Adaptive Model for Traffic Congestion Prediction

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Abstract. Traffic congestion is influenced by various factors like the weather, the physical conditions of the road, as well as the traffic routing. Since such factors vary depending on the type of road network, restricting the traffic prediction model to pre-decided congestion factors could compromise the prediction accuracy. In this paper, we propose a traffic prediction model that could adapt to the road network and appropriately consider the contribution of each congestion causing or reflecting factors. Basically our model is based on the multiple symbol Hidden Markov Model, wherein correlation among all the symbols (congestion causing factors) are build using the bivariate analysis. The traffic congestion state is finally deduced on the basis of influence from all the factors. Our prediction model was evaluated by comparing two different cases of traffic flow. We compared the models built for uninterrupted (without traffic signal) and interrupted (with traffic signal) traffic flow. The resulting prediction accuracy is of *79 %* and *88 %* for uninterrupted and interrupted traffic flow respectively.

1 Introduction

In recent years, there has been lot of research in the field of traffic congestion estimation in road networks. Traffic congestion is caused by multiple factors such as the road physical condition, the traffic flow parameters, etc. Most of the work in literature focused on pre-decided and fixed number of traffic flow parameters such as average speed, density, queue length, flow rate, etc., for estimating the traffic congestion. However, the influence or contribution of these factors in traffic congestion varies from one location to another. That is, in some locations, the low average speed of all the vehicles reflects the presence of congestion may be at some other locations congestion is not reflected by the recorded average speed of all the vehicles. Similarly at some locations, the weather factors also need to be considered. Therefore, we propose an adaptive model that can effectively incorporate different pairs of traffic factors based on road network.

From the literature, the existing methodologies to predict the traffic congestion were based on Hidden Markov Model (HMM) [4], Artificial Neural Network (ANN) [5] or on plain mathematical model [2]. For instance, traffic congestion estimation based on probabilistic model relying on video data [8,12] or plain

H. Fujita et al. (Eds.): IEA/AIE 2016, LNAI 9799, pp. 782–793, 2016.
DOI: 10.1007/978-3-319-42007-3_66

probabilistic models [9] considered few parameters to build the prediction model. Additionally from the work [4,9] HMM is proved to be one of the best suited model for modelling a traffic prediction model. Since HMM [10] architecture can very well reflect the problem of traffic congestion prediction, wherein traffic congestion state represents the hidden state and the set of congestion influencing factors (χ)[1] being the observed symbols. But native discrete HMM architecture can incorporate only single observed symbols. Therefore discrete multiple symbol HMM (MS-HMM) [11] was implemented which can very well represent all the values in χ.

Moreover, factors in χ vary with type of road considered [6] namely, freeways, uninterrupted roads, interrupted roads, etc. Other than this, contribution of each factor in traffic congestion vary with considered road network. Therefore an adaptive model which can efficiently incorporate any number of factors and adapt to any road network is needed, but the current state of traffic prediction models works on pre decided fixed number of congestion causing or reflecting factors[2]. Due to these limitations in the current state of traffic prediction models, we propose a model for traffic prediction that can easily be extensible (add or remove) to congestion factors and adapt to any road network. Wherein adaptiveness in model is realised by calculating impact factor *(I)* from correlation parameters of all factors in χ as discussed in the later sections. In short we propose an adaptive traffic congestion prediction model based on MS-HMM which can easily incorporate any number of factors effectively. Further, this adaptive model can be extended to many application such as dynamic routing, dynamic traffic signal scheduling, etc. In this paper, our two main contributions are, firstly an extensible model that can efficiently consider the contribution of different congestion reflecting factors based on the correlation parameters calculation and impact factor calculation. Other contribution is the usage of MS-HMM to build the prediction model based on the multiple congestion reflecting factors.

The paper is organised as follows, in Sect. 2 we discuss the system overview by briefly describing each step in building the prediction model. In Sect. 3, we discuss the prediction algorithm implemented in our system. In Sect. 4 experimental results are discussed and the proposed model is validated by building an baseline system. Finally, we conclude and outline the future work.

