space mean speed of all vehicles at segment i in kth time step

$t_n(k) =$ Travel time of nth vehicle passed in segment i in kth time step

$q_i(k) = \frac{m_i(k)}{T}$Traffic flow of vehicles passing segment i as a reference point in a time step τ

$\rho_i(k) = q_i(k) / v_i(k)$ Traffic density at segment i in kth time step

$\Delta\rho_i(k) = m_{i+1}(k) - m_i(k)$ Density variation at segment i in kth time step

$\Delta q_i(k) = q_{i+1}(k) - q_i(k)$ Flow variation at segment i in kth time step

In this paper a simplified model is used with no on-ramps and off-ramps or road junctions. Although some parameters have critical role in road traffic condition like FIFO (First In First Out), merge, diverge, ramp, lane change and length of cell, this is a valid assumption for a freeway stretch between two road junctions or for an inter-urban freeway with small in and out traffic along its length. If this assumption does not hold, additional measures such as ramp metering may be necessary. The model represents a freeway stretch of N segments, each of length $L[km]$ and λ number of lanes. The vehicles enter the stretch at segment 1 (upstream) and leave it from segment N downstream. The mean vehicle density ρ_i (veh/ km), mean traffic flow q_i (veh/h) and time mean speed v_i *(km/h)* for each segment are the discrete state variables and are measured *(i=1......N).* (Figure 1)

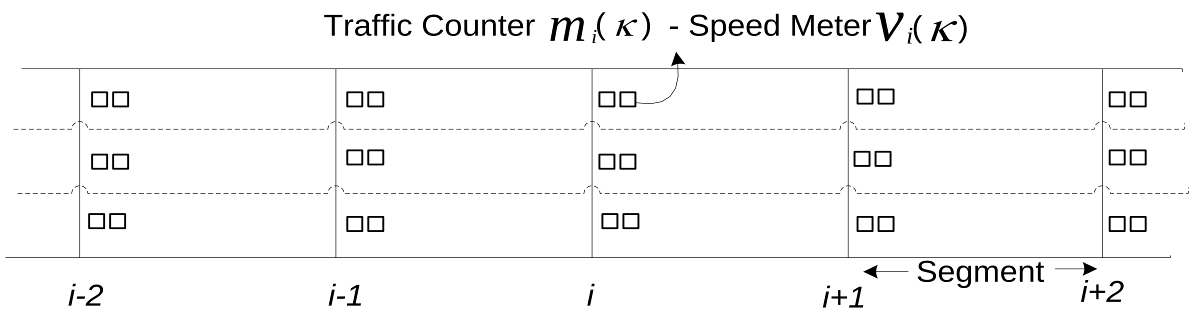

Figure 1. Space mean speed $v_i(k)$ and the number of passing vehicles $m_i(k)$,measured at the start point of each segment in every time step

To determine the exact quantity of *L*, τ and *T,* we have to attend the normal speed which causes the normal and constant traffic flow. Considering the normal speed, we try to adjust and find the optimum quantity of these parameters to have the same flow and density in two sequential segments at two consecutive time period of *T*. In other words the density and flow of *ith* segment in time period *kT* will shift to *(i+1)th* segment in time period *(k+1)T.*

3.2 Traffic Flow Characteristics during an Incident

Traffic flow characteristics during a freeway incident can be characterized in terms of the four flow regions illustrated in Figure 2 Flow region A is far enough upstream of the incident so that traffic moves at normal speeds with normal density. Flow region B is thearea located directly behind the incident where vehicles are queuing if traffic demand exceeds the restricted capacity caused by the incident. In this region, characterized by the upstream propagation of a shock wave, speeds are generally lower, and a greater vehicle density may exist. Flow region C is the region directly downstream from the incident where traffic is flowing at a metered rate, or incident flow rate, due to the restricted capacity caused by the incident. Depending on the extent of the capacity reduction, traffic density in region C can be lower than normal, while the corresponding traffic speed is generally higher than normal. Flow region D is far enough downstream from the incident such that traffic in D flows at normal density and speed, as in region A. The source of this figure is [Traffic Detector Handbook, 2006].

