A SMART TRAVEL TIME PREDICTION MODEL FOR URBAN TRAFFIC USING LONG SHORT-TERM MEMORY NETWORK

By

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THESIS DEDICATION

This research is dedicated to my parents who have inspired me
and
always pray for my every success.

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LIST OF ABBREVIATION

ITS	Intelligent Transportation System
ITMS	Integrated Traffic Management Systems
TM	Transportation Management
DMA	Dhaka Metropolitan Area
TE	Transportation Engineers
IoT	Internet of Thing
RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error (MAE)
MRE	Mean Relative Error
RMSE	Root Mean Square Error
HTG	Hatirjheel To Gulshan-2
CTW	Center To West
CTN	Center To North
STN	South To North
API	Application Program Interface
STK	Sainik Club To Kachukhat
KTS	Kachukhat To Sainik Club
RELU	Rectified Linear Unit
TT	Travel Time
TS	Traffic Speed

LIST OF SYMBOLS

$\overline{v}_t$	Time Mean Speed
$\overline{v}_s$	Space Mean Speed
u_0	Minimum Speed
u_f	Maximum Speed
h_t	Hidden Layer Output
w	Neuron Weight
x_t	Neuron Input
b_t	Neuron Bias
y_t	Predicted Output
f_t	Forget Gate
i_t	Input Gate
$\tilde{C}_t$	Candidate State
C_t	Cell or Memory
U	Input Weight
W	Previous cell Weight
σ	Sigmoid Function
t	Travel Time
K	Traffic Density
q	Traffic Flow
R	Correlation Co-efficient
α	Arbitary Scaling Factor
N_s	Input Samples
N_o	Output Neuron
N_i	Input Neuron

ABSTRACT

Traffic jams or traffic congestion is the most important factor of the urban road networks for advanced travel plans and managing the traffic flow. It causes service holders, travellers, riders, drivers and logistics to not reach their desired location in a timely manner. Traffic congestion cause's real-time traffic information to become a crucial part of advanced traveller information systems (ATIS) for daily travelling and smartly managing vehicle flow. An intelligent transportation system (ITS) is more essential for urban road networks. Travel time and traffic speed are major components in ITS to assist the travel planning and proactively managing traffic in the urban road networks. The study investigated the Google Maps traffic information in various aspects like Google Maps traffic information accuracy, multi-steps ahead travel time and traffic flow prediction on various urban road networks. Real-time traffic data were collected from Google Maps for several urban road networks of Dhaka city. A long short-term memory (LSTM) network model is developed to perform the multi-step ahead travel time and traffic flow prediction based on the historical traffic and weather data. The experimental results explored that, Google Maps provided current traffic information accuracy average 91.19%. The proposed LSTM model's mean relative error is varying between 5.84% ~ 10.93% for one-hour advance travel time prediction. Models predicted traffic flow error range 8.25% ~14.09% on three different road sections after mapping predicted traffic speed by using time-dependent correlation (TDC). Also, results showed that the proposed model prediction accuracy improves and is stable with the smaller time interval. The proposed prediction model is reliable for predicting multi-steps ahead of travel time and traffic flow prediction. It will be used in transportation systems road network planning, design, traffic policy-making, proactively managing traffic flow and smartly assist traffic signals management. Moreover, the proposed models are essential for smart travel planning, finding congestion and best route, time-saving, avoid traffic jams, cost-minimizing and ensure more trips for riders, drivers and logistic services in urban road networks.

Chapter 1

INTRODUCTION

Traffic demand increasing over the past couple of years in the urban road networks in all the cities in Bangladesh; especially in Dhaka and Chittagong. At the same time, urban travellers are facing a serious challenge due to the increasing traffic demand, traffic congestion, population growth and vehicle ownership. Moreover. day-by-day worsening the traffic situation and safety issues. As a result, for developing countries like Bangladesh, the allocation of the road networks are not compensating with the increased traffic congestion due to the unavailability of the integrated traffic management systems (ITMS) to incorporate the real-time traffic flow with the existing traffic policy and the nature of traffic. This can affect the overall traffic planning and design of the transportation systems, traffic routes, policy-making and developing alternate solutions strategies for private car, bus, taxi, ride-sharing and logistics services applications, etc. To avoid traffic jams and assist transportation management (TM), a travel time and traffic flow prediction model could be a better solution for ITS in urban road networks.

1.1 Research Background

The capital of Bangladesh, Dhaka city becomes one of the most densely populated cities in the world. The rural people are coming to Dhaka city for studying, job searching, visiting, business and medical treatment also. However, Dhaka city's development has not kept up with the city's rapid growth, resulting in a messy and uneven urbanization process. Currently, the urban transportation in Dhaka metropolitan area (DMA) mostly relies on road transport where the car, bus auto-rickshaw, rickshaw, motorbike which consequently induced serious traffic jam and traffic pollution along with air pollution resulting in severe the health hazard. The transportation engineers (TE) are facing challenges corresponding to traffic congestion and safety issues for increasing traffic demand day by day [1-2] within urban road networks. And it directly influences the social life and country economy.

In the meantime, so many solutions have been studied to mitigate the traffic congestion, reduce travel time, suitable travel planning over the advanced travel time status. Proactive traffic control systems are of great importance and is efficient for transportation management systems [3-4]. Specifically, one-step or multi-step advanced travel time and traffic flow prediction is an important factor for proactively traffic control, travel planning, transportation network planning, reduce fuel cost, time-saving, intelligently route guidance, location-based services and avoid traffic jams [5-12]. Moreover, the prediction may differ from the actual, due to a range of factors like properties of road networks, traffic mode, traffic policy, vehicle types, driving policy, natural disaster, socio-economic condition, weather condition, the political situation and instantaneous road traffic conditions such as ongoing construction or roadblock, accident, etc [6, 13-14]. The traffic policy may differ between developing and developed countries based on traffic management facilities, traffic signal systems, pedestrian facilities, adequate traffic roads and current traffic volume. Its cause affected transportation planning, policy making, user groups like taxi services, drivers, travellers, logistic departments and ride-sharing applications. Hence, an accurate travel time and traffic flow prediction model is essential for developing a sustainable traffic network system and bringing financial benefits by reducing time and costs [15].

1.2 Present State of the Problem

Presently, Dhaka city is one of the most populated cities in the world where more than twelve million people live and travel on a daily basis. The number of population increasing day by day and are badly affected by massive traffic jams in our daily life. Moreover, the number of traffic or vehicles in Dhaka city is higher than the existing road capacity and growing with time. Traffic jam is the main problem of the Dhaka city due to the number of traffic, existing traffic policy, ongoing road construction works, lane violation, unnecessary parking, narrow road space, overtaking tendency and lack of intelligent traffic management systems, etc. The traffic jam causes an important portion of working hours to be left on urban road travellers, riders, logistics services and drivers which are indirectly put into an adverse impact on the country economic system. Also, traffic jam causes serious air pollution, noise pollution and thus degrades the overall environmental conditions day-to-day.

The existing traffic management system is unable to reduce traffic jams for the limitation of traffic policy impose and existing road capacity as well as traffic growth. Moreover, the existing developed models are not suitable in developing countries like Bangladesh where mixed vehicles movement, inadequate traffic information, lane violation tendency, insufficient traffic GPS network, unavailable number plate tacking systems and absence of traffic tracking system and inadequate traffic database. The traffic jam causes drivers, riders, travellers and logistic services are facing serious problems in their daily life and impacted their health. Also, they are losing a huge amount of time and finance every day. Moreover, traffic jams directly impact our social life and the country's economy. This situation can be improved by minimizing traffic congestion or jam with an effective traffic management system.

1.3 Objectives of the Thesis

The study is concerned with the effectively travel time and traffic flow prediction for travellers, drivers, riders, logistic services, traffic flow control, traffic policy-making, smartly traffic management systems, transportation road network planning and design. The major objectives of the thesis are:

- To develop a technique for the collection of instantaneous travel time data of different road networks.
- To develop an LSTM based model for learning traffic patterns of a road network.
- To analyze different traffic situations and properties of the traffic network node.
- To validate the model against Google Maps and existing developed models.

1.4 Overview of the Thesis

The proposed models are a combination of stacked LSTM based travel time and traffic flow prediction and Google Map provided travel time accuracy. The Google Maps travel time accuracy is validated with the real-time collected travel time data and manually whereas, other models are simulated using Google Map provided current traffic information or data.

Traffic information or data were collected from Google Maps which is providing around 55 countries all over the world using satellite, crowdsourced, internet-enabled user phones, location services, internet of things (IoT), and ground data showing the real-time traffic data. The Google Maps provided traffic information accuracy increasing day by day due to the number of internet-enabled phone users are also increasing and traffic information available on the internet. Its traffic information represented by four colour codes; green, orange, red and dark-red are used to indicate the road congestion level from low to high. Recently, Google Maps traffic information service got more popular to the travellers, drivers, logistics service, uber, pathao and riders for getting the current status of the desired road instantly. However, to estimate the travel time or traffic flow for a road section it's required to develop the travel time or traffic flow prediction model which will learn the nature of instantaneous travel time or traffic flow and then generates the estimation accordingly.

Besides, the prediction accuracy of travel time and traffic flow results are highly laid on the data collection time interval and other impacted parameters; timestamp, holiday, weekday, adjacent road status, VIP movement status, weather condition, road properties, etc. If the interval of time is small, then the calculation is time-consuming and the travel time or traffic speed prediction result has high accuracy and is stable in each interval of the period in the urban road networks. Urban road traffic is frequently changing traffic patterns.

In general, travel time or traffic speed (space mean speed) represent sequential characteristic where future step depends on previous steps. In this context, LSTM and recurrent neural networks (RNN) are more well-known for predicting such sequences of time series data. However, RNN is more suitable for processing short-term sequences due to its inability to maintaining cell memory without further transformation and suffers from a gradient decent problem also the same as a conventional neural network.

The LSTM network removes such vanishing gradient problems by employing a memory cell with three input, forget and output gates. Also, it can learn long-distance information through the sigmoid functions and cell state information stored in the memory for future reproducing.

In this study, we proposed and developed a two-layer stacked LSTM deep learning model for one-step and multi-step ahead travel time and traffic flow prediction by correlating time-dependent traffic speed. Models are evaluated through mean absolute error (MAE), mean relative error (MRE) and the root mean square error (RMSE) to measure the model's performance. In addition, we find out the impact of time intervals on travel time, traffic speed and traffic flow prediction accuracy. Finally, we compare the model performance with the existing available model outcomes.

1.5 Organization of the Thesis

The thesis contains a total of eight chapters, references and appendixes. Chapter 1 gives an introduction of the relevant research background details, presents state of the problem, objectives of the thesis and overview of this thesis. Later, in Chapter 2, we focus on the review of the previous studies related to thesis papers and other sources related to both developed and widely practised travel time and traffic flow models by comparing different approaches and recommendations. In Chapter 3, we discuss basic concepts regarding travel time, space mean speed and speed flow relationship, RNN, LSTM, rectified linear unit, time-dependent correlation, intelligent transportation system and Google Maps. Chapter 4, describes the methodology and presents a developed model structure, stacked LSTM sequential data prediction, time-dependent correlation and algorithm for traffic flow. Chapter 5 highlights data collection prior to modelling the LSTM network, Data Pre-processing and formatting for LSTM network models illustrate for different intervals of data collection. In Chapter 6, we simulate developed models by training and evaluation including a flowchart. Chapter 7 discusses the simulated results in various aspects of developed models including tables and figures. In Chapter 8, we summarize the research and discuss recommendations and future research works.

Chapter 2

LITERATURE REVIEW

Since the last couple of years, the travel time and traffic flow prediction studies are increasing through various approaches based on long-term or short-term traffic condition forecasting models. While prediction is done more than sixty minutes or one hour simply called long-term and below sixty minutes or one-hour prediction called short-term prediction. Most of the studies are focused on short-term prediction models using various sources of the dataset. Generally, two types of methods are considered for travel time and the flow prediction approach; parametric and nonparametric. A method can be thought parametric when the structure is fixed and parameters are learned from a given dataset [16]. Similarly, nonparametric methods derive dynamic relationships directly from observed data and therefore are usually called data-driven approaches. The parametric methods are easy to implement and provide strong theoretical explanations with a clear calculation of the model structure. However, the parametric methods require high quality of data set [1]. The traditional techniques for travel time and traffic flow prediction mainly focuses on traffic data collection, usage technic and their model prediction performance. Few existing models are summarized below.

2.1 Urban Network Travel Time Prediction Using Probe Data

Probe-data based travel time prediction model was developed by Jenelius et al. in 2018 [17]. The proposed model was a multivariate probabilistic principal component analysis (PPCA) tool for traffic management, trip planning and online vehicle routing and the model is robust against noisy and missing data. Spatio-temporal correlations are inferred from historical data based on maximum likelihood estimation (MLE) and an efficient expectation-maximization (EM) algorithm for handling missing data. The proposed prediction model is performed in real-time by calculating the predictable distribution of link travel times in the future time intervals, conditional on recent current-day observations. The author showed that prediction with PPCA outperforms the k-nearest neighbour's prediction for horizons from 15 to 45 minutes and the combination of PPCA and local smoothing reduces root mean square error (RMSE) by almost 11% and provides highest accuracy.

2.2 Bus Travel Time Predictions Using Additive Models

Kormáksson et al. (2014) developed a framework for bus travel time prediction through the additive model with the GPS collected data [18] considering several factors such as weather, traffic, local event and others that directly influenced the prediction. The main advantage of additive models are ease of interpretability and flexibility while modelling complex non-linear relationships. The proposed model's GPS collected data holds information about the position of the bus's longitude and latitude, timestamp, bus ID, and route ID. The experiment result showed that three additive models; basic additive model (BAM), extended additive model (EAM), and additive mixed model (AMM) outperformed the Kernel Regression and SVM in all scenarios whereas additive mixed model's (AMM) mean absolute relative error is lower and its ranges from 13.2 % to 19.2 % for four experimented routes data.