2 System Overview

The primary aim of our work is to build an adaptive traffic prediction model. Such adaptive model would predict the traffic congestion considering the congestion causing factors relevant to considered road network, and not based on the pre defined factor or factors. Moreover consider the appropriate contribution of each considered factor, whereas data is recorded by loop detectors installed on the road network. In this paper, we propose a novel method according to

[1] χ is a set of congestion reflecting factors that may consist of factors such as occupancy, speed, waiting time, etc.

[2] Congestion reflecting factors and congestion causing factors are used interchangeably.

best of our knowledge which can adapt to the network, and reflect the appropriate effect of each congestion causing factor. The brief description of the model building steps are discussed in the next subsection, where whole model building is divided into 3 main steps (i) Adaptive Modelling, (ii) Data Discretisation and (iii) Prediction Model Building.

2.1 Adaptive Modeling

As discussed in the previous section, an adaptive model is the primary aim of our work. Wherein adaptability is realised by calculating the correlation parameters and later the impact factor. Basically adaptability is achieved in two step named as (i) Correlation parameter calculation and (ii) Traffic impact factor calculation. The correlation parameters are based on bivariate analysis of different factors with respect to single factor, using a characteristics graph[3]. Later from the characteristic graph of a particular factor two values, namely strength value *(c)* and relationship value *(r)* are calculated. These two parameters represent the contribution of individual factors, where c quantify the strength of correlation between different factors, which is calculated from the Eq. 1; which depicts c for factor *f*. Whereas, r denotes the degree at which one parameter changes with the change in other parameter, basically it is represented by the degree of curve in the characteristic graph.

$$c_f = \frac{covar(f^*, f)}{\sqrt[2]{var(f) \times var(f^*)}} \tag{1}$$

Where f is the congestion reflecting factor and f^* is common congestion causing factors, with respect to which correlation parameters of all the other factors are calculated. Whereas, n is number of total instance of factors or size of χ, and $var(f^*)$ and $var(f)$ are variance of common factor f^* and any other factor f respectively, $covar(f^*, f)$ is covariance value and c_f is strength value of factor *f*. Once we have pairwise correlation parameters for all the factors f with respect to a common factor f^*, we calculate the traffic impact factor I_t for every time step t; calculated from Eq. 2. Where, 2 represents the collective effect from all the factors by summing linear combination of correlation parameters of different factors for a particular time instance. Where n being the size of χ or number of factor considered and *val(f)* being the recorded value of respective factors.

The intuition behind the Eq. 2 is that each factor's involvement is defined by their correlation parameters, and also the correlation parameters will change with locations. So first we calculate the correlation parameters for each factor with respect to a single factor, so as to examine the influence of each factor from a common reference point. Later we calculate the resultant impact for every time step t, based on the recorded magnitude ($val(f_t)$) of factor f at time t

[3] The curve representing the change in one factor with change in other factor with time.

and its respective correlation parameters (c_f and r_f). Wherein c normalises the magnitude of all the factors and r denotes the degree at which factor f changes with respect to change in factor f^*; f^* can be any one of the congestion influential factor among the chosen set of factors. Finally, the summation of contribution by all the factors in the considered road network gives the resultant influence for traffic congestion. Moreover, this makes the model easily extensible to any other factors defining weather conditions, physical condition of road etc.

$$I_t = \sum_{f=1}^{n} (val(f_t) \times c_f)^{r_f} \tag{2}$$

2.2 Data Discretisation

The magnitude of congestion causing factors are recorded for every instance of time, similarly impact factor (I) is calculated for corresponding time stamp. Therefore congestion causing factors and impact factor are continuous in nature. However, our system is based on discrete MS-HMM, therefore we discretise the recorded data and *I*. We adopted a discretisation method based on equal width K-means clustering algorithm. Wherein, the continuous data is clustered into different classes on the basis of neighbourhood and these class represents a label. After discretisation of all the n factors and impact factor, we get n + 1 different set of labels. Where, n set of labels denotes the set of observation symbol (O) for n congestion causing factors and the other 1 set of labels represent the set of hidden states (Q) in MS-HMM. The K-means clustering algorithm is depicted in the Algorithm 1.