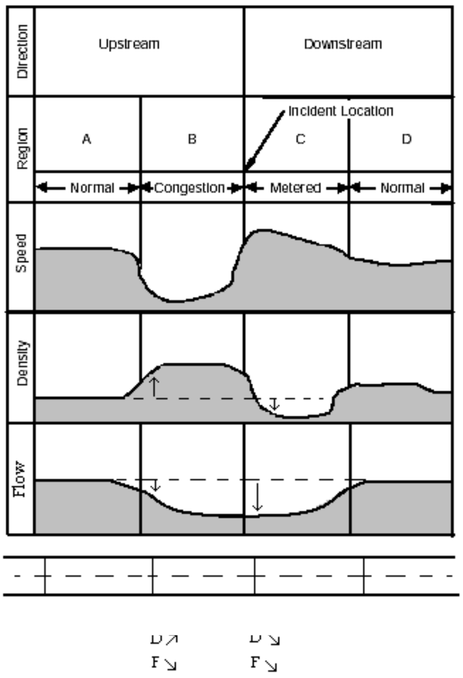

Figure 2. Traffic flow characteristics and direction of density and flow changes during an incident

By considering the density (ρ) and flow (q) of ith and $(i+1)th$ segment, it will be16 different circumstances for trend changes of density and flow (Table 1).

Table 1. Possible density and flow change trends in two sequential segments i and i+1

	Segment i		Segment i+1		Result	Prediction
	density ρ	flow q	density ρ	flow q		
1	↗	↗	↗	↗	No risk	*Normal*
2	↗	↗	↗	↘	Risk	*Toward congestion in segment i+1*
3	↗	↗	↘	↗	No risk	*Exit of congestion in segment i+1*
4	↗	↗	↘	↘	No risk	*N/A*
5	↗	↘	↗	↗	No risk	*N/A*
6	↗	↘	↗	↘	Risk	*Toward congestion in segments i and i+1*
7	↗	↘	↘	↗	No risk	*Toward congestion in segment i and escape of congestion in i+1*
8	↗	↘	↘	↘	High Risk	*congestion detection in segment i*
9	↘	↗	↗	↗	Risk	*Check segment i+2*
10	↘	↗	↗	↘	Risk	*Toward congestion in segment i+1*

11	↘	↗	↘	↗	No risk	*Exit of congestion in segments i and i+1*
12	↘	↗	↘	↘	No risk	*N/A*
13	↘	↘	↗	↗	No risk	*N/A*
14	↘	↘	↗	↘	Risk	*Toward congestion in segment i+1*
15	↘	↘	↘	↗	No risk	*N/A*
16	↘	↘	↘	↘	High Risk	*May be congestion in segment i-1*

Row 8 in Table 1 shows the situation of incident detected at segment i as it shows in Figure 2. Some other rows show different risk of congestion or abnormal traffic flows in segments $i$and $i+1$.

3.3 Direction Detection of q and ρ Trends

In predefined conditions, we collect $m(k)$ and $v(k)$and calculate $q(k)$ and $\rho(k)$from each segment. By attention to previous samples, the last n samples of traffic flow behavior in ith segment will be like below time series:

The time series of traffic flow:

$$q_i(1), q_i(2), \ldots, q_i(n) \qquad (1)$$

The time series of traffic density:

$$\rho_i(1),\ \rho_i(2),\ \ldots,\ \rho_i(n) \qquad (2)$$

And for the$(i+1)th$ segment:

$$q_{i+1}(1),\ q_{i+1}(2), \ldots,\ q_{i+1}(n) \qquad (3)$$

$$\rho_{i+1}(1),\ \rho_{i+1}(2) \ldots,\ \rho_{i+1}(n) \qquad (4)$$

In this condition:

$$q_{i+1}(n) = q_i(1) \text{ and } \rho_{i+1}(n) = \rho_i(1)$$

Autocorrelation refers to the correlation of a time series with its own past and future values. Positive autocorrelation might be considered a specific form of "*persistence*", a tendency for a system to remain in the same state from one observation to the next. In statistics, the autocorrelation of a random process describes the correlation between values of the process at different times, as a function of the two times or of the time lag. An important guide to the persistence in a time series is given by the series of quantities called the sample autocorrelation coefficients, which measure the correlation between observations at different times. The set of autocorrelation coefficients arranged as a function of separation in time is the sample autocorrelation function, or the *acf*. Equation (5) can be generalized to give the autocorrelation factor between observations separated by *k* time steps:

$$r_k = \frac{\sum_{i=1}^{n-k}(x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (5)$$