2.3 Travel Time Prediction with LSTM Neural Network

In 2016, Duan et al. proposed a travel time prediction model with LSTM networking using England Highway 66 links traffic data [7]. The Deep learning models are considering sequence relation and are capable of time series data prediction. The model outcomes were evaluated with three errors; mean relative error (MRE), mean absolute error (MAE) and root mean square error (RMSE) for multi-step ahead prediction. Evaluation results showed that the 1-step ahead travel time prediction error is relatively small, the median of mean relative error for the 66 links in the experiments is 7.0% on the freeway test dataset. The model investigated that, the structure of the LSTM neural network varies with different links amount of data. Also, it was showed that 1-step ahead predictions have relatively minor errors. The errors of multi-step predictions grow up with the number of steps. The model travel time prediction mean relative error range varies 7% ~ 11% on highway traffic data or freeway traffic data. Also, show the number of hidden neuron variations in each step travel time prediction.

2.4 Long Term Travel Time Prediction with Fuzzy Rules for Tollway

A fuzzy neural network-based hybrid model developed for long term travel time prediction, was proposed by Ruimin et al. in 2017 [5]. The model is validated by using travel time data compiled from electronic toll tags on a 14 km length section of the City Link tollway in Melbourne, Australia. The proposed model validation results emphasized the ability of the fuzzy neural network model to accommodate unclear and linguistic input information while providing consistent predictions of travel times up to a few days ahead. The developed models, which focused on predicting the mean travel time, were trained and tested on data from the same 326 and 163 workdays. The experimented percentage error range vary 6%~22% for the 90th percentile travel times and 4%-19% for the 10th percentile travel times. The percentage error of the developed method range from 5%-21%.

2.5 Estimating Travel Time Based on Deep Neural Networks

Wang et al. proposed a deep learning framework model for travel time prediction called DeepTTE that predicts the travel time for the entire route directly in 2018 [19]. A multi-task learning element is attached on the top of the DeepTTE framework that learns to predict the travel time of both the entire path and each local path concurrently during the training phase. An extensive investigation on two route datasets showed the DeepTTE exceptionally perform better than the state-of-the-art methods. They proposed a Spatio-temporal component to learn the spatial and temporal dependencies from the raw GPS sequences data: a) A geo-based convolutional layer that transforms the raw GPS sequence to a series of feature maps, capable of capturing the local spatial correlations from consecutive GPS points implicitly, b) LSTM that learn the temporal dependencies of the obtained feature maps and embedding's from the external factors. For estimating the entire path accurately, authors designed a multi-factor attention mechanism to learn the weights for different local paths based on their hidden representations and the external factors. The studies on two actual significant data sets which consist of GPS latitude and longitude produced by taxis in Chengdu and Beijing. The percentage error on these two datasets are 11.89% and 10.92% respectively.

2.6 Traffic Prediction Based on Randomly Connected LSTM Cell

A randomly connected LSTM cell-based deep learning model was introduced for traffic prediction in 2018 by Yuxiu et al. [20]. The model showed that 35% of LSTM cells can perform satisfactory level performance in traffic prediction compare to the conventional LSTM. When gradually add training samples, the performance of random connectivity long short-term memory (RCLSTM) becomes increasingly closer to the baseline of LSTM. Moreover, RCLSTM exhibits even superior prediction accuracy than the baseline LSTM while input traffic sequences have enough length. The model cell connectivity is similar while the training and validates traffic data less than 5000 instances.

2.7 Short-Term Traffic Speed Prediction under Different Data Collection Interval

In 2019, Zhanguo et al. proposed a seasonal autoregressive integrated moving average plus seasonal discrete grey model structure (SARIMA-SDGM) and it performed the traffic speed prediction under different data collection interval scenarios on freeway traffic data [1]. The experimental results showed that SARIMA-SDGM model performed better compared to the seasonal autoregressive integrated moving average (SARIMA), seasonal discrete grey model (SDGM), artificial neural network (ANN) and support vector regression (SVR) model. The experimental results indicated that the proposed model prediction accuracy is stable and improves with the time interval increase when greater than 10 minutes.

Three indicators including the mean absolute error (MAE), mean absolute percentage error (MAPE) and the root mean square error (RMSE) were used to measure the model's performance as well as time interval impacted on the traffic speed prediction accuracy. The SARIMA-SDGM model might improve the average prediction accuracy by 32.7%, 30.1%, and 27.9% respectively compared to the SARIMA model by three types of error measures. The investigation also showed that the SDGM model might improve the average prediction accuracy by 17.4% and 15.7% from the SARIMA model through the MAE and RMSE measures. The author stated that the SARIMA-SDGM model prediction accuracy is stable greater than 10 min data collection intervals.

2.8 Hybrid Method for Traffic Flow Forecasting Using Multimodal Deep Learning

Shengdong et al. proposed a hybrid multimodal multiple CNN-GRU deep learning method for short-term traffic flow forecasting, which can jointly and adaptively learn the spatial-temporal correlation features and long temporal interdependence of multi-modality traffic data by considering supplementary multimodal deep learning architecture [9]. The experimental results indicated that the proposed multimodal deep learning model is capable of dealing with complex nonlinear urban traffic flow forecasting with satisfying accuracy and effectiveness. A relative analysis of traffic flow, traffic speed and traffic journey time data which shows the nonlinear relationship of the three sequences data. From traffic speed and travel time data, it can show whether the traffic jams occur or not since the travel time is high and the traffic speed is low under the traffic jam condition. The experimental results showed that hybrid multimodal deep learning framework can improve the performance by fusing those deep features information. Through comparative analysis of experimental data using GRU compared to LSTM will result in better predictive performance through a hybrid model.

2.9 Travel Speed Prediction using Machine Learning Techniques

In 2017, Maha et al. proposed a travel speed prediction methodology that mines big data collected from mobile location devices (vehicle GPS tracking) to feed machine learning models [21]. The author expected that the added information obtained through big data mining should help these models to better predict travel speeds and travel times. From a methodological point of view, the proposed approach first asked for data cleaning, missing data pre-processing and geometrics validation. Then, unsupervised learning is used to reduce data dimensionality. Finally, future speed values in the road network were predicted through an LSTM. To evaluate the performance of the neural network, the study used the root mean square error (RMSE) and mean absolute percentage error (MAPE).
The proposed LSTM neural network predicted the travel speed between any two locations at a given time of a given day. This method gathered historical data from the delivery vehicles.

The LSTM model is trained on a large database of speed records obtained from an industrial partner who develops vehicle routing solutions for home delivery companies. The output of the neural network will then be fed to a previously developed vehicle routing optimization algorithm to show the benefits of more accurate travel speed predictions on the obtained delivery routes. Also, the author said that capturing features when modelling travel speed can have an immediate impact on commercial transportation companies that distribute goods by allowing them to optimize their routes to be more efficient and reduce their environmental footprint.

2.10 Deep SBU LSTM Network for Network-wide Traffic Speed Prediction

In 2017, Zhiyong et al. proposed a deep-stacked bidirectional and unidirectional LSTM (SBU-LSTM) neural network model by which considers both forward and backward dependencies in time series data, to predict network-wide traffic speed [22]. A bidirectional LSTM layer is utilized to record spatial features and temporal dependencies from the historical data. The proposed model can handle missing values in input data by using the SBU-LSTM and Traffic speed prediction performed by the LSTM network. The proposed model experimental data was collected by inductive loop detectors deployed on roadway surfaces at 5 minutes intervals of data. Multiple loop detectors are connected to a detector station deployed around every half a mile and covered four connected freeways road. The experiment result showed that SBU-LSTM model traffic speed MAPE range 5.6% ~ 6.22% for LSTM layer (N) 0 to 4. Also, the author compared the proposed model with the traditional and advanced models and achieved superior prediction performance for the whole traffic network in both accuracy and robustness.

2.11 Literature Review Summary

The above literature reviews showed that most of the developed models are short-term travel time, traffic speed and flow predictions are based on time series models, spatial correlation models, and hybrid models also. Compared to a single layer short-term traffic travel time or speed prediction model, a hybrid model can provide complex explanatory qualifications and time consuming during train but achieve better accurate results.

Consequently, a fuzzy neural network required a static set of rules for making prediction decisions and any uncertain condition decision will be the same for all. Also, these models have employed data from various sources like roadside cameras, GPS networks, traffic engineering databases, traffic microwave detectors, number plate detection, induction loop detection, probe data, sensor networks, authorized traffic monitoring data and different data collection intervals, etc. The loop detector is not suitable for our country due to mixed types of vehicles and other models also are not suitable due to costly, insufficient traffic database and traffic management networks. Roadside camera and probe data suitable for collection traffic data which are required continuous maintenance and follow-up also costly. Moreover, most of the traffic data collected from developed country freeways or highway and their everyday traffic patterns are almost similar compared to developing countries like Bangladesh. Whereas in Bangladesh, urban road traffic patterns are frequently updated with the time due to lane violation, lack of traffic policy, VIP movement, number of vehicles and overtaking tendency. These developed models also required additional algorithms or manual incorporation for missing data and collected data processing for their developed models.

In this research, the frequently updated real-time traffic data were collected from the most well-known Google Maps provided traffic information service using python programming language and maps distance matrix API for travel time and traffic flow prediction which are reliable, hassle-free, easily accessible, low cost and easily extractable 24/7 in a year. Moreover, Google Maps turned to crowdsourcing to improve the accuracy of its traffic prediction through internet-enabled android phone users while turn on their Google Maps app with GPS location enabled. Recently, the number of androids or other GPS enable phone users rapidly increasing and at the same time Google Map traffic information accuracy also increasing. In addition, Google Map is one of the reliable traffic information in a developing country like Bangladesh.

Chapter 3

BASIC CONCEPTS

Several terms and factors directly assist and influence the developed prediction model and its prediction accuracy. These terms and factors are more essential while simulated the developed models. In this research, the major and frequently used terms are travel time, traffic speed or space mean speed, speed-flow relationship, traffic flow, RNN, LSTM, rectified linear unit, time-dependent correlation, intelligent transportation system, deep learning and Google Maps. These terms are briefly discussed in the following.

3.1 Travel Time

Travel time is the concept of travelling between specific points in time or movement between two points in time. Travel time refers to the amount of time t (sec) required to travel from point A to point B through either transportation or walking at a certain speed v (meter/sec) shown in Fig-3.1. Travel time prediction is considered three types: real-time or online, short-term and long-term prediction. When predicting the travel time for vehicles which depart at the current time (t), such forecast is usually called real-time or online travel time prediction; Google Maps provided traffic information. Real-time prediction is the process of collecting valuable information from datasets in real time. The short term travel time prediction is typically defined as the evaluation of travel time for vehicles leaving in future time from current time t to t +60 minutes. The prediction is considered for a maximum of 60 minutes or less. The travel time prediction for vehicles leaving 60 minutes or more ahead of the current time t is classified as long-term travel time prediction. More than 60 minutes ahead of travel time prediction falls in long-term travel time prediction.

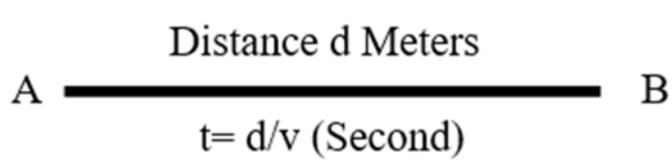

Fig-3.1 Travel time

This research investigated short-term travel time prediction for a maximum one-hour ahead in various aspects; Google Maps provided real-time traffic condition-based travel time data employed in this thesis.

3.2 Space Mean Speed or Average Traffic Speed

Traffic speed or space mean speed is a vehicle's rate of motion from one point to another point with a specific direction. Two types of traffic speeds are briefly discussed for research; time mean speed and space mean speed. The time mean speed $\overline{v}_t$= arithmetic mean of speeds of vehicles passing a specific point. Time mean speed $\overline{v}_t = \frac{1}{N}\sum_{n=1}^{N} vn$ where $\overline{v}_t$ is time mean speed and N is the number of observed speed, v_n is the individual point speed. Space mean speed is the average speed of all vehicles occupying a given section of a road over a specified time period. Space mean speed is required to compute the accuracy of travel times and traffic flows. It is also equal to average speeds over a length of roadway. Space mean speed equation as follows:

Space mean speed, $\overline{v}_s = \frac{N}{\sum_{n=1}^{N} \frac{1}{vn}}$ where $\overline{v}_s$ is space mean speed and N is the number of observed speed, v_n is the individual road or length speed. Simply, we define the space mean speed $\overline{v}_s = \frac{d\ (Mile)}{t\ (Hr)}$ Where d = distance travelled or length of roadway segments (km) t = average travel time (hr) of that segments. Space mean speed is mapped with the number of vehicles passed for a time interval through the time-dependent correlation equations.

3.3 Speed Flow Relationship

The speed-flow relationship is fundamental for traffic simulation and volume forecasting for any road section. The speed and traffic flow follow each other or vice versa and speed is being zero while the road is saturated. At a certain speed, both are increasing and as well as decreasing. Traffic flow streams are described by using three variables; density (k), speed (v), and flow (q) measured respectively in vehicles per lane per km, km per hour, and vehicles per lane per hour. At the macroscopic level, these variables are defined under stationary conditions at each point in space and time and are related by the identity $q = k \times v$.

Vehicle driver behaviour makes an additional useful relationship between the three above variables. Speed–flow functions have been developed by several transportation experts to predict accurately the speed of urban road networks. In the highway capacity manual, speed-flow curve, BPR curve, MTC speed-flow curve, Akçelik speed-flow curve are some extraordinary efforts to define the shape of the speed-flow curve [23].

The flow rate is the number of vehicles passing a point in a given period usually expressed as an hourly flow rate or a certain interval of time. And the saturation flow rate is the equivalent maximum hourly rate at which vehicles can traverse a lane or intersection approach under prevailing conditions assuming a continuous queue. Speed is calculated by dividing the average travel time by the measured distance. The speed flow relationship curve is shown in Fig-3.2 for a road section. The traffic speed represents by v where v_0 minimum speed and v_f maximum or free-flow speed. Similarly, q represents flow. According to Fig-3.2, the traffic flow increases and while speed is decreasing, at maximum flow, the speed will be zero and considering the road capacity max or saturated. At free-flow speed number of traffic may be zero.

