Cellular Network Based Real-Time Urban Road Traffic State Estimation Framework Using Neural Network Model Estimation

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***Abstract*— Road traffic flow information using In-vehicle mobile phone as a probe has great potential for improving the estimation accuracy of road traffic situations, particularly where no traffic surveillance technologies are installed. Besides, applications of Intelligent Transport System like advanced Traffic Transport System dependents on proper utilization of road traffic state information. There are different factors affecting quality of road traffic state estimation activity- data collection technologies, state estimation models etc. Based on the analysis of relevant studies on road traffic state estimation, a framework dealing with In-vehicle mobile phone probe data along with a Neural Network estimation model to estimate traffic states on urban roads is proposed in this paper. The framework integrates several models with appropriate technologies to realize traffic data collection, processing, analysis, state estimation and optimization and presentation of traffic flow information to road users. To evaluate the framework, simulation data based on the microscopic simulator "Simulation of Urban Mobility" (SUMO) which is used to model the arterial road network and real world data using In-vehicle A-GPS mobile phone moving in all journey of a vehicle on the sample roads is used. Performance indicators RMSE and MPAE are used to evaluate ANN model and on average the MPAE is less than 1.2%. The trained ANN model is also used to estimate the sample road link speeds and compared with ground truth speed (aggregate edge states) on a 10-minute interval for 1hr. The estimation accuracy using MAE and estimation availability indicated that reliable link speed estimation can be generated and used to indicate real-time urban road traffic condition.**

I. INTRODUCTION

Intelligent Transport System (ITS) applications like Advanced Traveler Information Systems (ATIS) offer integrated traveler information to road users. One form of users' information to be presented is real time road traffic state which also is used as an indicator for quality of service for network operators. This makes the estimation of traffic state with acceptable accuracy very challenging due to theoretical, technical and methodological nature.

Thus, to find out the traffic flow conditions on an urban roads, more and more new road traffic flow data collection systems like mobile probe-based road traffic surveillance systems [1] are used to supplement the information provided by the conventional fixed sensor technologies (inductive loop detectors, Video Image Processing (VIP) [2]) and improve the accuracy of real-time traffic state estimation.

Recently, utilizing the existing cellular network infrastructure for real time road traffic state estimation activity has been introduced as it offers large coverage capability, traffic data can be obtained continuously and also it is faster to set up, easier to install and needs less maintenance [3].

In relation to this, different researches are conducted on the feasibility of using mobile phones as road traffic probe [4]-[6]. And in most of these literatures, network-based mobile positioning methods which use the cellular network signal information like handoff, Angle of Arrival and Time of Arrival are employed. Few of them applied handset-based mobile positioning method to estimate road traffic flow. For example, Mobile millennium [7] and Tao, et al [8] employed the handset-based (GPS-enabled mobile phone) method in experimenting the use of cellular network for road traffic flow estimation.

Over the years, variety of traffic state estimation models have been developed. And the existing road traffic state estimation techniques can be either model based or data driven based approach [9]. Although current practices on urban road traffic state estimation applied data driven approaches, no single predictor had yet been developed that presented itself to be universally accepted as the best, and an effective traffic state forecasting model for real-time traffic operation. But from all data driven traffic state estimation models, Artificial Neural Networks are very flexible in producing accurate multiple step-ahead estimation with less effort and are chosen to be best traffic modeling tool [10].

Recently, to overcome limitation of a single traffic state estimation model by advantage of another, hybrid models combining model based and data driven method drew much attention. For example, Anderson and Bell [11] used the model based microscopic traffic flow VISSIM with Neural Network for traffic state estimation techniques and a queuing model for travel-time prediction in urban road networks. The work of Tao et al. [12] also presented the use of Kalman filtering integrated with a microscopic simulation model SUMO in urban traffic

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state estimation using A-GPS based vehicle location data. Habtie et al [13] also proposed hybrid method of combining Artificial Neural Network (data driven approach) and the microscopic simulation model SUMO (model based approach) to estimate road traffic flow on sample road networks of Addis Ababa.