The quantity is called the autocorrelation coefficient at lag *k*. The plot of the autocorrelation function as a function of lag is also called the *correlogram*. If the function (5) is well-defined, its value must lie in the range $[-1, 1]$, that 1 indicating perfect correlation and -1 indicating perfect anti-correlation. The autocorrelation at lag 3 for two time series of$\rho_i(k)$and $q_i(k)$of equations1 and 2with 12 samples (every sample is the average of 5 minutes data) of the last 60 minutes for the ith segment are:

$$r_3[q_i(k)] = \frac{\sum_{k=1}^{T-lag}\left[q_i(k) - \overline{q_\iota(k)}\right]\left[q_i(k+3) - \overline{q_\iota(k)}\right]}{\sum_{k=1}^{12}\left(q_i(k) - \overline{q_\iota(k)}\right)^2}$$

Where

$$\overline{q_\iota(k)} = \frac{1}{12}\sum_{k=1}^{1224} q_i(k) \qquad (6)$$

And

$$r_3[\rho_i(k)] = \frac{\sum_{k=1}^{T-lag}\left[\rho_i(k) - \overline{\rho_\iota(k)}\right]\left[\rho_i(k+3) - \overline{\rho_\iota(k)}\right]}{\sum_{k=1}^{12}\left(\rho_i(k) - \overline{\rho_\iota(k)}\right)^2}$$

Where $\overline{\rho_\iota(k)} = \frac{1}{12}\sum_{k=1}^{1224} \rho_i(k)$ (7)

The results of two above equations are between 1 and -1. If it is a positive number, it means a persistent trend on changing ρor$q$, but it does not show the positive trend or negative trend (increasing or decreasing of ρ or q). If it is equal to zero, it shows a fully random changes and non-existent trend. To determine the direction of the trend, it's enough to calculate:

$\left[\overline{q_\iota(k)} - q_i(1)\right]and\left[\overline{\rho_\iota(k)} - \rho_i(1)\right]$
(8)

If the result is a positive number, it shows the positive trend and if the result is negative, it shows the negative trend. The same equations could be generated for $r_3[q_{i+1}(k)]$ and $r_3[\rho_{i+1}(k)]$ to find any existent trend of density and flow in segment $(i+1)th$. Now by applying the trend directions of density and flow of two sequential segments, $ith$and $(i+1)th$, in the Table 1, the traffic condition or abnormality in segment ithwill be detected.

4. Implementation

We evaluated the proposed method using different data sources of real traffic scenes from Tehran-Qom freeway, Iran. The source of data is the database of Road Maintenance and Transportation Organization (RMTO). A total of 480 minutes, which corresponds to interstate highways, are chosen for testing. The number of passed vehicle and mean speed are collected by six traffic counter every 1 minute and time period of algorithm is 24minute. Table 2 shows total number of passed vehicles and time mean speed in six segment at one time period of algorithm(T). (Table 2)
The normal traffic situation can be roughly categorized into two states, open and congestion. But we observed that such a classification is not enough to describe the traffic situation. Thus, according to the table 1, our model is implemented 3-state traffic patterns; No Risk (NR), Risk (R) and High risk (HR) are defined.

Table 2. Total number of passed vehicles and time mean speed in 6 segments at one time period of algorithm

m	Seg1	Seg2	Seg3	Seg4	Seg5	Seg6	V(km/h)	Seg1	Seg2	Seg3	Seg4	Seg5	Seg6
1	3087	4794	5618	2968	4744	5291	**1**	91	61	113	72	109	86
2	3099	3490	5282	3446	4594	5426	**2**	96	61	116	71	110	88
3	3075	5071	5361	3036	4622	4789	**3**	100	62	116	73	110	91
4	2906	2748	5197	2541	4505	3405	**4**	99	58	118	71	112	96
5	2758	1894	5828	1715	4949	2467	**5**	102	70	116	70	109	98
6	2854	2366	7068	1467	5947	1395	**6**	102	72	111	69	102	99
7	3121	1779	7271	1212	6126	693	**7**	97	70	97	68	74	99
8	2989	1167	7191	881	5813	464	**8**	99	78	106	70	62	99
9	3380	557	6373	738	5864	629	**9**	102	78	27	68	35	100
10	2747	391	4807	374	4690	1332	**10**	107	79	22	68	38	98
11	1481	509	7227	309	5366	4245	**11**	104	80	58	65	43	90
12	1038	1081	6955	290	5599	5646	**12**	106	81	95	64	68	86
13	853	3876	6213	326	4921	5273	**13**	110	73	99	68	90	84
14	853	5942	5071	689	4034	4881	**14**	108	64	101	71	94	86
15	753	5259	3810	1628	3021	4437	**15**	108	65	104	72	99	89
16	512	3201	2353	1739	1831	4326	**16**	111	22	107	72	104	91
17	275	5746	1152	1797	880	4169	**17**	117	61	108	72	108	97
18	181	5210	667	1988	503	4285	**18**	121	64	108	71	107	99
19	216	5243	773	2095	577	4649	**19**	118	64	109	71	109	98
20	438	4921	1459	1946	1027	5315	**20**	121	66	109	72	106	95
21	2028	4895	3456	2120	2935	6373	**21**	110	65	114	70	109	88
22	2904	3856	5640	2063	4814	6330	**22**	105	66	109	69	102	79
23	2697	4070	5388	2145	4617	6722	**23**	100	63	112	72	106	85
24	2622	3988	5447	2727	4615	6392	**24**	94	61	114	71	109	83