Algorithm 1. Factor Labelling

1: **procedure** CLUSTER
2: Input: L is number of labels
3: $X \rightarrow \{x_1, x_2, x_3, \ldots, x_n\}$ is set of data points
4: Output: Indices of cluster
5: Start
6: $C \rightarrow \{c_1, c_2, c_3, \ldots, c_L\}$ is set of centre of cluster
7: **for** all X $i \rightarrow 1$ to n **do**
8: **for** all C $j \rightarrow 1$ to L **do**
9: $d_{ij} \rightarrow |c_i - x_j|$
10: **for** all d $i \rightarrow 1$ to k **do**
11: (It gives value of i to which j belongs)
12: $cluster_j \rightarrow$ value_of_i$(min(d_{ji}))$
13: **Recalculating the new cluster centre**
14: $v_i \rightarrow (\frac{1}{c_i}) * \sum_{i=1}^{c_i}(x_i)$
15: (where, c_i is number of points in i^{th} cluster)
16: **Repeat 5 to 16 until cluster remain same**
17: **End**

2.3 Prediction Model Building

Our Prediction model based on discrete MS-HMM, which is built using discretised data obtained from the previous section. The MS-HMM [11] is mathematically represented as $\lambda = (T, E, \pi)$, producing the sequence of observation symbols O. Where $T = P(Q_{n+1}|P(Q_n)$ represents transition probability, $\pi = P(Q_{t=1})$ represents the initial probability and $E = P(O|\lambda)$ represents emission probability [11]. The graphical representation of the MS-HMM for 4 symbols model is depicted in the Fig. 1, where s_t, wt_t, ql_t, and oc_t are labels of average speed, waiting time, queue length and occupancy [6] respectively at time t. Wherein, the average speed (s) is the average speed of all the vehicles at particular time instance, queue length (ql) is the average length of queue of the vehicle waiting at the cross section, waiting time (wt) is the average waiting time of the vehicles and occupancy (oc) is the percentage of road occupied by the vehicles.

Further, training and building of the prediction model λ is done according to the steps depicted in Fig. 2. Wherein, a model in the new learning environment is first initialised to random traffic data or traffic data of previous road network if any, then this initialised model is trained to adapt to this new road network. Further, sequence segmentation is used to segment the training and test data in equal sequence length for prediction. Training is done on the training set of the previously recorded data. Finally we get model λ, which has been adapted to the considered road network based on the recorded data.

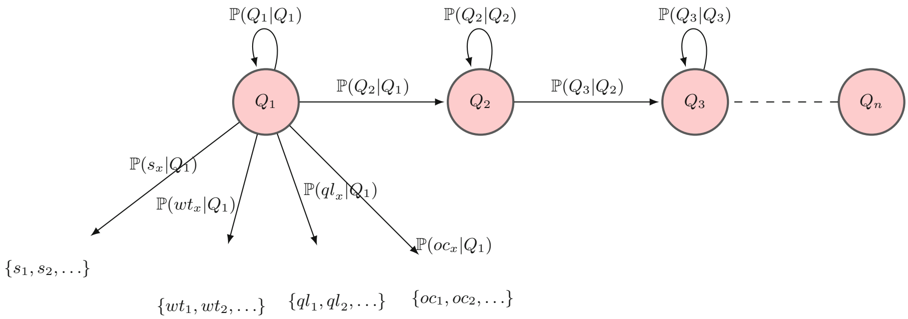


Fig. 1. MS-HMM architecture

3 Prediction Algorithm

After building a trained prediction model λ, the model λ is used for prediction of traffic state. In this section, we discuss the extension of the trained model λ to predict current state using model hidden state predictor (HSP) and future state using the model future state predictor (FSP). The trained model is used