In this paper cellular network based real-time road traffic state estimation framework using Neural Network model estimator and its application is presented. The organization of the paper is as follows. Section II presents the proposed framework. Section III discusses the experimentation results on the application of the framework and the conclusion is made in Section IV.

II. PROPOSED ROAD TRAFFIC STATE ESTIMATION FRAMEWORK

Proper real-time Road Traffic State Estimation activities using the existing cellular network include location data collection, mobility classification, map matching and route determination, road traffic condition estimation and dissemination of traffic information to road users [14]. Authors like [2], [15], [16] developed a three layer architecture for road traffic flow estimation system, the data collection layer which is responsible to collect real-time location data of vehicles on the road and send the data to the next road traffic state estimation layer which does the data preprocessing, updating data to the database server, estimating real-time traffic flow and disseminate the information to road users on mobiles or on to the Internet. And the third layer, database server, stores digital map which is used for road traffic state estimation and information dissemination processes.

In our research [17], the proposed real-time road traffic state estimation framework, depicted on Fig. 1, based on the existing cellular network infrastructure comprises five basic components: traffic data collection, data preprocessing, data analysis, model identification and optimization, traffic state estimation and estimation results dissemination and evaluation component.

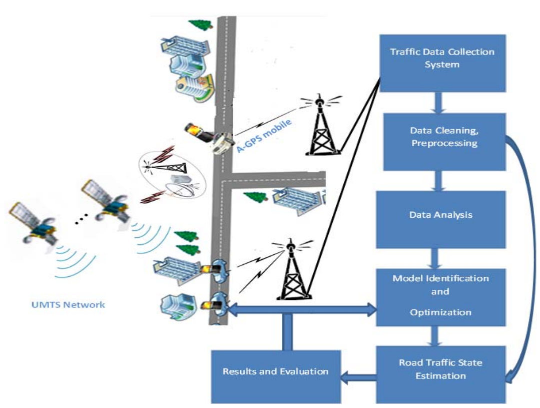


Fig. 1. Proposed real-time road traffic state estimation framework [17]

In the model identification and optimization component of the framework, a three layer ANN is used. In-vehicle mobile phones are used as a probe to collect traffic data and the data collected contain vehicle position, time stamp and vehicle speed on the road link, position, time stamp and speeds are used as input data in the ANN model and the structure of the ANN model adapted from Zheng and Zuylen [18] as cited in [17] is shown on Fig. 2.

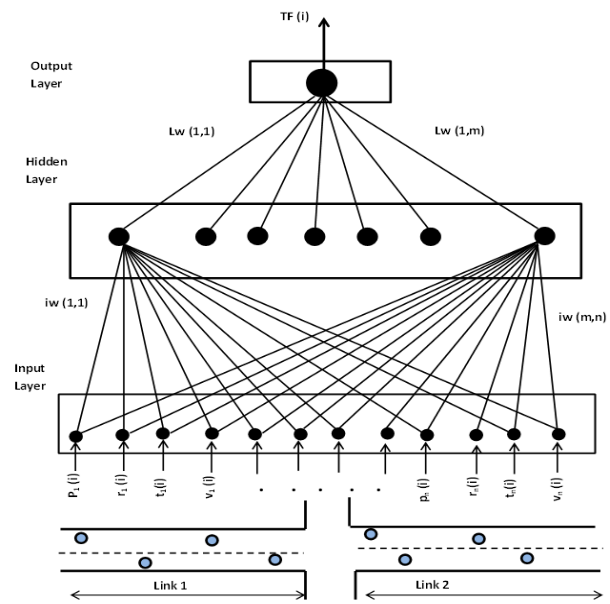


Fig. 2. Artificial Neural Network model for link traffic flow estimation [17]

The mathematical model for the input layer, hidden layer and output layer is as follows.