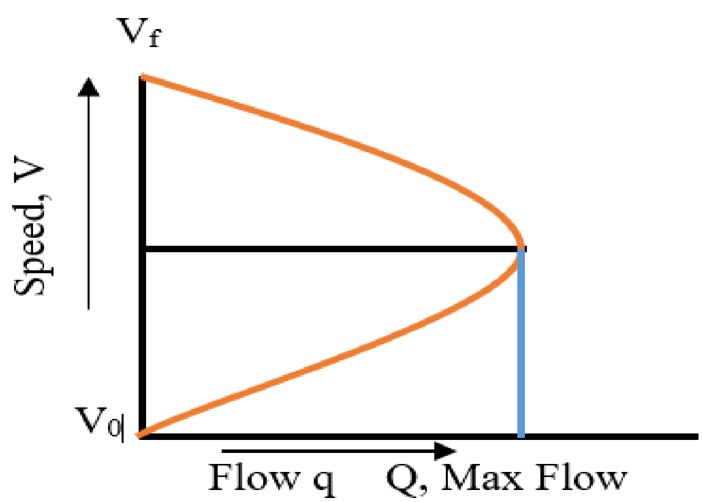

Fig-3.2, Speed-flow relationship curve.

While speed will be reached minimum like zero, the traffic flow will be maximum and occupied the road section. No movement of the vehicles on this road section due to filling up the road section or saturated.

3.4 Recurrent Neural Network

A recurrent neural network (RNN) is a class of artificial neural networks where networks between two nodes form a directed graph along with a chronological sequence. RNN output from the previous step is fed as an input to the current step; that's why it's called recurrent. The RNNs can usage their internal state or memory to process a series of inputs. The advantage of RNNs is to make use of short-term sequential information or data processing. In a traditional neural network, all inputs or outputs are independently working with each other. The conventional neural network is unable to process sequential data where the current step depends on the previous step. Suppose, we want to predict the next word in a sentence that we better know which words came before it. The RNN can do it smoothly or easily. The RNNs are called recurrent because they perform the same task in every cell or element sequentially and each element output is dependent on the previous cell. The basic structure of RNN is shown in Fig-3.3.

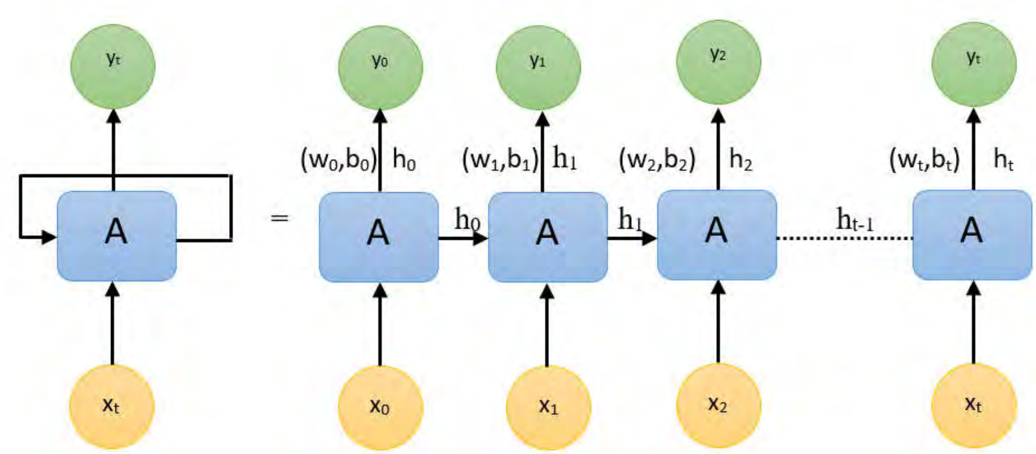

Fig-3.3, Recurrent neural network (Unrolled)

RNN usages the same parameters for each input and it performs the same task on all the inputs or hidden layers to produce the cell output. Each layer holds its own weight and bias that's why each of these layers is independent of each other. They do not memorize the long-term previous outputs due to a lack of memory cells. The RNN adapts the self-governing activations into dependent activations by providing the same weights and biases to all the layers, thus reducing the complication of increasing parameters and learning previous cell output by giving each output as input to the next cell hidden layer. How to calculate the output in the last state through the RNN is shown below.

Formula for current state calculation:

$h_t = f(h_{t-1}, x_t)$ where h_t is current state, h_{t-1} is previous state and x_t is input state

Formula for applying Activation function (tanh):

$h_t = \tanh(w_{t-1} \,.\, h_{t-1} + w_t \,.\, x_t)$ where w_{t-1} is weight at recurrent neuron and w_t is weight at input neuron

The formula for calculating output (y_t):

$\mathbf{y_t} = (w_y \,.\, h_t + b_t)$, where y_t is output and w_y is weight at the output layer

In the above formula, each state depends on the previous state output for calculating the current state output. Such types of operations are required for sequential data processes like language processing, speech recognition, image processing, and translation and time-series data processing. In the last few years, there has been unbelievable success applying RNNs for solving several problems. The core reason that recurrent neural networks are more exciting is that they allow us to operate over sequences of vectors: sequences in the input, sequence of output, or in the most general case both. RNNs are considered to take a series of inputs with no fixed limit on size. RNN also remembers the information for short time but it exists gradient vanishing, sometimes becomes very difficult training and cannot process very long sequences if using tanh as an activation function.

3.5 Long Short-Term Memory (LSTM)

LSTM is a special kind of recurrent neural network, capable of learning long-term dependencies through the cell or memory state and three gates like input, forget and output gates. The LSTM was introduced by Hochreiter & Schmidhuber in 1997. LSTM works tremendously well on a large variety of complex problems and is now widely used in time series data analysis. LSTMs are explicitly designed to avoid the long-term dependency and vanishing gradient descent problem which would not possible by the recurrent neural network. Information remembers or memorize for long periods is basically their default character, not something they struggle to learn. The LSTM was invented over RNN for resolving the vanishing gradient problem and avoid long-term dependencies.

The LSTM cell overcomes the long-term dependence and vanishing gradient problem by using three control logic gates. To understand the vanishing gradient problem, we have to know how a feed-forward neural network trained or learns. In the conventional feed-forward neural network, the weights are updating on a particular layer by multipling the learning rate. While happening any error, sometimes product of all previous layers' errors. When handling with the activation functions; sigmoid function, the small values of its result multiply multiple times and moved towards to the starting layers. As a result, the gradient during training almost vanishes and it becomes difficult to train these layers.

On the other hand, LSTM makes small changes to the information by multiplications and additions and gradient kept remain for training. In addition, LSTM cell or memory stored required information for future reproduced; that's why it can remember long distance sequences also. The basic internal structure of the LSTM cell is shown in Fig-3.4 and briefly discuss the elements.

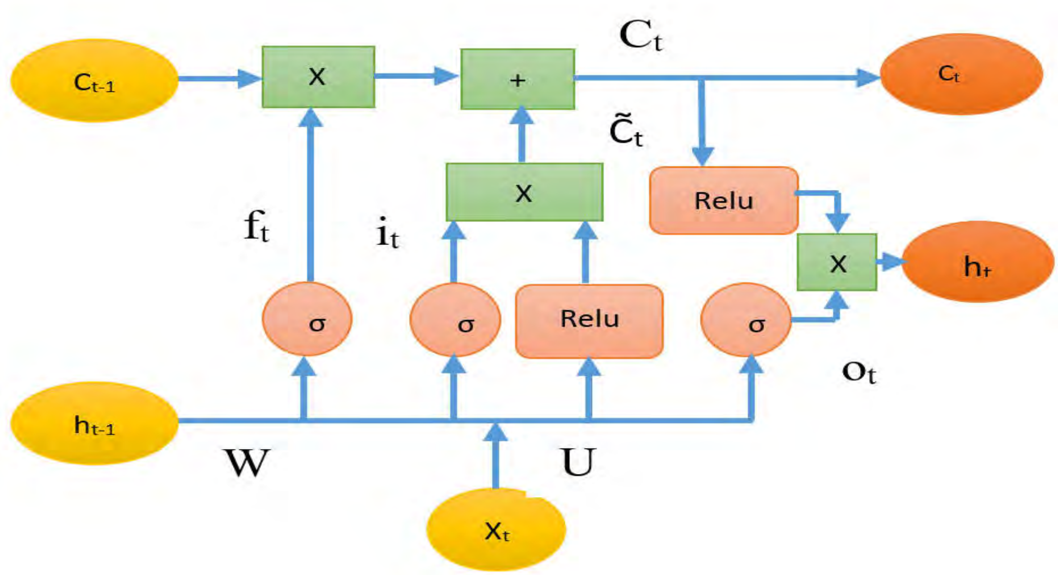

Fig-3.4, LSTM cell structure

LSTM information flows through a mechanism known as cell states. This cell can selectively remember or forget information. The cell or memory blocks are responsible for remembering information and manipulations is done by three major mechanisms, called gates. The function of these three gates are briefly described below.

Forget Gate:

A forget gate is responsible for discarding or keeping information from or to the cell state. If the previous cell information is no longer required or has less important for the LSTM cell, then it will be discarded. The forget gate is essential for improving the performance of the LSTM network. The output formula of forget gate is

$$f_t = \sigma(U_f \, . \, x_t + W_f \, . \, h_{t-1} + b_f)$$

Where f_t is the forget gate output, W_f, U_f and b_f are forget gate weights and bias accordingly. The forget gate takes in two inputs; h_{t-1} and x_t where h_{t-1} is the hidden state from the previous cell or the output of the previous cell and x_t is the input at that particular time step. The forget gate or sigmoid function outputs either 0 or 1. Basically, the sigmoid function is responsible for deciding which values to keep and which will be discarded. If gate output is 0 for a particular value in the cell state, it means that the forget gate wants to discard the information fully. Similarly, if the gate output is 1 then the gate wants to remember or keep the entire information.

Input Gate

The input gate is responsible for the addition of input information to the cell state. This addition of information is basically done by the three-step process as shown in below.

a. Managing which values need to be added to the cell state by sigmoid function from h_{t-1} and x_t input sequences.
b. Generating a vector having all potential values that can be added to the cell state by using the rectified linear unit (relu) function f(x) = max (0,x).
c. Multiplying the input gate output value with the output of relu function and then adding this valuable information to the cell state via addition operation.

The input gate calculation formulas are:

Input gate output is $i_t = \sigma(U_i \, . \, x_t + W_i \, . \, h_{t-1} + b_i)$

Cell input state is $\tilde{C}_t = relu(U_c \, . \, x_t + W_c \, . \, h_{t-1} + b_c)$

Final information will be added to cell state like $i_t * \tilde{C}_t$

Where i_t input gate output, $\tilde{C}_t$ candidate state, ($W_{i,}$, U_i , b_i), (W_C, U_c , b_C) are weight and bias of input gate and candidate state.

Cell or Memory

The cell or memory state is stored important information by using forget gate and input gates outputs. The cell or memory C_t information is the sum of the previous cell state and current cell input information by deciding these gates. It will be forwarded to the next cell as input. The cell state or memory basic calculation function is shown below. Calculate cell state or memory state is $C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$, basically the sum of forget and input gate outputs.

Output Gate:

The output gate is responsible for how many portions of the memory state will be represented as prediction output. The output gate activities are done in three steps:

1. Making a vector after applying relu function to the cell state
2. Generating output from h_{t-1} and x_t, input sequences as a result of output gate by using a sigmoid function.
3. Finally multiplying the value of step 1 and step 2, and sending it as an output of the hidden cell state for the next cell.

The output gate result is $o_t = \sigma(U_o . x_t + W_o . h_{t-1} + b_o)$ and final prediction output is $h_t = o_t * relu(C_t)$. Here, o_t is the output gate result, h_t is the current cell predicted output, (W_o , U_o , b_o) is the output weights and bias, C_t cell or memory state. The current cell and predicted output feed to the next cell recurrently that's why LSTM is also called a recurrent neural network.

LSTM is more popular for sequential data processing like time series, sentence making, speech recognition, natural language processing, image processing etc. The largest websites Amazon and Google usages the LSTM network for sequential data processing. The study employed a two-layer stacked LSTM deep network with rectified linear unit activation instead of tangent function tanh for minimizing the CPU processing time and avoid the training process hang up.

3.6 Time-Dependent Correlation

Correlation is a statistical measure that determines the degree to which two or more variables fluctuate together. While two or more variables are increase or decrease in parallel it's called positive correlation. Similarly, one variable increases and the other variable decrease and vice-versa, such type of relation is a negative correlation. While two or more variables correlate over time called time-dependent correlation. The correlation among variables is strong or weak depended on the correlation coefficient R square. A correlation coefficient measures the degree of changes in one variable value and predict change to the value of another variable. A strong correlation indicates R square very close to 1 and weak indicate below 0.5 of R square value.

In this study, time-dependent correlation drive from the hour, minute and traffic speed for the target variable traffic flow through the six consecutive five-minute intervals of data. In the urban road network, the traffic average speed or mean speed remain within a range multiple times every day causes considering a maximum of six consecutive intervals of data to drive strong correlation equations where the correlation coefficient value is always positive. While the correlation coefficient is near about 1, the mapped predicted traffic flow will be more accurate in respect to predicted traffic speed and time.

3.7 Intelligent Transportation System(ITS)

An ITS is an advanced application that goals to deliver advanced services relating to different modes of transport and traffic management and enable users to be better informed and make safer and smart the use of transport network systems. Some of these technologies include emergency services generated when an accident occurs on the road, sometimes using cameras to impose traffic laws or signs that mark speed limit changes depending on the traffic conditions. An ITS may improve the efficiency of the transportation system in several situations, i.e. road transport, traffic management, mobility, etc. The basic example of intelligent transport systems; car navigation, traffic signal control, container management systems, variable message signs, automatic number plate recognition.

3.8 Google Maps

Google Maps is a web-based mapping service developed by Google corporation. It offers satellite images, aerial photography, street maps, 360° panoramic views of streets, real-time traffic conditions and route planning for travelling by the transportations. Initially, Google Maps was a desktop-based program at Where 2 technologies. In October 2004, the company was acquired by Google then converted into a web application. Later in February 2005, Google Maps launched a real-time traffic analyzer through geospatial data. Google Maps was released on Android and iOS devices in September 2008 including GPS turn-by-turn navigation and dedicated parking assistance features. Google Maps is providing real-time traffic information around 55 countries all over the world using satellite, crowdsources and the internet enables user's phone and ground data showing the real-time traffic data. Google Maps launched real-time traffic information within Dhaka city in 2017.