Autoc

orrelation of the density and flow for six segments at the 24 sample time (24 minutes) based on equation 5 are shown in figure 3. This 24-minute section of 480 minute is selected because at least one HR has occurred in this interval. As can be seen acf for density and flow are positive but direction of the trend is changed. According to equation 8, the directions of flow and density trend are shown in figure 4 for six sequential segments. In figure 4, '1' is determined positive trend and '-1' is determined negative trend. By considering the result of figure 4, the situation of incident for each of the six sequential segments are detected like{ 'R' ,'NR','NR', 'R','HR' } by considering the trend of density and flow changes. (Figure 3,4)

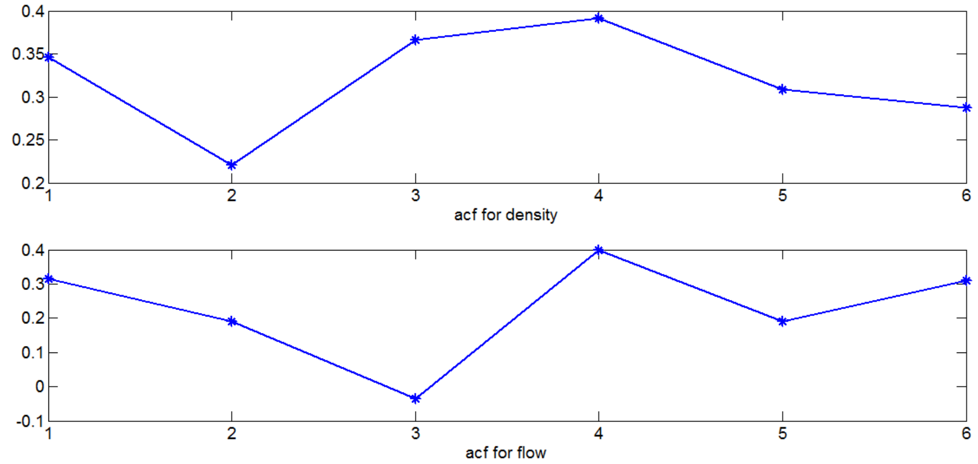

Figure 3. Autocorrelation of the density and flow for six segments at the 24 sample time

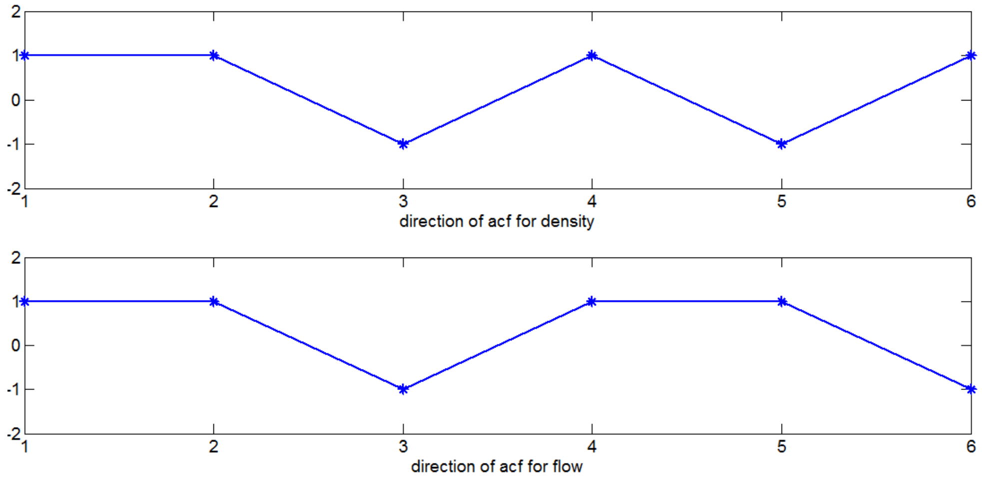

Figure 4. Directions of flow and density trend of figure4 (the results of eq. 8)