a) Input layer

$$\mathrm{x(i)} = \begin{bmatrix} x_1(i) \\ \vdots \\ x_n(i) \end{bmatrix} = \begin{bmatrix} p(i) \\ r(i) \\ t(i) \\ v(i) \end{bmatrix},\ p(i) = \begin{bmatrix} p_1(i) \\ \vdots \\ p_n(i) \end{bmatrix},\ r(i) = \begin{bmatrix} r_1(i) \\ \vdots \\ r_n(i) \end{bmatrix},$$

$$t(i) = \begin{bmatrix} t_1(i) \\ \vdots \\ t_n(i) \end{bmatrix},\ v(i) = \begin{bmatrix} v_1(i) \\ \vdots \\ v_n(i) \end{bmatrix}, \tag{1}$$

where p(i) is position vector, r(i) is link id vector, t(i) is time stamp vector and v(i) is speed vector *b) Hidden layer*

$$H(i)=\begin{bmatrix} h_1(i) \\ \vdots \\ h_m(i) \end{bmatrix}=\begin{bmatrix} \varphi(\sum_{j=1}^{N} w_{j,1}x_j(i)+b_1) \\ \vdots \\ \varphi(\sum_{j=1}^{N} w_{j,m}x_j(i)+b_m) \end{bmatrix}, \qquad (2)$$

where $h_m(i)$ denotes the value of the mth hidden neuron, $w_{j,m}$ represent the weight connecting the jth input neuron and the mth hidden neuron, b_m is bias with fixed value for the mth hidden neuron and φ is the transfer function.

c) Output layer

$$y(i)=TF(i)=\varphi(\sum_{k=1}^{m} w_k h_k(i)+b), \qquad (3)$$

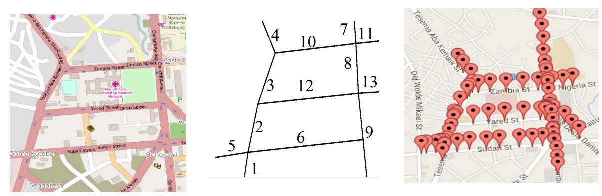
where $y(i)$ and $TF(i)$ denote estimated traffic flow of probe vehicle i on the link under consideration, w_k represent the weight connecting the kth hidden neuron and the output neuron, b is bias for the output and φ is the transfer function.

III. FRAMEWORK APPLICATION

To model the arterial road traffic, a microscopic simulation package "Simulation of Urban Mobility" (SUMO) [19],[20] is employed. To generate road network and vehicle route, the SUMO packages NETCONVERT and DFROUTER are used. From SUMO simulation aggregated speed information for each road link named "aggregate edge states" and floating car data (FCD) export file are generated for further analysis. The information on aggregate edge states include road edge IDs, time intervals, mean speeds, etc. The aggregate speeds are used to determine ground truth of traffic flow. Whereas the FCD output file records the location coordinates of every moving vehicle on the sample road at every timestamp, vehicle speed, edge IDs and this data file is used as simulation for in-vehicle mobile based traffic information system.

A. Test Urban Road Network

As it is shown in Fig. 3(a), part of Addis Ababa city road network is chosen as simulation case study. The OpenStreetMap (OSM) xml file of the selected road network is edited using Java OpenStretMap (JOSM) [21] to remove road edges that can't be used by vehicles like road ways to pedestrian etc., and also for simplicity all road edges are set to one-way. The simplified road network consists of 13 nodes, 12 links with length range from 169m to 593m and 4 traffic lights as shown on Fig. 3(b). On SUMO command window, network file encoding traffic light logic, speed limit of road links and road link priorities is generated from the OSM file using NETCONVERT. Then using DUAROUTER random routes of vehicles traveling on the road network, number of vehicles to be emitted to the road, start and end of traffic flow are determined. These randomly generated vehicles and their routes are run on SUMO and as a result of 3600-secods interval, 718 probe vehicles are generated with random trips. In order to mimic the real traffic situation on this road, free flow traffic demand is used with maximum speed 30Km/hr., which is the speed limit on the real situation. In addition to the data sets from the simulated network, real world data set was collected by a car with A-GPS device driving on the sample road networks and location updates in terms of longitude and latitude, time stamp and speed were recorded every 3 sec. The real world A-GPs location data collected within 45 minute is depicted in Fig. 3(c).