The traffic information represents four colour codes like green, orange, red and dark-red are used to indicate congestion levels from low to high. The Map changes road networks colour depending on the traffic congestion and movement of vehicles. Green indicates there is no traffic on the road; orange indicates medium traffic; red indicates traffic delays, and dark red indicates traffic gridlock. Traffic density is gathered via crowdsourcing from smartphone users using Google Maps on a mobile application in a route. Google collects traffic data from smartphones running the Google Maps apps. Google Map is sent small anonymous bits of data to the devices and collects the user GPS coordinates. From those coordinates, Google Map determines user location, the direction of travel, and average speed. They combine that with data from other people on the same road and department of transportation (DoT) sensors to come up with their real-time traffic maps.

Recently, Google Maps is more popular to travellers, drivers, logistics, uber, patho and riders for getting the current status of the desired road instantly. Besides the traffic information, Google Maps is providing advanced travel time prediction with a range of possible values using previous historical data only and there is exact prediction accuracy.

Therefore, an advanced traffic information system is essential for travellers, drivers, riders logistic department, traffic signal controlling, traffic policymaker and intelligent transportation systems to save their travel time, cost, smartly handle the traffic flow and avoid the traffic congestion on urban roads. The Google Maps traffic information graph is shown in Fig-3.5.

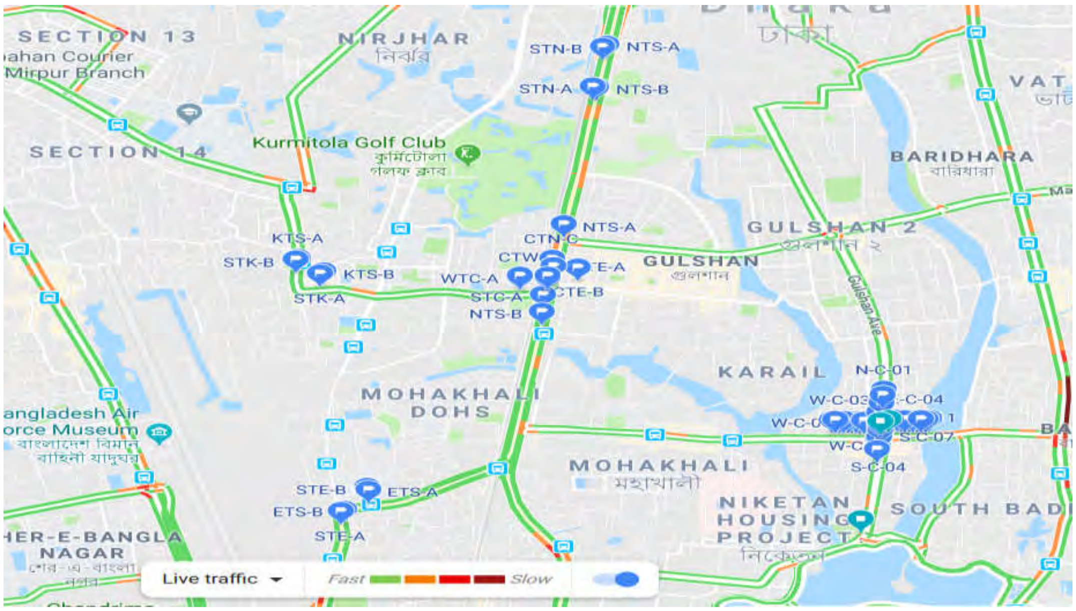

Fig-3.5, Google Maps real-time traffic graph.

3.9 Rectified Linear Unit (relu) Activation Function

An activation function is a mathematical equation that is attached to the neuron and regulates the output of a neural network. Rectified linear unit (relu) is a newer type of activation function used in neural networks with a simple mathematical form $f(x)$ = relu (x) = max {0,x}. Some activation functions required normalized the output of each neuron to a range between -1 and 1. The problem of such activation is a saturated situation with the large input. Sometimes produce a gradient of zero for large inputs, which can slow or halt the learning process. The relu activation function $f(x)$ = max (0, x) doesn't saturated for large positive inputs. The rectified linear activation function is simply a calculation and returns the value either zero for less than 0 or real that provided as input directly. The relu activation function graphical look like below Fig-3.6:

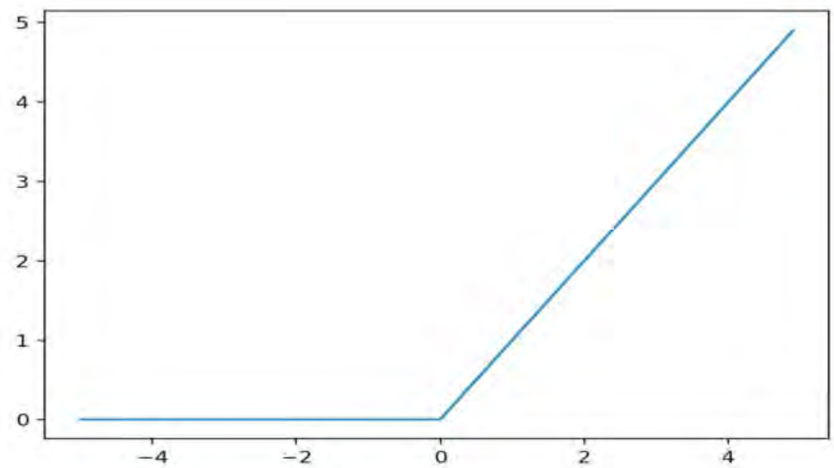

Fig-3.6, Rectified linear unit

The main advantages of relu function over other activation functions are it does not activate all the neurons at the same time; It reduces the exponential and CPU activities.

3.10 Deep Learning

Deep learning structures the algorithms into multiple layers in order to create an artificial neural network**.** Deep learning is an artificial intelligence that works like a human brain for processing input data and making patterns for use in decision making. Also, Deep learning is a subset of machine learning that has capable to learn unsupervised data from the unstructured or unlabeled. Deep learning is just neural networks with a lot of hidden layers and neurons and interconnection. Deep learning is concerned with developing much larger and more complex neural networks for solving analogue data, such as image, text, audio and video. Recurrent Neural Networks (RNNs) and LSTMs are the most popular deep learning algorithms. Deep learning can be tuned in various way and it takes a long time to train due to work with a large dataset.

3.11 Summary

The most frequent usage terms are discussed above several points for clearing their functions, properties, benefits and application in this research. Travel time is the key term in this thesis and it's discussed briefly for understanding their types. Also shortly discussed the traffic speed and its relation with traffic flow in different road situations. How RNN and LSTM calculate the prediction and its differences are shown at glance. The predicted speed is mapped with time-dependent correction for traffic flow prediction also shortly discussed. Intelligent transportation systems application also shortly discussed which is part of this thesis. How Google Maps collect and represent traffic information using four-colour codes is shown in this section. The newer type of activation function is rectified linear unit and its behaviour and main advantages show up shortly and finally what is deep learning and its application areas are shown at a glance.

Chapter 4

PROPOSED MODEL

In this research, we developed a two-layer stacked LSTM deep learning prediction model for travel time and traffic flow by applying Google Maps provided travel time and average traffic speed. In addition, comparing accuracy between actual or spot travel time and Google Map predicted travel time for a road segment to investigate the Google Map current prediction accuracy status. Two separate stacked LSTM models are developed for travel time and traffic speed prediction for different road segments or sections in Dhaka city. For investigating the traffic flow, several time-dependent correlation equations are derived using regression analysis technique from spot collected vehicles, traffic speed and time. In each road section, six consecutive intervals of traffic speed data are employed for deriving each correlation equation by considering the field level or spot collected traffic flow and timestamp. An algorithm is developed to explore the traffic flow in certain time intervals for all road sections for mapping predicted traffic speed into predicted traffic flow through these time-dependent correlation equations. LSTM deep learning is more popular in various application services; Amazon, Google, Apple and Microsoft use it for processing sequential data such as speech and handwriting recognition, two-dimensional image processing, Google translate, sentence making, natural language processing and time series data analysis [1,24,25-27].

The stacked LSTM network with the rectified linear unit (relu) activation function model developed for sequential time-series data processing to achieve higher prediction accuracy and minimizing the computation process. The stacked LSTM networks make the model deeper by employing first layer output placed into the next layer LSTM as input. The stacked LSTM is an extension of the single hidden layer model which has multiple hidden LSTM layers where each layer contains multiple memory cells. The deep learning LSTM model holds several hidden layers where each layer processes some part of the task and passes the output to the next layer. In this sense, the deep learning model processing as a pipeline in which each layer solves a part of the task before passing it on to the next until the last layer provides the final output.

In addition, the activation function is responsible for transforming the summed weighted input and bias from input into the output of a node. The rectified linear activation function is a linear function that will provide output from the input directly if positive; otherwise, it will output zero. The relu activation function is employed in this model for easier to train achieves better performance and overcomes the vanishing gradient problem in the multi-layers model.

Moreover, the relu activation is the default activation when developing multilayer perceptron and convolutional neural networks. Both one-step and multi-step ahead predictions were explored by developing and simulating two layers stacked LSTM network models. The n number of ahead predictions is done by considering previous n-1 sequences of observations. The details of the proposed model development are described in the following.

4.1 Data Collection for Test Model Developing

The data collection is an important task for this research model analysis and model development. The data was collected through several phases for developing an initial travel time prediction model. In the first phase, necessary data was collected in 2018 from Shahabag to Motsha Bhaba route in order to verify the Google Map colour code and required travel time to that travel path. After verifying the Google Maps colour code, a single-layer LSTM prediction model was developed and we measured the model prediction accuracy through the Google Maps traffic data at five minutes intervals.

The traffic data was collected from Google Maps by developing an algorithm in Python using Google Maps distance matrix API. In the second phase, several road segment data were collected from Farmgate to Motijheel road segment using the same process and we analyzed the LSTM model prediction accuracy. Finally, travel time and traffic speed data were collected for developing final stacked LSTM models from others road segments which are described in the next sections.

4.2 Google Map Provided Travel Time Accuracy Model

The Google Maps provided travel time accuracy model is investigated by collecting actual or spot or field level real travel time and Maps provided travel time for a road segment like Sainik club to Kachukhat and vice versa at the same interval through a manual process and we developed data collection algorithm. The investigated road segment distance is around 1251 meters in both directions which are divided into three sections for considering high accuracy travel time. The cumulative and direct travel time in both directions of this road segment is extracted from Google Maps and at the same time, field-level travel time are collected. Three road sections for both directions are STK-1, STK-2, and STK-3 from Sainik club to Kachukhat and KTS-1, KTS-2, KTS-3 from Kachukhat to Sainik club are shown in Fig-4.1. The actual or field level travel time was recorded using GPS logger and at the same time, Google Maps provided travel time collected by developing an algorithm. Travel time data was collected through three and seven rounds on two different days whereas traffic flow was regular and the weather was a sunny day. The Google Maps provided travel time denoted (G_{TT} second) and actual or spot or field level travel time denoted (F_{TT} second). The Google Maps provided travel time accuracy is calculated by using the below formulas:

Provided travel time accuracy (%) = 100 - abs ((F_{TT} – G_{TT}) / F_{TT})*100

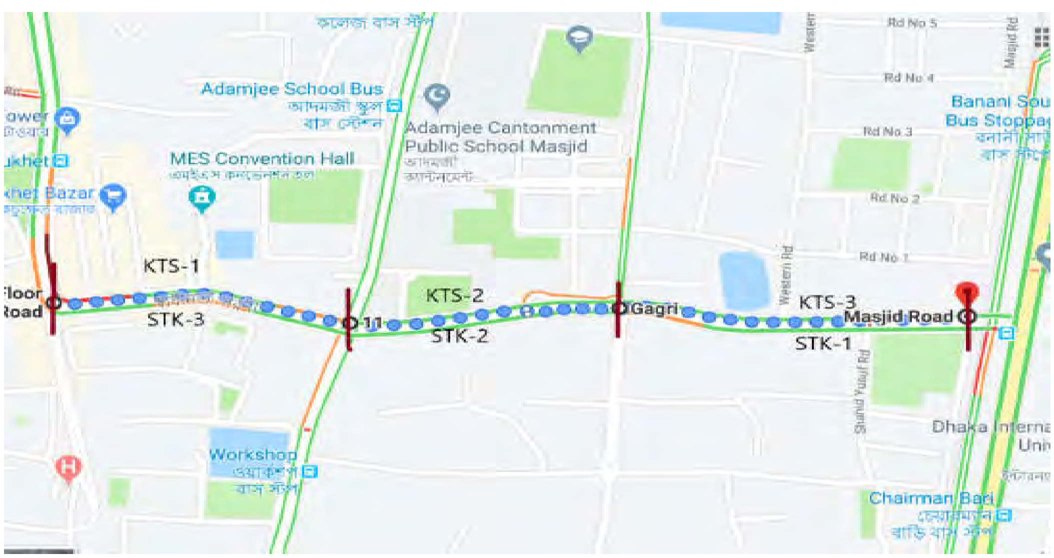

Fig-4.1, Sainik club to kachukhat road segment travel time collection

4.3 LSTM Model Development for Travel Time and Traffic Speed Prediction

Two layers stacked LSTM model developed by considering the two categories of sequential data analysis; travel time and traffic speed which are collected from different road segments for this research. After investigating the data pattern, we developed two separate LSTM deep network models for one-step and multi-step ahead targets prediction. The developed travel time (TT) and traffic speed (TS) prediction model block diagram is shown in Fig-4.2. The developed model consists of various blocks where each block process data or task independently. The data collection block extracted data from two different external sources like Google Maps and the weather forecasting website through an algorithm developed using Python and Google Maps distance matrix API.

The data collection algorithm fires according to the defined time interval. It can collect travel time and traffic speed data separately at five minutes intervals as a defined process. Data collection algorithm collected data are stored in the disk in .xls format initially in multiple files and continue to append newly extracted data sequentially. Secondly, collected raw data are filtered, merged and formatted into .CSV files using a defined process through important or selective features that are directly influencing the travel time or traffic speed for a road section. The LSTM model required data in specific shapes like sample, time-step and features. An algorithm is responsible for formatted arrangement in three dimensions shape according to the required steps and features. After that, reshaped data are split by a process as per defined rule for train, validation and prediction.