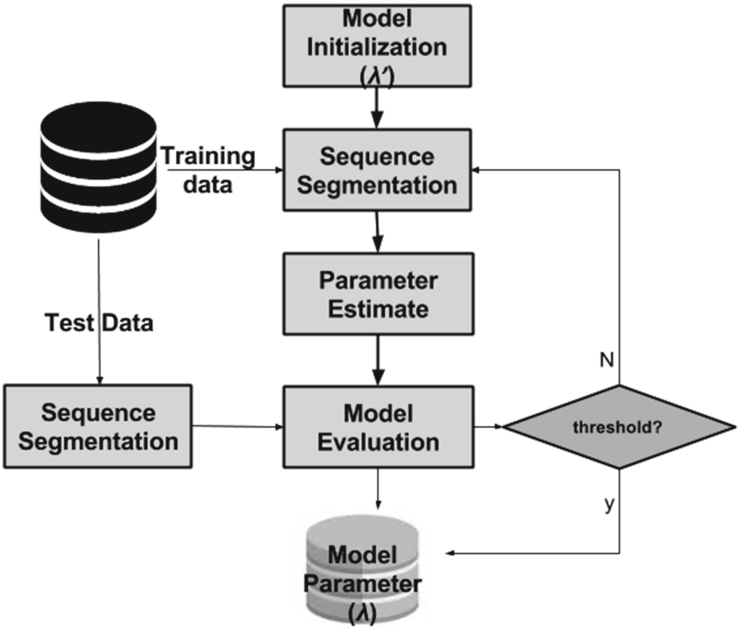


Fig. 2. Model training

for the traffic state prediction. Prediction of sequence of hidden states from the sequence of observation symbols is done by implementing the Viterbi algorithm [10]. Wherein, sequence of hidden states are predicted from the past observed symbols. The Eq. 3 represents the hidden state predictor on the recorded stream of observation symbols. Where, 3 represents the conditional probability of occurrence of a hidden states in the set Q, on the given sequence of observation symbols s, wt, ql, and oc at time $t = n$. Furthermore, the HSP module output is used by FSP for further state prediction.

Our next interest is to predict the future state of the road network from the given past sequence of data. The FSP is a modified backward algorithm [10] to fit into MS-HMM. The *FSP* algorithm is depicted in Fig. 3, where *FSP* algorithm takes input from *HSP* along with learnt model λ. It can be seen in the Fig. 3, each *FSP* block gives the next hidden state label. In order to maintain the accuracy at each step, the model λ is trained with online data with the building step shown in Fig. 2. Then the modified model λ is given to next *FSP* block to predict the next future state. The validation of proposed methodology is discussed in the next section.

$$P(Q_{t=n}|(s,wt,ql,oc)_{t=n}) \approx P(Q_{t=n}|s_{t=n}) \times P(Q_{t=n}|wt_{t=n}) \times P(Q_{t=n}|qt_{t=n}) \times P(Q_{t=n}|oc_{t=n}) \quad (3)$$

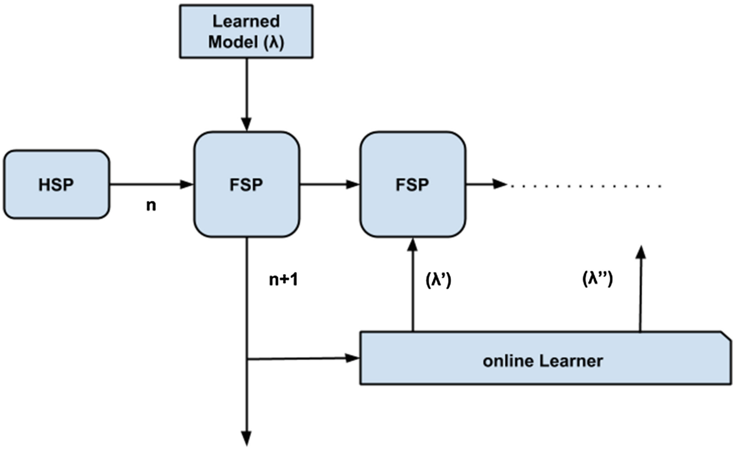


Fig. 3. FSP

4 Experimental Results

The tools used in the experiments were WEKA [13] for clustering and labelling of the data, SUMO [3] for running the simulation, and MATLAB toolbox [7] for building the prediction model. In order to study the working of the proposed model, which should be able to reflect the adaptability to different types of road networks and their respective traffic causing factors, we considered 4 values in χ; namely, s, oc, wt and ql to build the baseline prediction model as per the proposed method. The model is based on MS-HMM, built using the steps discussed in the above sections. Wherein building and validation of the model was done by simulating a traffic of a road network. The main objective of the experiment was to showcase the capability of the model to adapt to different road types and predict the traffic congestion for the same. So, in order to examine the adaptability of the model, we calculate the correlation parameters for two different road network setting fed with the same traffic flow data. Later, correlation parameters for both the road setting is analysed and traffic congestion is predicted. We used *SUMO* to simulate traffic of few roads from Enfield area in London along with its traffic counts data of the heterogeneous traffic, available at [1]. From which we record the values for each χ in two different settings, namely, interrupted traffic flow (with traffic signal) and uninterrupted traffic flow (without traffic signal).