(a) (b) (c)

Fig. 3. Sample road network for simulation: (a) sample road network from OpenStreetMap (b) simplified diagram from SUMO (c) Real A-GPS based moving vehicle location data.

B. Data Preparation

The SUMO simulation is conducted for 1-hour without incident. Data from the first 15 seconds of simulation were considered to be warm-up period and were not used in the analysis. Every second, position, time stamp and speeds of vehicles were recorded. The output files "aggregate edge states" and FCD output, before used for further analysis, data screening and preprocessing is performed.

1) *Data Screening and Preprocessing:* The first challenge in using the cellular network based mobile probe system is distinguishing non-valid probes (pedestrians etc.). But probe data in this system come from our service subscribers and validity of traffic probes is not an issue. Other criteria considered in the screening and preprocessing include:

- Speed estimates greater than 13.89m/s of speed limit are eliminated as the speed limit in Addis Ababa city vary from 8.3 m/s (30km/hr) to 13.89m/s (50km/hr).
- Location estimates with distance to nearest link larger than 20m is eliminated. As the positioning accuracy of A-GPS positioning method is maximum of 20m [22] and also to differentiate closely spaced parallel urban roads, an accuracy of 20m is expected [23].
- In-vehicle mobile location estimated with coordinate (0, 0) and with zero speed are eliminated.

2) *Aggregation of link speeds:* From SUMO simulation conducted for 1 hour, to characterize traffic flow condition on every road link of the sample road networks aggregation of link speed estimates over a specific time interval is performed. Previous works on road traffic state estimation [24], [4] discussed a 10 minute aggregation time is a reasonable choice considering real-time requirement and data availability. And the average speed along road link r during the time interval $\lfloor t_{k,} t_{k+\Delta T} \rfloor$ is given as:

$$V_{av}^{\ r}\left(t_k, t_{k+\Delta T}\right) = \frac{1}{n^{r}_{\ t_k, t_{k+\Delta T}}} \sum_{k=t_k}^{t_{k+\Delta T}} v_r(k) \ , \qquad (4)$$

where $v_r(k)$ is the available speed estimate on link r and $\frac{1}{n^{r}_{\ t_k, t_{k+\Delta T}}}$ is total number of available speed estimates.

The mean traveling speed of the road links on a 10-minute time interval is recorded in the "aggregated edge states "and it is depicted on Fig. 4.

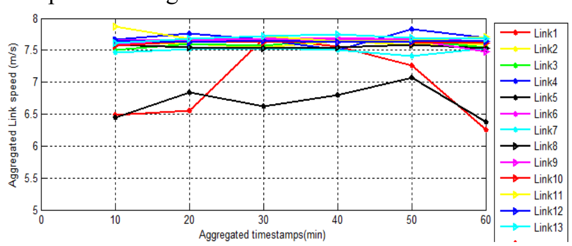


Fig. 4. Aggregated road link speeds –"ground truth speed".

From Fig.4, all road links except link 1 and link 5 is expected to have smooth traffic flow as their speed is above 7m/s (link speed limit is 30km/hr). However, link 5 has medium traffic flow and link 1 is with medium traffic flow from 10 to 20 and 50 to 60 minutes. From 20 to 50 minutes the traffic flow on this road link is improved.