In the intermediate stage, the two-layer stacked LSTM model is defined through hidden cells or neurons as per optimum hidden cell rule, epoch and batch size defined according to the keras recommendation and standard activation function for the highest level of prediction accuracy. The two-layer stacked LSTM model processes input data through two layers: 1st layer process a few portions of the target task and is forwarded to the second layer for completing prediction as final outcomes. The LSTM block performs major activities like the train, validate and predicting through various parameters like the number of hidden neurons, train period (epoch), batch size, data shape, optimizer and activation function. The train and test loss functions also perform in this block. The LSTM layer outputs either predicted travel time or traffic speed based on the employed input dataset.

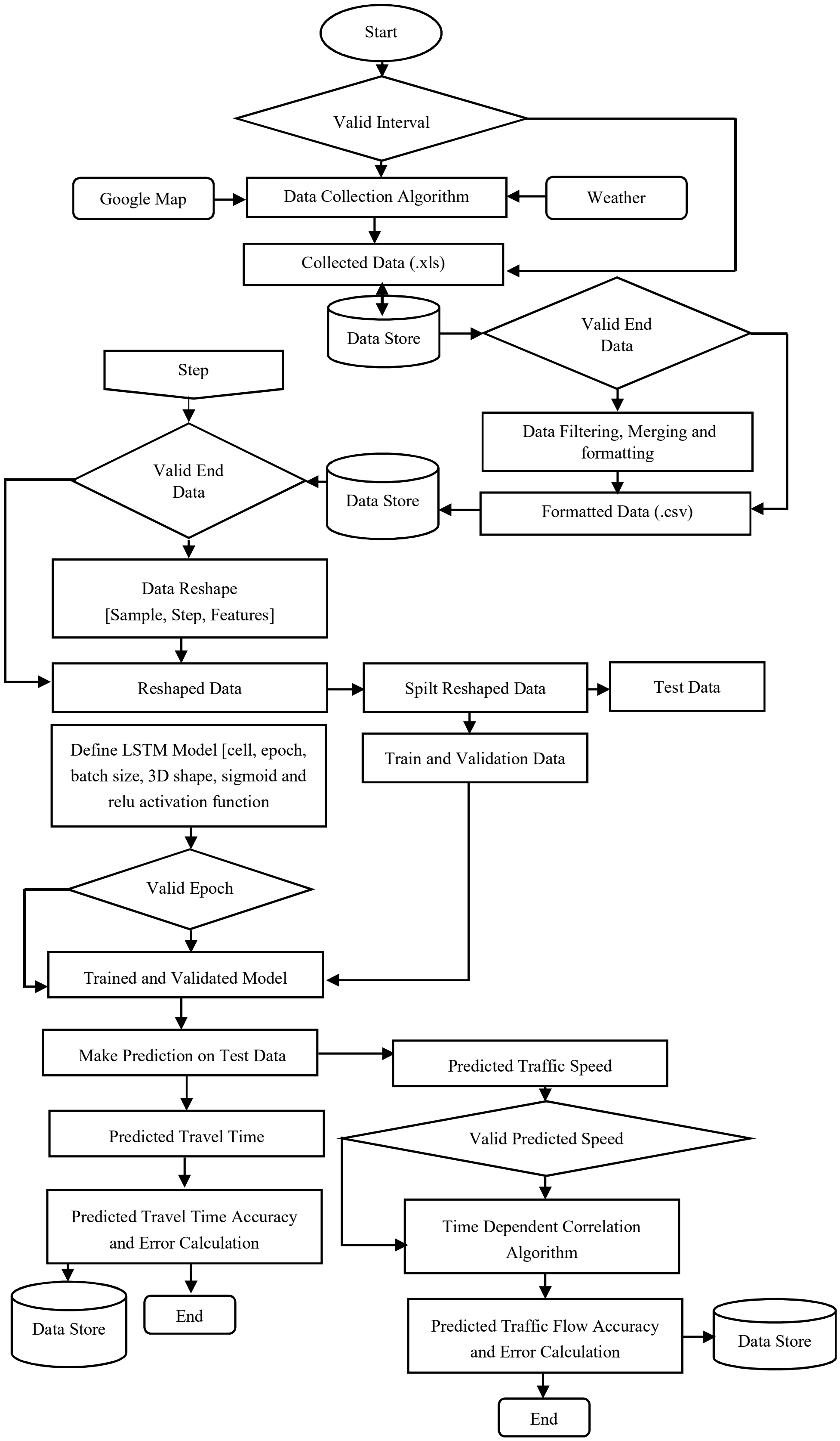

Fig-4.2, Developed LSTM model for travel time and traffic flow prediction

The LSTM block predicted travel time accuracy is measured by using three types of formulas: MRE, MAE and RMSE. Only predicted traffic speed employed a time-dependent correlation algorithm for getting target outcomes (traffic flow) for a road section. Finally, calculate the predicted traffic flow accuracy and performance through the above three terms. The above errors indicate a developed model accuracy level. Model accuracy depends on the number of hidden cells or neurons, trained time or epoch and model faster execution performance based on batch size. Higher hidden cells stored more information during train and ensure high accuracy and consumed more time during train. Higher cells or neurons performed the same task for target output and ensure high accuracy from higher cell output. Similarly, smaller cells or neurons performed the same task and ensure less accuracy. For optimum prediction accuracy, a standard equation exploring for calculating hidden cells based on sample, features and output neuron.

4.4 LSTM Basic Cell Structure and Prediction Procedure

The stacked LSTM models are developed for one-step and multi-step ahead predicting travel time and traffic speed prediction. The stacked LSTM deep learning model is developed using optimized sized cells or memory by considering the training dataset. The basic LSTM cell or memory structure is shown in Fig-4.3. Information adds or removes to or from the cell state or memory through a control unit called a “gate” [15]. The LSTM cell consists of three gates – input, forget and output with a sigmoid activation function which is multiplied by the output of other neurons [28]. Using the forget gate, LSTM can selectively remember or forget previous cell information to the current cell state or memory that does not get passed through an activation function [7].

Similarly, input and output gates control the input and prediction through the rectified linear unit (relu) activation function. For example, LSTM receives input x_t at time t when the previous cell output is h_{t-1} and cell state is C_{t-1}. Calculating hidden layer output h_t and cell state C_t by using equations 1-6. Both outputs C_t and h_t will be transferred to the next cell as inputs and memory state onward. That’s why LSTM is called a recurrent neural network.

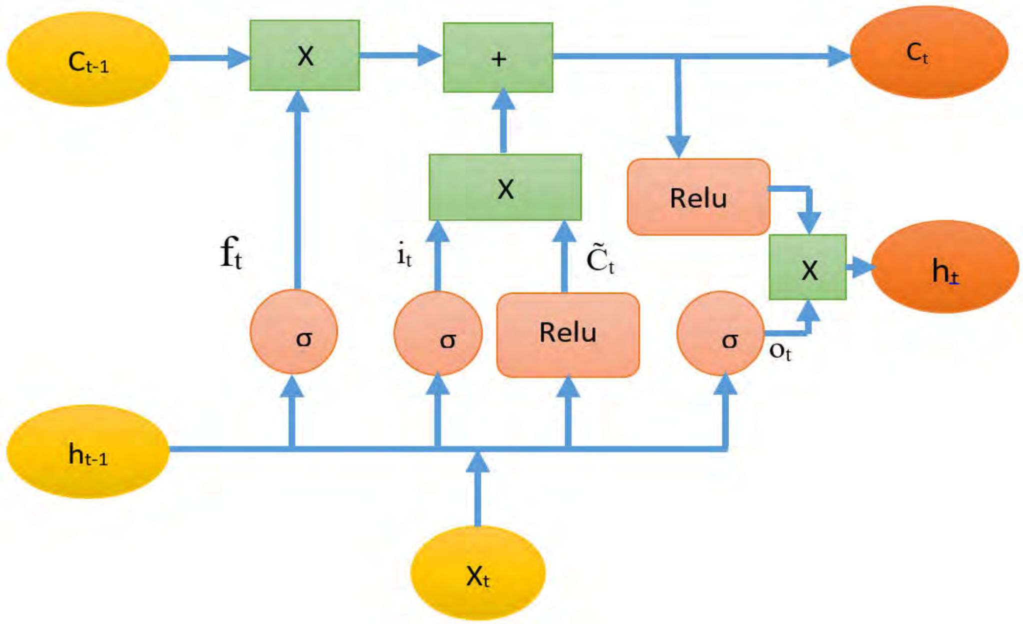

Fig-4.3, Developed model cell structure

Forget gate, $f_t = \sigma(U_f \,.\, x_t + W_f \,.\, h_{t-1} + b_f)$ (1)

Input gate, $i_t = \sigma(U_i \,.\, x_t + W_i \,.\, h_{t-1} + b_i)$ (2)

Output gate, $o_t = \sigma(U_o \,.\, x_t + W_o \,.\, h_{t-1} + b_o)$ (3)

Cell input state, $\tilde{C}_t = relu(U_c \,.\, x_t + W_c \,.\, h_{t-1} + b_c)$ (4)

Cell output state, $C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$ (5)

Here, f_t, i_t, o_t, $\tilde{C}_t$, C_{t-1} and C_t are carrying the same dimension. The U and W are weight vectors of forget, input, output gates and cell state, b_f, b_i, b_o, b_c are the input bias of these three gates and cell input. The symbol σ represents the sigmoid function $f(x) = 1/1+e^{-x}$ which are control three gates and relu represents the rectified linear function f(x) = max (0, x). The hidden cell output, h_t can be calculated as per Eq. 6.

$$h_t = relu(C_t) * o_t \quad (6)$$

4.5 Sequential Data Prediction Using LSTM Networks

The LSTM network is suitable for analyzing sequential or time-series data in various aspects like travel time and traffic flow prediction through different types of models [7,15,22,25,27,29]. Time-series data is a sequence of numerical data points in successive order.

The time series or sequential data maintain an order where the next step depends on the previous step. Travel time and traffic speed data are sequential data in which current travel time or traffic speed information depend on the previous step. The LSTM process of predicting the future step using current and previous data. The model prediction accuracy depends on properly training the model through the previous historical and current dataset. The multi-layer LSTM model prediction accuracy higher compare to the single layer. In this research, we developed a two-layer multi-block of stacked LSTM network for predicting multi-step travel time and space mean speed which are shown in Fig-4.4.

For example, considering at t time, the input of LSTM network is the historical data of travel time or space mean speed like x_{t-1}, x_t , x_{t+1} and the predicted output at one-step ahead are $\tilde{y}_t$, $\tilde{y}_{t+1}$ and $\tilde{y}_{t+2}$ respectively. Two step-ahead prediction input sequences like, $\{x_{t-1}, x_t\}$, $\{x_t, x_{t+1}\}$,$\{x_{t+1}, x_{t+2}\}$ and predicted outcomes are $(\tilde{y}_{t+1})$, $(\tilde{y}_{t+2})$ and $(\tilde{y}_{t+3})$ respectively. Similarly, three-step ahead prediction $\tilde{y}_{t+3}$ can be done by previous three steps $\{x_t , x_{t+1}, ,x_{t+2}\}$ sequences of observations. Now, the actual output of the stacked LSTM network will be as per the below equations.

$$\tilde{y}_t = w_y . h^2_{t-1} + b \quad (7)$$

$$\tilde{y}_{t+1} = w_y . h^2_t + b \quad (8)$$

$$\tilde{y}_{t+2} = w_y . h^2_{t+1} + b \quad (9)$$

Where W_y is the weight matrix between output and hidden layer and b is the bias of the output layer. One step ahead prediction requires the previous one as an input while two-step requires previous sequential two-step observation as an input. In such a way, historical time series information goes through the networks by recurrent calculation and sequential prediction is attained by the long short-term memory of the network states.

In the travel time prediction, the LSTM model output considers as predicted output whereas the predicted traffic speed of each interval is correlating with the time-dependent correlation equation through the developed algorithm for getting the traffic flow for a road section.

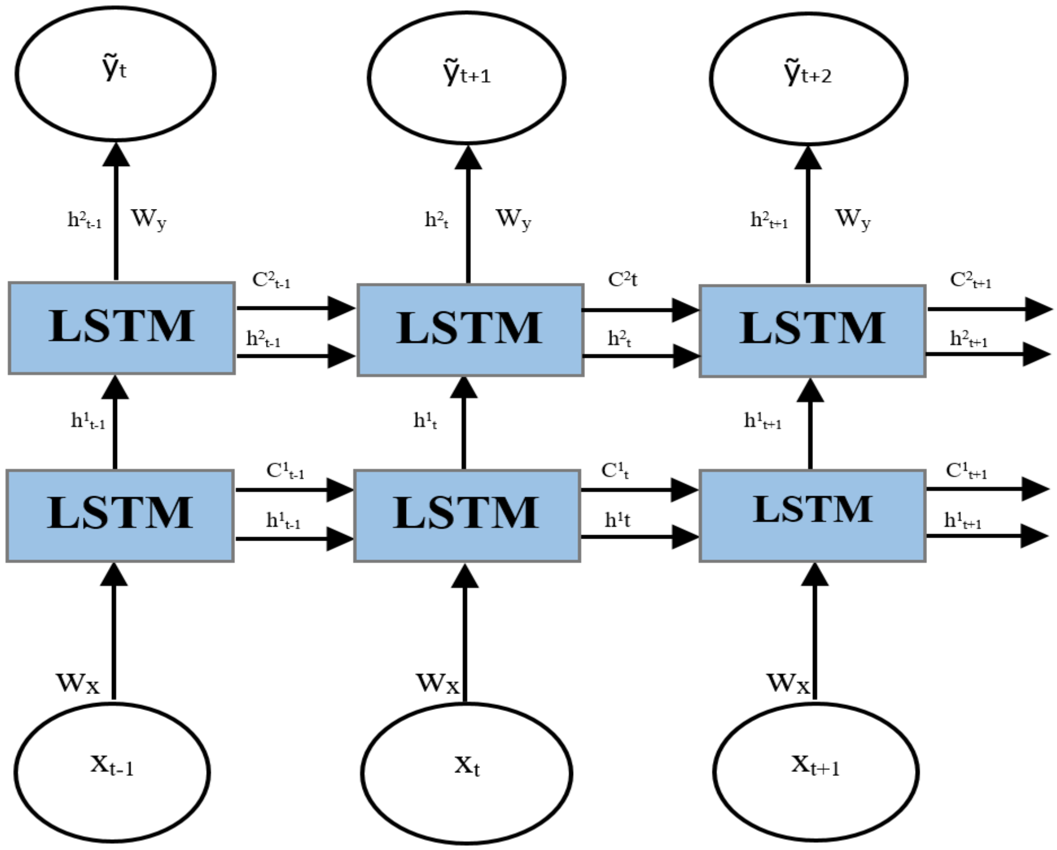

Fig-4.4, Stacked LSTM sequential structure

4.6 Traffic Flow Prediction Algorithm through Time-Dependent Correlation

Stacked LSTM model predicted traffic speed employed to time-dependent correlation for forecasting the traffic flow for a road section. In this context, traffic speed and traffic flow data are collected for several road sections from Google Maps and actual or field level at the five-minute interval for a day from 8:00 AM to 12 PM and 3:00 PM to 7:00 PM. A time-dependent correlation is developed using traffic speed collected from Google Maps and field level real-time traffic flow according to their timestamp for each road section. Time-dependent correlations between traffic speed and traffic flow have some positive and negative correlations [30]. Every day, traffic speed range are limited and same speed exist in multiple time at morning and evening hours whereas traffic flow is different for the same traffic speed.