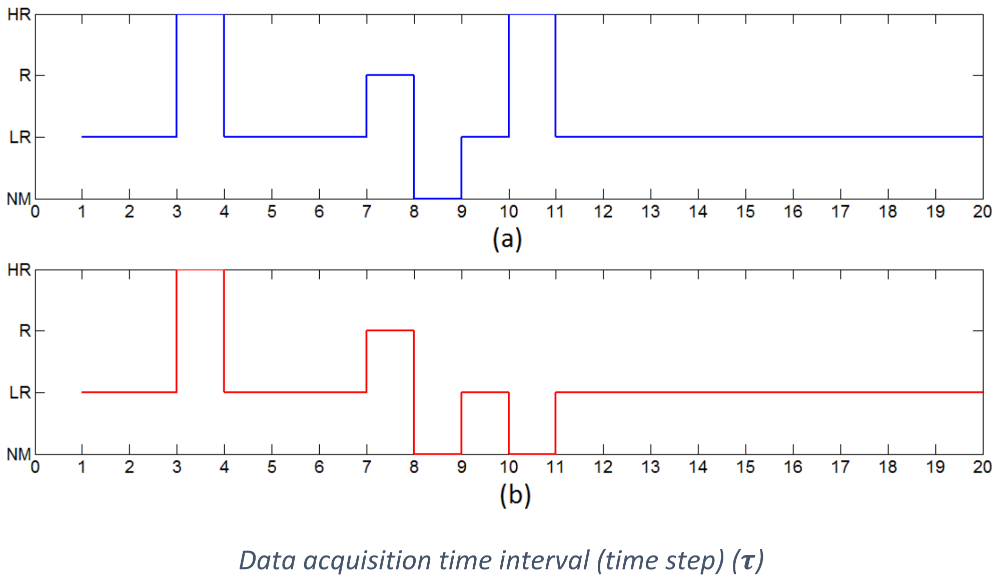

Figure 5. a) Actual b) estimated, traffic states for segment 1 over 20 time intervals of T

We have compared results of this method with the actual events in the same period of time in Tehran-Qom freeway. Figure 5(a) is the real traffic situation for segment 1 over 20 time intervals of T and figure 5(b) is the results of the proposed method. As shown in figure 5, the model has estimated correct traffic conditions for most of the intervals just for T 10 to 11. It shows %95 accuracy rates for traffic condition estimation using this

5. Conclusion

In this paper we discussed the model of using autocorrelation of flow and density of freeway traffic to predict the short time traffic condition. After implementing proposed method using a total of 480 minutes data of real traffic scenes from Tehran-Qom freeway, Iran, autocorrelation of the density and flow for six segments at the 24 sample time (24 minutes) showed us the trend direction of changes in flow and density of traffic. According to the model definitions 3-state traffic pattern

prediction implemented as No Risk (NR), Risk (R) and High risk (HR). The situation of incident for each of the six sequential segments are detected like{'R' ,'NR','NR', 'R','HR' } in the mentioned case study by considering the trend of density and flow changes. This technique will be applicable for any other conditions. The best scenario can be designed for different conditions after adjusting and finding the optimum quantities for the parameters: normal speed, segment length, time period, time interval of data acquisition and the autocorrelation lag and the same table can be achieved .The proposed model estimated traffic condition properly with 95 percent accuracy rate.

In further research we can consider the impact of ramp traffic in freeway condition and also attend to implement some algorithms to change the speed limit in upstream in order to avoid the secondary incidents and shock wave traffic.

6. References

-Abdulhai, B. and Ritchie, S. G. (1999) “Enhancing the universality and transferability of freeway incident detection using a Bayesian-based neural network”, Transportation Research Part C 7, pp. 261–280.

-Adeli, H. and Karim, A. (2000) “Fuzzy-wavelet RBFNN model for freeway incident detection”, Journal of Transportation Engineering Vol. 126, No. 6, pp. 464–471.

-Ahmed, S. A. (1983) “Stochastic processes in freeway traffic”, Traffic Engineering Control, pp.306–310.