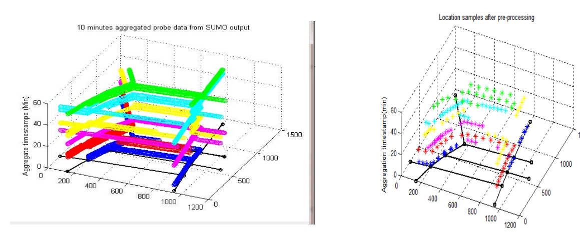
3) *Data Sampling Process:* From the 1 hour SUMO simulation, the simulation output file**,** FCD output, generates large amount of simulated mobile probes at real-time. At every second location updates (in terms of x, y or longitude, latitude) for the mobile probes is recorded. There are in total 437 probes and the time they spent range from 10 second to 202 seconds. Fig. 5(a) shows location data collected from these probes, which are aggregated in 10 minutes. The FCD output file contains detail information of each vehicle/mobile and grows extremely large. Hence converting this location data in to more compressed one is necessary [8]. Accordingly, to degrade location data, one can set up a specified percentage of simulated vehicles/mobiles to be traffic probe. Previous studies suggest that for arterial roads reliable speed estimation, a minimum penetration rate of 7%, i.e. at least 10 probe vehicles traversing a road section (every road link) successfully is required [24], [25],[26] although factors like road type, link length and sample frequency affects the minimum sample size.

In this research work the sample is taken considering the road link length as it is indicated in Table I and sampling frequency is based on Pinpoint-Temporal [17].

Table I, Number of probes taken for the sample from the FCD output based on road link length

Link #(Street Name)	Link length (m)	Number of sample probes	Number of location updates per probe
1 (Tesema Aba Wekaw Street)	274.6	10	15
2 (Tesema Aba Wekaw Street)	233.4	10	15
3 (Tesema Aba Wekaw Street)	258.8	10	15
4 (Tesema Aba Wekaw Street)	194.2	10	15
5 (Sudan Street)	194.2	10	15
6 (Sudan Street)	695.8	20	15
7 (Churchill Avenue)	593.9	15	15
8 (Churchill Avenue)	233.3	10	15
9 (Churchill Avenue)	531.4	15	15
10 (Zambia Street)	484.3	15	15
11(Nigeria Street)	69.5	10	15
12 (Yared Street)	601.7	20	15
13 (Ras Damtew Street)	214.6	10	15

As it is presented in Table I, for road link length 300m and below 10 probes are taken (which is the minimum recommended in the literature), 300m to 600m 15 probes and more than 600m link length 20 probes and totally 165 probes (37.6%) are considered in the sample. The sampling frequency employed is "Pinpoint-Temporal" with 10second time interval and 15 location updates of each probe is collected including the first and last probe information as the proposed state estimation method, which is discussed in section II E is integral method (IM). Fig. 5(b) plots location data of the sample probes aggregated in 10 minutes.



(a) (b)

Fig. 5. Probe location data aggregated at every 10-minute: (a) Probe location data generated from FCD output file, (b) Sample probe location data

4) *Data for Training and Evaluation:* After the sampling process, the extracted data were used for training the neural network and estimating the link travel speed. Total of 165 probe data were simulated and using random approach of dividing the

available dataset for ANN development [27], 110 probe data (two-third of the data) were used for training process and the other 55 probe data (one-third of the data) were used for performance evaluation.

C. Neural Network Training

A training process is needed before the ANN model can be applied to estimate traffic state. In the process three procedures including training, testing and validation were conducted. The total training data set (110 probe data) were divided in to three subsets [28] which are 88 probe data (80%) for training, 11 probe data (10%) for testing and 11 probe data (10%) for validation. During the training process different hidden neurons like 10, 15, 20, 25 were chosen. During testing the performance in terms of Mean square error (MSE) for the case of 10, 15, 20 and 25 neurons is compared and 15 hidden neurons were used to build the network. During training Levenerg-Marquardt algorithm (Trainlm) [29] was chosen so that the over fitting phenomenon can be avoided. Moreover, the algorithm can provide fast convergence even for large networks with few hundred weights. The trained ANN model is applied to estimate link traffic state under free flow but proved even in over saturated condition [30].

D. Evaluation

To evaluate how the ANN model performs, the performance indicators Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used and defined as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(v_{pv,k} - v_{true,k})^2}, \quad (5)$$

$$MAPE = 100 * \frac{1}{n}\sum_{k=1}^{n}\left|\frac{v_{pv,k} - v_{true,k}}{v_{true,k}}\right|, \quad (6)$$

where $v_{pv,k}$ is the estimated travel speed of the kth probe vehicle and $v_{true,k}$ is the true link speed of the kth probe vehicle recorded by data collection points.