Table 1. Uninterrupted traffic flow

	Avg. speed	Wt. time	Q. length
r	1.2	2	2.5
c	1	0.80	0.60

Table 2. Interrupted traffic flow

	Avg. speed	Wt. time	Q. length
r	0.5	1.5	3
c	0.4	0.65	0.96

The prediction models for both the scenarios, interrupted traffic flow *(inp)* and uninterrupted traffic flow *(unp)* is represented as λ_{inp} and λ_{unp} respectively. The experimental results of each step are mentioned in the next section.

4.1 Correlation Parameter

As discussed above, 4 parameters were extracted from the simulation for both the scenarios, *inp* and *unp*. Later, the correlation parameters for each factor in the respective scenario is calculated. Figures 4 and 5 depicts the characteristics graphs for scenario *unp* and *inp* respectively. Further, from these characteristics graph, two correlation parameters c and r with respect to occupancy *(oc)* are calculated for both the scenarios. These correlation parameters for *unp* and *inp* scenarios are given in Tables 1 and 2 respectively.

As discussed before, the state of traffic is defined by the labels of the I obtained after discretisation. Whereas, labels of each factor in χ represents the sequence of observed symbols. In order to evaluate both the trained models λ_{unp} and λ_{inp}, we compared the predicted traffic states and the actual traffic states. The actual traffic state was calculated manually using Eq. 2. Now, in order to test the prediction model, we consider a total of 100 instances of data from the recorded data, where each instance is of length 5 min. Moreover, for prediction of traffic state, 15 latest known observation sequence, and the updated λ from the online learning module is fed to the *FSP* algorithm. Further, we repeated the prediction process 3 times, to test if the result is replicable.

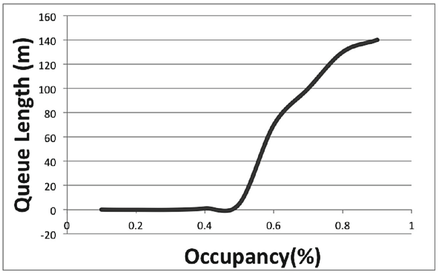
4.2 Model Evaluation

The prediction results of both the models λ_{unp} and λ_{inp} are compared with their corresponding actual data, which is depicted in Fig. 6. Where *y-axis* represents the traffic state based on value of *I*, the *x-axis* represents the time series starting from the 16^{th} time step. Now, from the prediction characteristic graphs (Fig. 6) of both the models, it can be said that the predicted state curve accurately follows the actual state curve, and also accuracy % for the models λ_{unp} and λ_{inp} were *79 %* and *88 %* respectively. The accuracy was calculated using the Eq. 4, which represents the ratio of correctly predicted data and total data to be predicted.

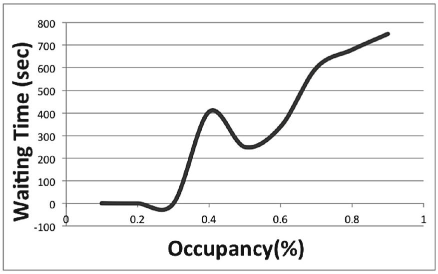
$$\%error = \frac{Correctly\ labeled\ stream\ of\ data}{Total\ length\ of\ stream} \times 100 \tag{4}$$