-Aultman-Hall, L., Hall, F.L., Shi, Y. and Lyall, B. (1991) “A catastrophe theory approach to freeway incident detection”, Proceedings of the Second International Conference on Applications of Advanced Technologies in Transportation Engineering, The American Society of Civil Engineers, New York, NY, pp. 373–377.

-Chang, E. C.-P. and Wang, S.-H. (1995) “Improved freeway incident detection using fuzzy set theory”, Transportation Research Record Vol. 1453, 75–82.

-Cook, A. R. and Cleveland, D. E. (1974) “Detection of freeway capacity-reducing incidents by traffic-stream measurements”, Transportation Research Record, Vol. 495, pp.1–11.

-Daganzo, C. (1995) “The cell transmission model, Part II: Network traffic” Transportation Research,Part B, Vol. 29, No. 2, pp.79–93.

-Dudek, C. L. and Messer, C. J. (1974) “Incident detection on urban freeways” Transportation Research Record, Vol.495, pp. 12–24.

-Golob T. F., Will, Rocker and Yannis, Pavlis (2008) “ Probabilistic models of freeway safety performance using traffic flow data as predictors”, Safety Science, Vol.46 (2008) pp.1306-1333

-Hoogendoorn, S. P. and Bovy, P. H. L. (2001) “State of the art of vehicular traffic flow modelling“, Jornal of Systems and Control engineering, Vol.215(4)

-Hsiao, C.-H., Lin, C.-T. and Cassidy, M. (1994) “Application of fuzzy logic and neural networks to automatically detect freeway traffic incidents” Journal of Transportation Engineering Vol.120 (5), pp.753–772.

-Ishak, S. and Al-Deek, H. (1999) “Performance of automatic ANN-based incident detection on freeways” Journal of Transportation Engineering, pp.281–290.

-Kerner, B. S. (2013) “Criticism of generally accepted fundamentals and methodologies of traffic and transportation theory”, A brief review Physic A: Statistical Mechanics and its Applications Vol. 392 (21), pp. 5261-5282.

-Kurzhanskiy, A. and Varaiyav, P. (2010) “Active traffic management on road networks: a macroscopic approach“. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, Vol. 368(1928), pp. 4607-4626

-Levin, M. and Krause, G. M. (1978) “Incident detection: a Bayesian approach” Transportation Research Record Vol.682, pp.52–58.

-Lin, W.-H. (1995) “Incident detection with data from loop surveillance systems: the role of wave analysis”, Dissertation, Institute of Transportation Studies, University of California at Berkeley.

-Payne, H. J. and Tignor, S. C. (1978) “Freeway incident detection algorithms based on decision trees with states”, Transportation Research Record, Vol. 682, pp.30–37.

-Porikli, F. and Li, X. (2004) “Traffic congestion estimation using HMM models without vehicle tracking”, Mitsubishi Electronic Reserch Labratories

-Qiu, T.Z., Lu, X., Chow, A. H. F. and Shladover, S. E. (2010) “Estimation of freeway traffic density with loop detector and prob vehicle data“, Transportation Research Record, Jornal of Transportation Research Board, No. 2178, pp. 21-29.

-Stephanedes, Y. J. and Chassiakos, A. P. (1993) “Application of filtering techniques for incident detection”, Journal of Transportation Engineering, Vol. 119, No. 1, pp.13–26.

-Torfehnejad, H. (2011) “A practical dynamic speed limit control method using real-time traffic counting systems“, 18th ITS World Congress, 16-20 October, Orlando Florida, USA

-Torfehnejad, H. and Adamnejad, Sh. (2014) “A practical symple technique to detect abnormal traffic flow in freeway“, 21th ITS World Congress, 7-11September, Detroit, USA

-U.S. Department of Transportation. Federal Highway Administration (2006) “Traffic detector handbook“, Third edition- Volume 1

-Whitson, R. H., Burr, J. H., Drew, D. R. and McCasland, W. R. (1969) “Real-time evaluation of freeway quality of traffic service” Highway Research Record, Vol. 289, pp.38–50.

-Willsky A. S., Chow E.Y.,. Gershwin, S. B, Greene, C. S., Houpt, P. K. and Kurkjian, A. L. (1980) “Dynamic model-based techniques for the detection of incidents on freeways“ , IEEE Transactions on automatic control, Vol. AC-25, No.3

-Yang, L. and Sahli, H. [n.d.]“Motion-based traffic analysis and incident detection“ , IBBT/VUB-ETRO, FLEXYS