E. Results based on Simulation Data

The trained ANN model is used to estimate link travel speed with a simulation data input. A correlation between the estimated link travel speed based on ANN model and the true link travel speed which is computed from the simulation data using the integration method (IM) of calculating vehicle speed is performed. And as it is depicted on Fig. 6, the estimated link travel speed has very high correlation with the true link travel speed (R^2>99%). the linear regression between the estimated and true (simulated) link speed that predicts the best performance among these values has an equation y = 0.997*x + 0 indicating the trained ANN model performs reasonably well, where x represents true speed and y estimated link travel speed.

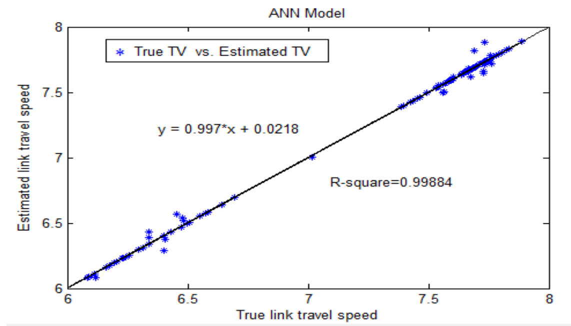


Fig. 6. Correlation between estimated link travel speed and true link travel speed.

The performance of the estimation method in terms of RMSE and MAPE is 0.029325 and 0.127% respectively with average speed of 7.191m/s.

F. Results based on Real A-GPS Data

The trained ANN model was also applied to estimate travel speed based on real world A-GPS data. A car with A-GPS based mobile phone traveled on the sample road network and location updates in terms of longitude, latitude, timestamp, speed and accuracy is recorded at every 3seconds for about 45minute (see Fig. 3(c)). A sample using "Pinpoint-Temporal" method with 10second time interval is taken and at every road link, 15 location points i.e. total of 195 A-GPS based vehicle location points are taken. The estimation result is shown on Fig. 7. Each point represents travel speed on each tripe i.e. , at every road link. From the regression formula in the figure, it can be seen that the trained ANN model performs very good. The RMSE and MAPE are 0.101034 and 1.1877% respectively which show the possible application of the ANN model to real link travel speed measurements.

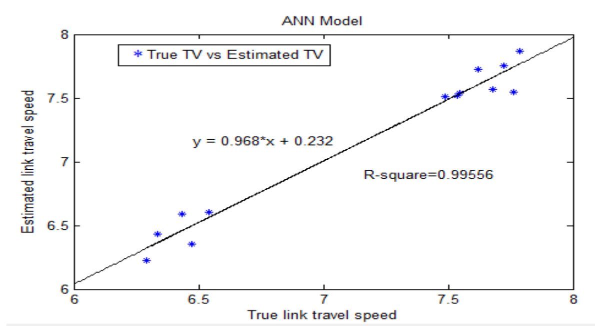


Fig. 7. Correlation between estimated link travel speed and true link travel speed using real A-GPS data.

G. State Estimates of Road Links

As it is presented in sections III E & F, the trained ANN model provides a very good link travel speed estimation using both simulated as well as real world A-GPS data. In this section the trained ANN model is applied to estimate sample road link states using link travel speeds and a comparison is made against the ground truth speed estimates named as “aggregated edge states”. For this analysis a sample with 195 probe vehicle points are taken from SUMO FCD output file based on “Pinpoint-Temporal” sampling frequency method with a 10minute time interval. The result of the analysis is shown in Table II.