In this situation, six consecutive five minutes intervals, traffic speed and field level traffic flow data are employed for getting strong correlation equations where co-efficient R square is a positive or strong correlation. Hourly two correlation equations are considered for morning hour to evening hour based on collected data for a road section and similar for others road section. The traffic flow calculation is done by using an algorithm where b, c, d are coefficients of predicted speed, minute, hour and a is the intercept for a road section. The algorithm is mapped traffic flow prediction based on time and predicted traffic speed. Please see the appendix-I for details.

4.7 Summary

The research included several methodologies like data collection, data pre-processing, and LSTM model development, manually process Google Maps travel time prediction and time-dependent correlation development for predicted traffic flow by using predicted traffic speed. The optimum hidden cell, epoch, batch size are considered according to the keras recommendation and the best activation function is also utilized in the developed model. The relu activation function basically employed the developed model to properly train and avoid the gradient descent problem.

The developed two layers stacked LSTM model investigated for a maximum of one hour ahead travel time and fifteen minutes ahead traffic flow prediction considering minimum error. The developed model can predict n number of steps ahead or advanced prediction with minimum highest accuracy through the 24 hours collected trained dataset. For 12 hours dataset, the model predicted error will be increased while increasing steps due to the model will be learned through the next day starting or morning dataset after 8:00 PM of each day. It can be overcome by considering 24 hours trained dataset extracted.

Chapter 5

DATA COLLECTION AND PREPROCESSING

The LSTM deep learning prediction model requires a higher number of training data set for obtaining high accuracy. The data collection process is a very challenging and hard job for any research. The developed model prediction accuracy depends on a collected dataset that is employed for training and validation. Our developed model data collection technic is easy and smart compared to the conventional models like roadside cameras, probe data, induction loop detectors and GPS networks. The travel time and traffic speed data were collected from an urban city in Dhaka, Bangladesh through an algorithm from Google Maps in phase by phase and sometimes parallel. Initially, Sainik club to Kachukhat, around 1200 meters distance and vice-versa road segments were selected for studying the accuracy between Google Map provided travel time and actual or field level real-time travel time or the traffic condition. In this context, actual or field-level travel time and Google Maps provided travel time data were collected on two different days and two different time slots like 20/03/3019 (Wednesday) and 24/03/2019 (Sunday) from 8:00 AM to 12:00 PM and 3:00 PM to 7:00 PM whereas, the actual or field level travel time collected through GPS logger. A private vehicle was rented for collecting actual or field travel time data collection on said days. Both data collection processes started at the same time and ended separately after reaching the destination individually. The data collection was performed by three rounds in one day and seven rounds on another day. The average Google Maps prediction accuracy investigation is done through ten rounds of collected data.

In the second phase, one-step and multi-step ahead travel time prediction model's data were collected from 8:00 AM to 8:00 PM at five minutes intervals of Hatirjheel to Gulshan-2 (HTG) around 2.5 km and it's divided into five road sections (each approximately 500m). The collected travel time data were the sum of five segments cumulative (segment-wise) and direct road segment. The sum of five road segments and direct 2.5 km road segment travel time accuracy difference maximum 1%~2% vice-versa. That means there is no difference between direct source to destination travel time and the sum of segment-wise travel time. This is because Google Maps updates traffic information in real-time through the crowdsourced.

Also, their prediction accuracy is much closed to each other. Here direct road segments travel time data is employed as an input of LSTM deep learning for simulating by considering the high accuracy. At the same time, adjacent road speed, VIP road speed and weather information in each interval for improving the model prediction accuracy. Travel time data were extracted from Google Maps using a defined algorithm which is mentioned in the methodology section. The duration of the travel time data collection period continued for fifteen days and each day around 145 instances were collected from Google Maps and weather forecasting information from the respected website. The total collected amount of data is 2,098 instances whereas the first 1953 instances were used for training and validation and the next 145 instances were used for testing or predicting purposes. These data are prepared for feeding to the stacked LSTM network model into 3 dimension shapes like [sample, steps and features]. In this model, 67% of travel time data was employed for training and the rest 33% for model validation out of 1953 training instances. The model considered 19 features like a holiday, weekday, month, hour, minutes, weather information, VIP road speed and several adjacent roads travel time information are considered for this road segment travel time prediction. The three different time intervals of collected data on a specific day is shown in Fig-5.1.

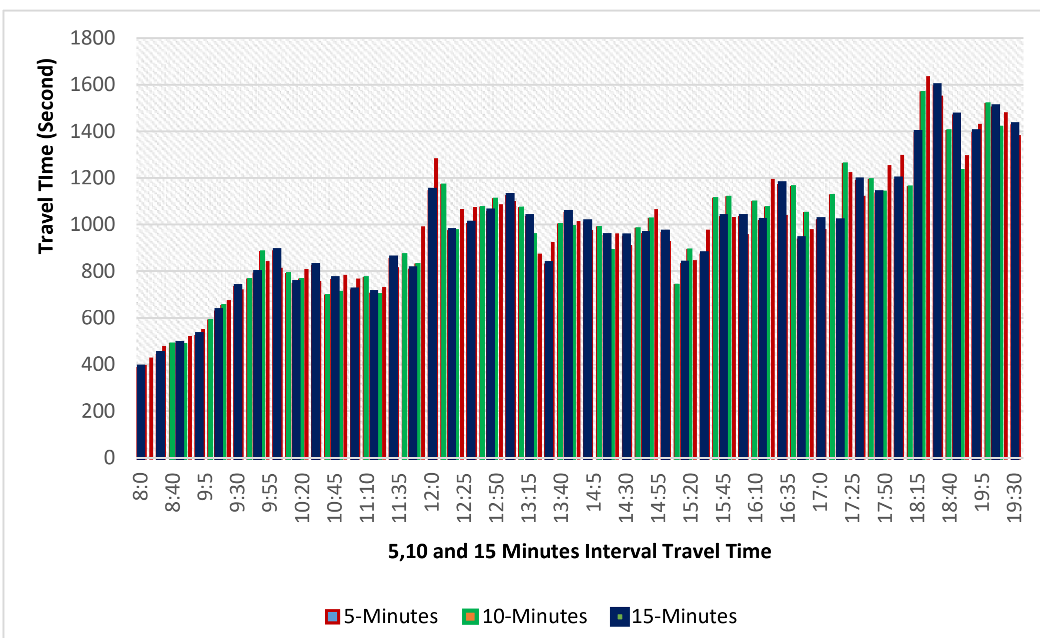

Fig-5.1, Three different time interval data, HTG

The travel time increased linearly from morning 8:00 AM to 8:00 PM for three different time intervals. Also, the travel time indicates that traffic flow at morning hours was lower compared to the evening hours. In different time intervals, the travel time for this road section is almost the same. The collected all travel time data were non-negative and greater than zero.

In the third and final phase, traffic speed or space mean speed data were collected from three different signalized, non-signalized and freeway road segments at five minutes intervals from 8:00 AM to 12:00 PM considered morning hour and 3:00 PM to 7:00 PM considered as evening hour whereas each segment length range 140m to 300m. At the same time, weather information and adjacent road speed as well as VIP movement road speed data were also collected for getting the highest level of prediction accuracy. These three road segments are Sainik club intersection (two road sections) as shown in Fig-5.2.

Fig-5.2, Sainik club segment or intersection

The two road sections are CTW (centre to west), CTN (centre to north). The Sainik club road is the most important and busy road in this research. The multi-step traffic flow prediction considered five-minute intervals on CTW road section at evening hour only for three-step considered as little bit traffic demand whereas CTN road section as one of the busy road section and considered high demand traffic flow analysis.

Army stadium road section STN (south to north) is considered as free flow or freeway traffic analysis and is shown in Fig-5.3. The army stadium road section is considered as freeway traffic flow due to its speed range is higher compared to other road sections. These three road sections data collection were done by two different hours like morning and evening.

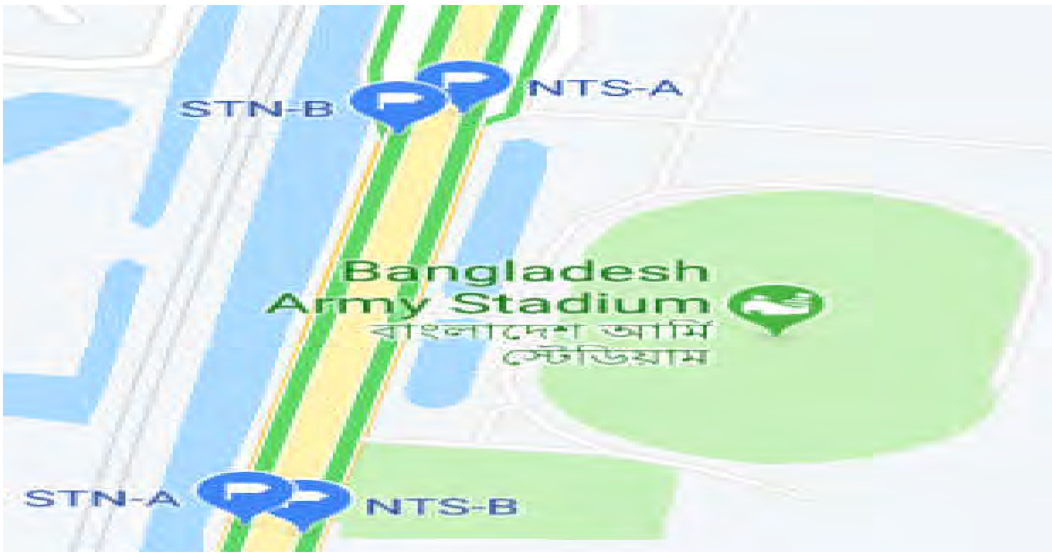

Fig-5.3, Army stadium road section

Every day, we collected traffic speed data around 48 instances for morning and 48 instances for evening hour and the total collected data per day is 96*3 instances for three intersections. In such a way, the data collection duration was continuous one month long. To develop a time-dependent correlation with the real-time traffic flow and Google Maps traffic speed, field-level real-time traffic flow data were collected for these three road sections. The traffic speed data and traffic flow data were collected at the same time for considering the strong relation between them in each interval. The travel time, speed, segment, lanes, adjacent road's speed, VIP road speed and weather information were extracted from Google Maps and another respected website by using distance matrix API with necessary python libraries.

The CTW road section field level collected traffic flow pattern data graph is shown in Fig-5.4 at morning hour. The traffic pattern is classified into five categories like a motorcycle (MC), car, CNG, bus and non-motorized vehicles (NMV).

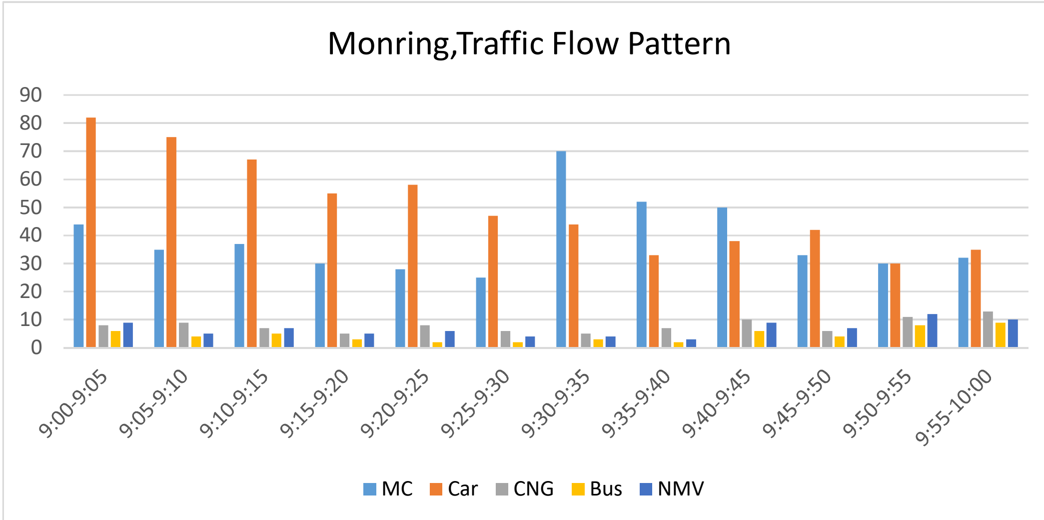

Fig-5.4, 9:00AM to 10:00AM traffic flow pattern of CTW

The above Fig-5.4 indicates that the number of cars in the morning hour is higher compared to motorcycle (MC) and at evening hour, number of motorcycles flow was higher compared to cars whereas other's type categories of the vehicle remain almost similar. The evening hour traffic flow pattern graph is shown in Fig-5.5. The car, bus and non-motorized vehicles flow variation is similar with other days and times. But the number of motorcycles are differed at time basis due to ride-sharing and number car owner are increasing day by day.