4.3 Discussion

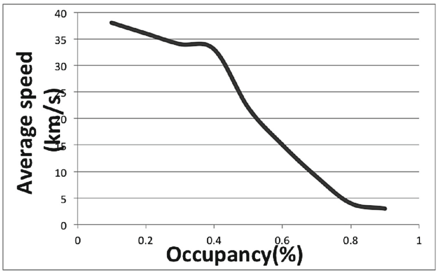
In order to validate the adaptiveness and prediction of the proposed traffic congestion model, we compare the correlation parameters and the results obtained from both the models λ_{unp} and λ_{inp}. Firstly, by comparing their characteristic graphs for the average speed from Figs. 4c and 5c, of λ_{unp} and λ_{inp} respectively, It can be seen in Fig. 4c that the occupancy is inversely correlated to the average



(a) Queue Length

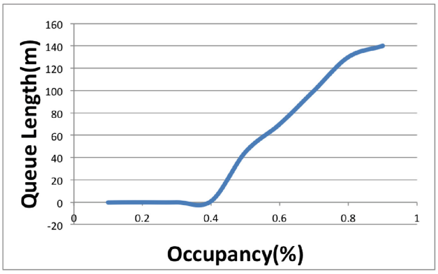


(b) Waiting Time

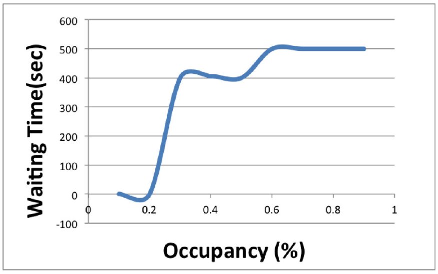


(c) Speed

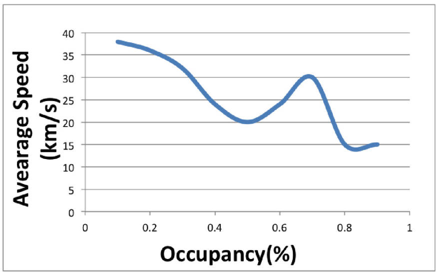
Fig. 4. Characteristics graph for *unp*



(a) Queue Length

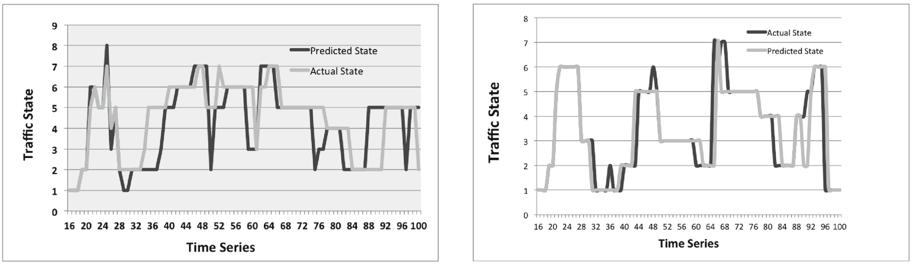


(b) Waiting Time



(c) Speed

Fig. 5. Characteristics graph for *inp*



(a) Model λ_{unp} (b) Model λ_{inp}

Fig. 6. Evaluation of the model

speed. But such correlation cannot be seen from Fig. 5c. Such change in correlation with the change in model can be interpreted as, the average speed decreases with increase in the occupancy in the uninterrupted traffic flow. But this is not true in the interrupted traffic flow. Because in the interrupted traffic flow, the average speed can also decrease because of interruption[4], which is the red traffic signal in our case. Therefore contribution of average speed for causing traffic congestion, in the uninterrupted traffic flow is more as compared to contribution in the interrupted traffic flow. Furthermore, such change in contribution is reflected from the values of their correlation parameters of the average speed in Tables 1 and 2. Similarly contribution of other factors, change with the change in traffic flow environment. Thus, on basis of correlation parameters values, one can decide the significance of a factor in traffic congestion. So, if the values of correlation parameters for any factor are negligible, then that factor can be ignored, thus removing the insignificant factors. Other than this, introduction of impact factor calculation makes the model extensible, and also incorporate the factors based on their respective contribution. This gives the flexibility to add or remove factors from the model, based on the considered road network.

Thus by comparing the correlation parameters for different road setting on the same traffic dataset, it can be said that the correlation among the congestion reflecting factors changes with the road traffic settings. Since our prediction model is based on the values of these correlation parameters, therefore it can be said that model prediction is adapted to the learning environment. Moreover, the prediction accuracy of the model is not compromised over extensibility, thus giving satisfying prediction accuracy.