Table II, Ground truth vs. ANN model based average link speeds

Aggregated Ground Truth Speed	ANN model based Speed Estimates with 10min Interval												
Link # (Street Name)	0-10min		10-20min		20-30min		30-40min		40-50min		50-60min		MAE
1(Tesema Aba Wekaw St.)	6.48	6.29	6.56	6.91	7.69	7.01	7.56	7.43	7.26	7.07	6.26	6.29	0.28
2(Tesema Aba Wekaw St.)	7.61	7.37	7.60	7.82	7.55	7.31	7.64	7.53	7.59	7.99	7.60	7.56	0.21
3(Tesema Aba Wekaw St.)	7.50	7.11	7.60	7.91	7.57	7.15	7.68	7.69	7.65	7.66	7.55	7.20	0.23
4(Tesema Aba Wekaw St.)	7.67	7.63	7.77	7.53	7.67	7.48	7.50	8.35	7.84	8.02	7.69	7.82	0.23
5 (Sudan St.)	6.45	6.62	6.84	6.69	6.63	6.02	6.80	6.61	6.98	6.67	6.38	6.89	0.32
6(Sudan St.)	7.59	7.28	7.65	7.97	7.67	7.98	7.65	7.27	7.68	7.48	7.64	8.09	0.33
7 (Churchill Avenue)	7.47	7.09	7.52	7.17	7.53	7.52	7.50	7.79	7.41	7.98	7.53	7.84	0.32
8 (Churchill Avenue)	7.59	7.49	7.55	7.07	7.54	7.08	7.55	7.33	7.59	7.56	7.54	7.84	0.26
9 (Churchill Avenue)	7.66	8.06	7.67	7.58	7.68	8.07	7.70	7.77	7.67	7.78	7.48	7.33	0.21
10 (Zambia St.)	7.57	7.07	7.64	7.35	7.62	7.36	7.62	7.97	7.62	7.55	7.62	7.86	0.29
11(Nigeria St.)	7.87	7.81	7.68	7.69	7.72	7.32	7.64	7.33	7.63	7.91	7.71	7.93	0.14
12 (Yared St.)	7.65	7.41	7.62	7.05	7.65	7.85	7.62	7.81	7.65	7.68	7.64	7.80	0.23
13(Ras Damtew St.)	7.61	7.88	7.69	7.49	7.72	8.00	7.75	7.72	7.70	7.82	7.68	7.52	0.18

Two performance indicators, Mean Absolute Error (MAE) and Estimation Availability are used to evaluate the ANN model estimation accuracy and system coverage respectively. MAE is defined as mean of absolute difference between the ground truth speed on a link and the estimated speed. And the estimation speed availability is the fraction of links having speed estimation in the time interval considered.

Considering the state-of-the-art traffic speed classification in urban areas [30], speed thresholds are employed to classify the estimated road traveling speed. Accordingly three traffic condition levels : Green, Yellow and Red where green level (smooth traffic) if link speed is above 7m/s, yellow level (medium traffic condition) when link speed is between 4m/s and 7m/s and red level (congested traffic condition) when link speed is below 4m/s are used as it is shown in Table II. From the table it is shown that medium traffic condition is detected on link 5 and partly on link1. The average estimation accuracy based on MAE is 0.28m/s and all sample road networks have link speed estimation using the trained ANN model. Moreover, these estimated traffic conditions will be color-coded on the road network and presented on road users’ mobile display for real-time analysis.

IV. Conclusion

This paper presents a comprehensive framework for road traffic state estimation that utilizes the existing cellular network infrastructure for road traffic data collection. To evaluate the framework, a three-layer Artificial Neural Network model is proposed to estimate complete link traffic state. The inputs to the ANN model include probe vehicle’s position, time stamps and speeds. Based on the microscopic traffic simulation SUMO, “aggregate edge state” which is the ground truth link travel speed and FCD output data is generated. From the FCD output, a sample based on “Pinpoint-Temporal” method is extracted and the dataset is divided to train as well as evaluate the ANN model. Besides, real world A-GPS data gathered using A-GPS mobile phone on a moving vehicle on the sample roads is used to evaluate the ANN model. The performance of the ANN model is evaluated using the performance indicators RMSE and MPAE and on average the MPAE is less than 1.2%. The trained ANN model is also used to estimate the sample road link speeds and compared with ground truth speed (aggregate edge states) on a 10-minute interval for 1hr. The estimation accuracy using MAE and estimation availability indicated that reliable link speed estimation can be generated and used to indicate real-time urban road traffic condition.

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