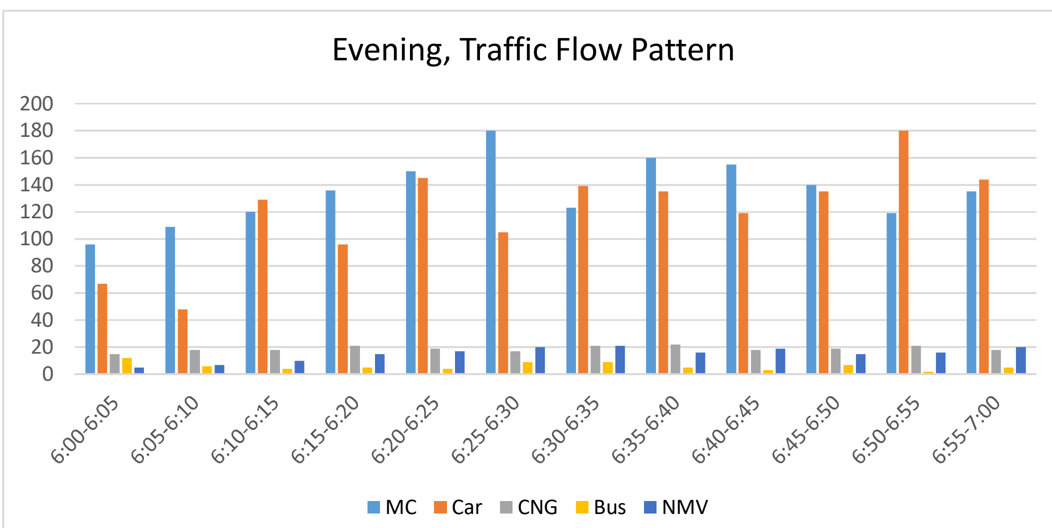

Fig-5.5, 6:00PM to 7:00PM traffic flow pattern of CTW

The motorcycle and car cause the total number of traffic flow frequently changed; e.g., three number sections specially CTW and CTN road sections are highly impacted. Moreover, the motorcycle's movement did not maintain the traffic policy. They have frequently changed the lane and also traffic speed frequently changes from one interval to the next interval as well.

The developed model data collection was included manually and automated through the various procedures for these road sections. The travel time and traffic speed data were collected in parallel at 8:00 AM to 8:00 PM and 8:00 AM to 12:00 PM and 3:00 PM to 7:00 PM. We manually collected actual or field level traffic flow data for driving time-dependent correlation equations. In this study, CTW, CTN and STN road sections traffic data are considered for model simulation including their adjacent road information for ensuring high prediction accuracy.

CTW road section data for normal traffic flow but interrupted by two signals and CTN road section considered busy traffic and STN (army stadium) for freeway traffic for three-step ahead traffic flow prediction. Hatirjheel to Gulshan-2 (HTG) road section data is considered for multi-step (one hour) ahead or advanced travel time prediction. Moreover, manually collected travel time data from Sainik club to Kachukhet was used to find out the Google Maps provided travel time accuracy in respect of actual traffic conditions.

The travel time, traffic speed and spot collected data are initially saved in .xlxs separate files; then formatted with python programming language according to model input shape. Google Maps collected or extracted data are formatted automatically for model required shape whereas only manually collected data are processed through .xlxs files.

The Google Maps provided traffic information server was performed excellently during the data collection period whereas the data collection server was interrupted fewer times in a day. Continuous internet connection and power must be ensured in the data connection server for smoothly completing the desired road sections traffic data.

Chapter 6

MODEL SIMULATION

Developed models simulation or experimental process were performed in two different ways: manually and LSTM deep learning network models. The Google Maps provided travel time accuracy in respect to actual or field level real-time travel time is performed by manual and two separate two-layer stacked LSTM deep network models are developed to predict travel time and traffic speed for specific road sections based on current travel time, speed, road properties, historical data, VIP movement, adjacent road's speed, weather condition, holiday, weekday, month, hour and minutes etc. The dimension of the stacked LSTM network input and output at each time step is equal to the dimension of the travel time and traffic speed in each time. The first layer processed partial output is considered as input of the second layer for completing outcomes. According to the stacked LSTM properties, the first layer process some part of the task and passes the output to the next layer for final prediction.

Moreover, the number of cells or memory is higher compare to the single-layer LSTM model or vanilla model. The higher number of cells causes the same task to process multiple cells at a time and prediction accuracy is higher compared to the small number of hidden cells. The number of hidden neurons n_h for a model is determined by Eq.10. For better prediction accuracy and performance, the number of epochs can be reached a maximum of 500, the batch size equal to 128 and appropriately hidden neurons for both travel time and traffic speed prediction model as per keras recommendation for adequate train, validation and prediction. The developed model included early-stopping with patience and model checkpoint for higher accuracy with variable epochs to minimize the CPU utilization.

The travel time prediction model simulated on Hatirjheel to Gulshan-2 (HTG) road segment on Monday's (06/05/2019) data for twelve-step ahead and other three separate models like CTW road section low demand traffic flow, CTN road section is considered high traffic demand or more busy traffic and STN road section is considered freeway traffic for three-step ahead traffic flow prediction on Mondays (25/03/2019).

The simulations are carried out for one-step ahead prediction: suppose $\tilde{y}_{t+1}$, $\tilde{y}_{t+2}$, $\tilde{y}_{t+3}$ considering the past observation step as $\{x_t\}$,$\{x_{t+1}\}$ and $\{x_{t+2}\}$. Two steps and three steps ahead prediction: suppose $\{\tilde{y}_{t+2}\}$ and $\{\tilde{y}_{t+3}\}$ considering the past observations steps as $\{x_t, x_{t+1}\}$ and $\{x_t, x_{t+1}, x_{t+2}\}$. Each model number of hidden neurons are assigned as per below Eq. 10 for optimum accuracy and performance.

$$n_h = N_s/(\alpha^*(N_i + N_o)) \qquad (10)$$

Where N_s is the number of observed samples, N_i Input features, N_o is the number of output neurons and α is an arbitrary scaling factor usually range 2-10. In this model, we employed an arbitrary scaling factor α=2 and got optimum prediction accuracy and minimum error in each road segment. Each model simulation is done by training and evaluation process.

6.1 Developed Model Training and Validation

Model train and validation are part of the simulation process. A two-layer stacked LSTM deep network model is developed based on the model train and test data for predicting travel time and traffic speed. Two different types of models are developed for two separate types of data prediction. Similarly, training and testing are performed in these two types of models separately. Proper training is the first prerequisite for getting better prediction accuracy through the developed LSTM network model. Moreover, the optimized parameter setting is an important part of the model train and validation phase. A stacked LSTM network requires determining the model parameters for accurate prediction of the targets with respect to the input sequences.

In the stacked LSTM models, the dimension of the hidden layers n_h are varying considering input observations, training samples and output steps to achieve the best fit of the model where batch size equal to 128 and epochs range is 500 maximum for obtained minimum training loss and high prediction accuracy. Early stopping with patience and model checkpoint is considered during training the model for optimum learning.

The early stopping monitors the value train & test loss and stops the training process while minimizing the loss and model checkpoint saved the best model trained state while training. The model check-point strategy is to save the model weights to the same file, if and only if the validation accuracy improves. Patience is the number of epochs with no improvement after stop the training. The model training epochs are varying and it depends on the minimization of the trained loss. Moreover, an LSTM model structure and parameters can vary on the number of input samples and usages application's type (as per keras) for better accuracy and performance. During the simulations period, trained and validated the model separately for travel time and traffic speed through Eq. 1-7 for time t and predicted travel time and space mean speed or traffic speed accordingly. In this research, predicted travel time data is directly considered as target outcomes whereas predicted space mean speed or traffic speed data are correlated with the time-dependent correlation equations for obtaining the traffic flow.

During the training period, we split train input samples into 67% and 33% for training and validation for both models and 145 instances for travel time prediction and 48/96 instances for traffic speed prediction according to the road segment. Travel time and vehicle flow prediction model trained flowchart is similar and only predicted traffic speed employed to the time-dependent correlation equations using an algorithm for obtaining traffic for an instant of time. Both model's training, validation and prediction flowchart is shown in Fig-6.1. The model parameters are adjusted based on the training samples and observations dataset. The basic model parameters are hidden layers, batch size, epoch, activation function sigmoid, relu, optimizer algorithm like adams, loss calculated by mean absolute error, early-stopping and model checkpoint.

The model prediction accuracy depends on these parameters. Adam is an optimization algorithm that can be used instead of the classical stochastic gradient descent procedure to update network weights iterative based on the training dataset. The algorithm is called Adam. Adam name is derived from adaptive moment estimation. This optimizer default learning rate 0.001 and optimum hidden neuron employed using equation (10) during training and testing.

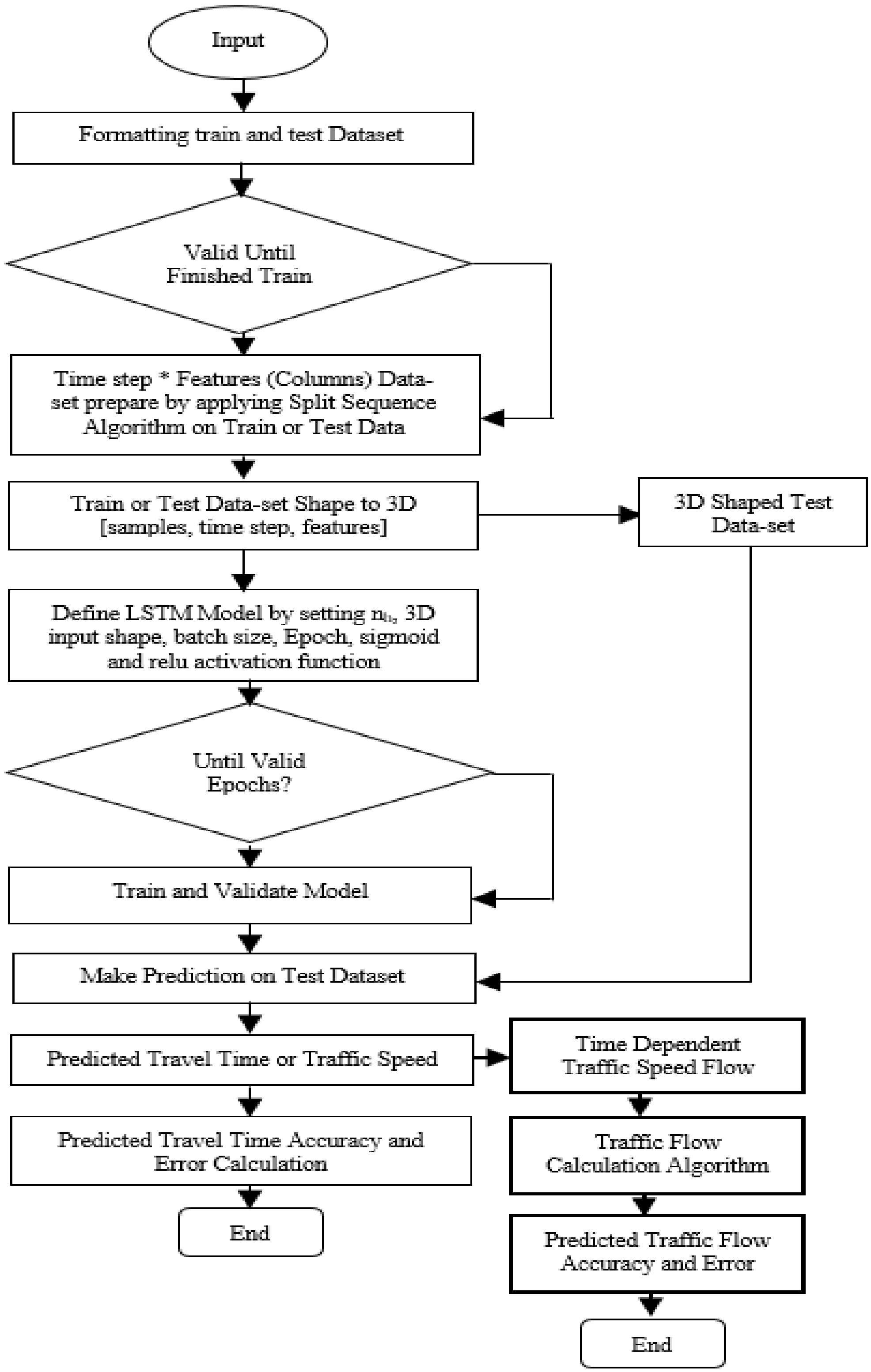

Fig-6.1, LSTM train, validation and Test flowchart

6.2 Developed Model Evaluation

The model outcomes are investigated through the model evaluation process. Model evaluation means, how the model performs on test data after training and validating the model. During the simulation, training and validation samples are 1,953, 983 and 660 for travel time and 2688 and 1344 samples are employed for the traffic flow prediction model with respect to five minutes time intervals. The training, validating and testing are performed on 2.5km single road section for travel time and CTW, CTN and STN road section's data for traffic flow prediction. Similarly, (145, 73, 49) and (96, 48) samples are considered for travel time and traffic flow prediction or test on different time interval datasets.

To evaluate these models on the above test datasets, performed forward propagation recurrently by using Eq. 1-7 for computing $\{\tilde{y}_{t+1}\},\{\tilde{y}_{t+2}\},\{\tilde{y}_{t+3}\}$ at time $\{t\},\{t,t+1\},\{t,t+1,t+2\}$ input for one-step, two-step and three-step ahead prediction. In this research, three criteria's to measure the model prediction error and accuracy as presented in Eq. 11-13. The prediction accuracy measures the relative error or mean relative error of the model. A small mean relative error indicates a high predictive performance of the model. Also, models prediction performance is shown by mean absolute and root mean square error for comparing how deferred model prediction from actual.

The Mean Absolute Error (MAE),

$$MAE=\sum^{N} (|x_{t+1} - \tilde{y}_{t+1}|)/N \tag{11}$$

Root mean square error (RMSE),

$$RMSE= \{\sum^{N} (x_{t+1} - \tilde{y}_{t+1})^2 /N)\}^{1/2} \tag{12}$$

And Mean Relative Error (MRE),

$$MRE= \{(\sum^{N} |(x_{t+1} - \tilde{y}_{t+1})^{|} / x_{t+1})/N\} \tag{13}$$

Where N is the total number of test or predicted samples.