5 Conclusion

We proposed an adaptive mathematical model for traffic prediction based on MS-HMM. The adaptiveness of the model was achieved by impact factor calculation. Our primary aim was to build an extensible model, and incorporate

[4] Interruption: Hindrance in normal flow of traffic because of traffic signal, cross sectional traffic flow, speed limit zone, etc.

different traffic congestion factors. The model should appropriately reflect the varying contribution of each factor with the road networks. Therefore correlation parameters were calculated for each factor. As a baseline system, we built our prediction model based on 4 factors: occupancy, average speed, queue length and waiting time. To validate the adaptability of the model to a road network, we compared the correlation parameters in uninterrupted and interrupted traffic flow environment. Finally, the prediction accuracy for the model in uninterrupted and interrupted environment was *79 %* and *88 %* respectively. Thus our proposed model has the ability to adapt to road network, and also give satisfying prediction of traffic state. Other parameters such as road, weather conditions and other sensor data can be incorporated for the better prediction of the congestion based on the considered road networks. Otherwise any factor can be removed having negligible correlation parameters.

As a future work, we intend to focus on decision making problem by integrating a prediction model with dynamic routing and dynamic traffic signals. Thus building a smart recommendation system for the drivers in the sense that it can provide the shortest and the less congested paths. Integrating the current model with the extended application can solve real life problems and contribute to a smarter traffic management system.

Acknowledgement. The research results have been achieved by Congestion Management based on Multiagent Future Traffic Prediction, Researches and Developments for utilizations and platforms of social big data, the Commissioned Research of National Institute of Information and Communications Technology (NICT).

References

1. Road traffic dataset. http://www.dft.gov.uk/traffic-counts/index.php
2. Antoniou, C., Koutsopoulos, H.N., Yannis, G.: Traffic state prediction using Markov chain models. In: Proceedings of the European Control Conference (2007)
3. Behrisch, M., Bieker, L., Erdmann, J., Krajzewicz, D.: Sumo-simulation of urban mobility. In: The Third International Conference on Advances in System Simulation (SIMUL 2011), Barcelona, Spain (2011)
4. Geroliminis, N., Skabardonis, A.: Prediction of arrival profiles and queue lengths along signalized arterials by using a Markov decision process. Transp. Res. Rec. J. Transp. Res. Board **1934**, 116–124 (2005)
5. Li, X., Parizeau, M., Plamondon, R.: Training hidden Markov models with multiple observations - a combinatorial method. IEEE Trans. Pattern Anal. Mach. Intell. **22**(4), 371–377 (2000)
6. Manual, H.C.: Highway capacity manual, Washington, D.C. (2000)
7. Murphy, K.: Hidden Markov model (HMM) toolbox for matlab (1998). http://www.ai.mit.edu/~murphyk/Software/HMM/hmm.html
8. Porikli, F., Li, X.: Traffic congestion estimation using HMM models without vehicle tracking. In: IEEE Intelligent Vehicles Symposium, 2004, pp. 188–193. IEEE (2004)
9. Qi, Y.: Probabilistic models for short term traffic conditions prediction. Ph.D. thesis, Louisiana State University (2010)

10. Rabiner, L.R.: A tutorial on hidden Markov models and selected applications in speech recognition. Proc. IEEE **77**(2), 257–286 (1989)
11. Schenk, J., Schwärzler, S., Rigoll, G.: Discrete single vs. multiple stream HMMs: a comparative evaluation of their use in on-line handwriting recognition of whiteboard notes. In: Proceedings of the International Conference on Frontiers in Handwriting Recognition, pp. 550–555 (2008)
12. Sen, R., Cross, A., Vashistha, A., Padmanabhan, V.N., Cutrell, E., Thies, W.: Accurate speed and density measurement for road traffic in India. In: Proceedings of the 3rd ACM Symposium on Computing for Development, p. 14. ACM (2013)
13. Witten, I.H., Frank, E., Trigg, L.E., Hall, M.A., Holmes, G., Cunningham, S.J.: Weka: practical machine learning tools and techniques with Java implementations (1999)