6.3 Train and Test Loss

The train and validation loss is an important factor in LSTM deep network. The training loss is the error on the training set of data. The test or validation loss is the error after running the validation or test set of data through the trained network. The train and test loss difference indicates the model performance on the test or target dataset. While train and validation loss are in same or equal, then the model will be considered the best or perfect fit for predicting the target. The perfect model train and test loss is shown in Fig-6.2. The best prediction model train and test loss or error is near about zero. In the real sense, training and validation loss error near about zero is quite impossible.

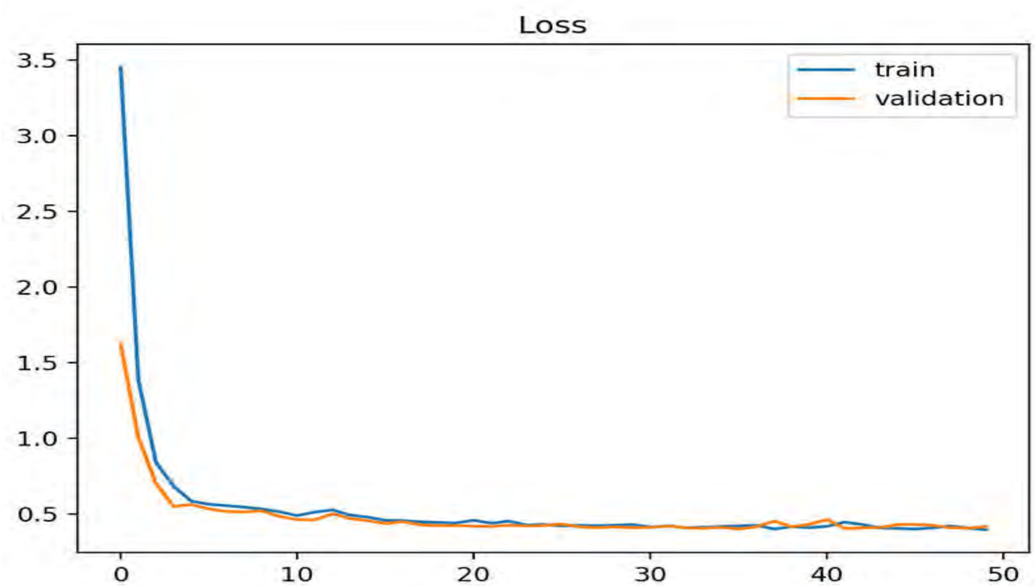

Fig-6.2, Best or good fit model for train and test

While validation loss is smaller than the training loss the model is called under-fitting the model. The underfitting model is shown in Fig-6.3. The under-fitting can be avoided by using more data and also more features, high variance model should be used. All unnecessary features must be removed from the train and test dataset. Sometimes prediction model required for data preprocessing procedure changes for better accuracy. The model is learned through the input observations and sequences of data. Whereas validation performed how the model reacts after being trained on few test data or validate dataset.

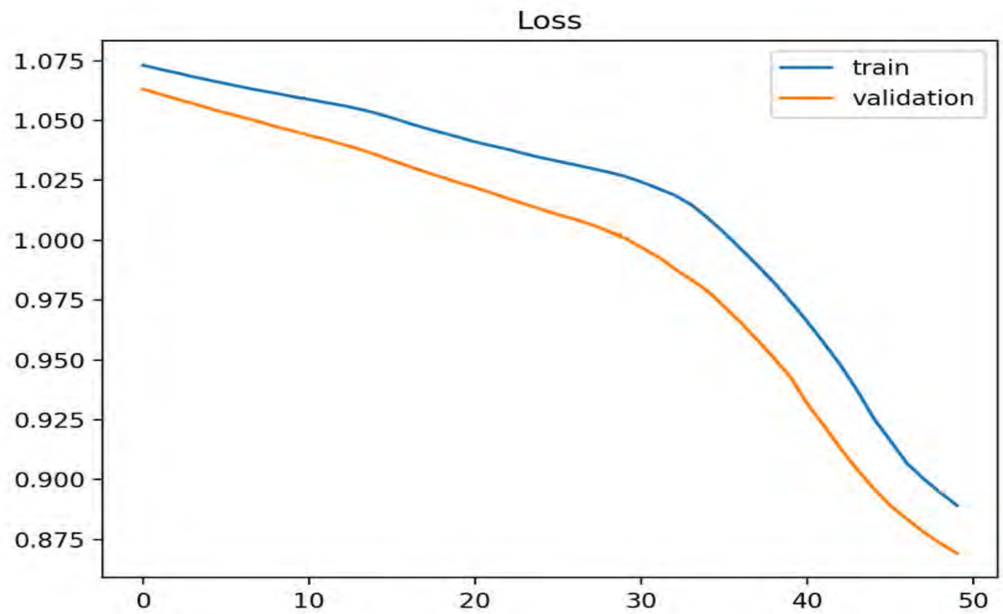

Fig-6.3, Underfitting model for train and test

When validation loss is higher than train loss, such a model is called overfitting. It can be prevented by adding more data, use data augmentation, generalize the architecture, add regularization and reduce complex architecture. The overfitting model train and test loss graph is shown in Fig-6.4. The overfitting cause, model prediction accuracy degrades and prediction error also increases. So that, it must be reduced by applying earlier features.

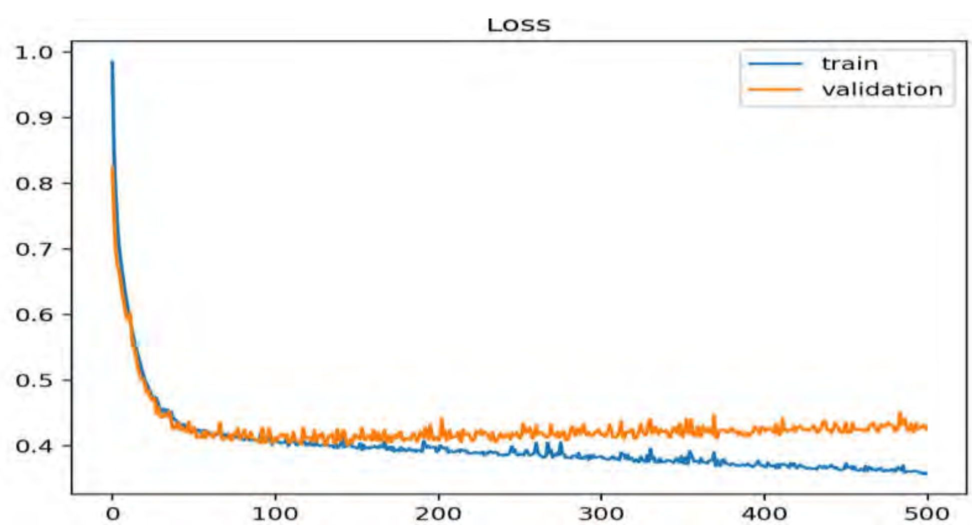

Fig-6.4, Overfitting model for train and test

6.4 Developed Model Simulation Summary

Developed models are simulated with a sufficient dataset for travel time prediction. In traffic volume prediction, models are also trained and validated with sufficient datasets. During simulation, train data is divided into two-part as per neural network like train and validation activities. Optimized hidden neurons and batch, epoch and other structural parameters are employed during simulation for getting higher accuracy. To minimize the CPU time, we employed optimum hidden neurons and relu activation function. Traffic flow prediction models simulation procedure similar to travel time prediction. Only extra mapping was performed after predicting speed with time-dependent correlations.

Simulated model prediction performances evaluated by mean relative error. If the error is small then model prediction accuracy will be high. During the training process, evaluated developed model train and validation loss and trained the model until train loss is almost equal to validation loss for getting best fit. Based on the model outcome modified structure and inputs dataset parameter in order to avoid overfitting and underfitting. Developed models overall performance achieved better compared to existing prediction models.

Chapter 7

RESULTS AND DISCUSSION

In order to investigate the developed model prediction accuracy and performance, three different types of experiments are performed through two types of models and as well as manually process datasets. The first excrement performed by manually process the dataset for Google Maps provided travel time accuracy obtained and two types of models are developed by stacked LSTM network deep learning for travel time and traffic prediction model. The stacked LSTM network models are employed for travel time and traffic speed prediction. The traffic speed prediction was developed by three separate models for three road sections. These model's simulation results are explored in below couple of sections.

7.1 Google Map Provided Travel Time Accuracy

The first experiment performed for computing the Google Maps provided travel time accuracy through the concern of actual or field or spot level collected travel time for a specific road segment. In this context, we considered a road segment like Sainik club to Kachukhat and vice-versa around 1251 meter distance for analyzing the accuracy of Google Maps existing travel time with respect to actual or field level collected at each interval. The field travel time data were collected on two different days by ten rounds considering the regular traffic flow, sunny-day and other impacts are out of the scope. The Google Maps provided travel time accuracy regarding the actual or spot or field level travel time is shown in Table-7.1.

Table-7.1, Google Maps travel time in respect to actual travel time

Round	Direction	Field TT	Google TT (Direct)	Google TT (Cumulative)	Accuracy (Direct) %	Accuracy (Cumulative) %
1	Sainink-Kacukhet	304	285	281	93.75	92.43
2	Kachukhet-Sainik	342	318	293	92.98	85.67
3	Sainink-Kacukhet	218	241	234	89.44	92.66
4	Sainink-Kacukhet	233	206	190	88.45	81.51
5	Kachukhet-Sainik	340	365	348	92.62	97.64
6	Sainink-Kacukhet	220	194	185	88.15	84.09
7	Kachukhet-Sainik	203	193	198	95.03	97.53
8	Sainink-Kacukhet	198	204	202	96.96	97.96
9	Kachukhet-Sainik	208	180	177	86.53	85.09
10	Sainink-Kacukhet	209	234	236	88.03	87.08

From the Table-7.1, rounds 1 to 3 data were recorded one day and 4 to 10 rounds of data were recorded on another day. The field level and Google Maps data collection starting times were the same and the ending times were different in each round and each direction. According to the Table-7.1, Google Maps direct (source to destination) and cumulative (segment-1 + segment-2 + segment-3) travel time almost closed each other in both directions. Both actual and Google Maps collected travel time data measured in seconds. The experimental result showed that Google Maps direct and cumulative travel time average accuracy are 91.19%, 90.16% in respect to the actual or field level travel time. The experiment also tells the Google Maps provided travel time accuracy is higher, reliable and broadly using authorized countries in the world for temporary avoiding the traffic jam. Moreover, its accuracy increasing day by day due to internet-enabled or smartphone users are increasing rapidly. In this research, we employed such 91.19% accuracy or Google Map direct provided accuracy data for travel time and traffic flow prediction.

7.2 Travel Time Prediction Model

To demonstrate the travel time prediction model, we considered Hatirjheel to Gulshan-2 (HTG), a 2.5KM road segments observed data including various features like weather condition, holiday, weekday, month, hour, minute, adjacent road's speed and VIP movement status for this road segment. These features directly influence the travel time variation and also play a vital role in travel time prediction. The travel time prediction model is simulated a maximum of one hour or twelve-step ahead prediction by using 28 to 98 hidden neurons, 128 batch-size, variable epochs and 19 features at five, ten and fifteen minutes intervals of a dataset. The prediction accuracy depends on proper training and validation of the model through a sufficient dataset.

The simulated stacked LSTM model is best fitted for predicting travel time to avoid over-fitting and under-fitting. The simulated model train and test loss graph at five minutes intervals is shown in Fig-7.1. The model is being best fitted from 10 epochs to continue according to Fig-7.1 for one step ahead prediction at five minutes intervals. And it's slightly overfitting and underfitting, while simulated at ten and fifteen minutes interval datasets.

Train and test loss slightly degrade due to data set decrease while ten and fifteen minutes interval data set processing for prediction. According to this Fig-7.1, the training loss was initially high then reducing over the period of train time or epochs.

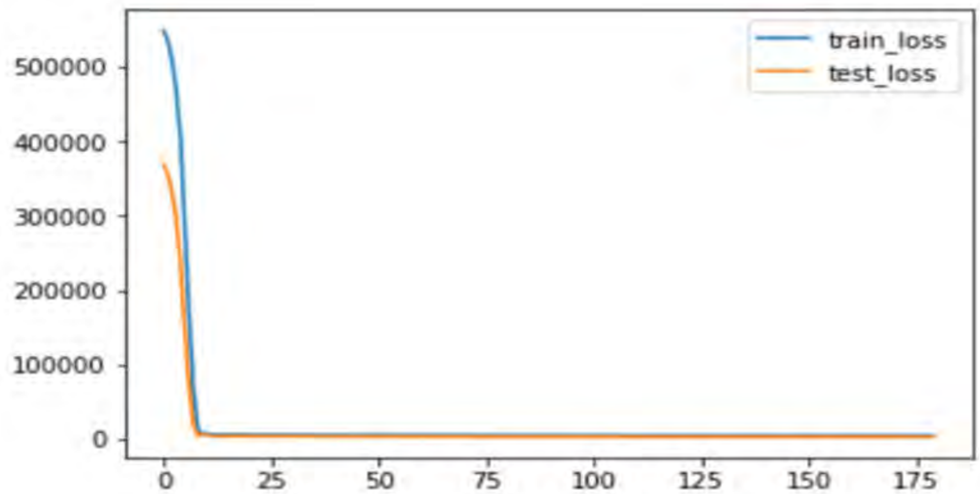

Fig-7.1, Train and test loss travel time at five-minute interval

The multi-step ahead predictions are simulated through the developed stacked LSTM model and got the prediction accuracy error range 5.84% ~ 10.93% in respect to mean relative error for five, ten and fifteen minutes interval data. The model travel time prediction errors are shown in Table-7.2. According to the table-7.2, the prediction errors are minimum while time interval is five minutes even twelve-step (one hour) ahead or advanced prediction and increases while predicting ten and fifteen minutes of interval data one hour ahead prediction. Here, one-step-ahead prediction at five minutes intervals indicates the next five minutes ahead prediction. Two and three-step ahead prediction at five intervals indicates the next 2*five minutes, 3*five minutes and twelve-step mean 12*five (one hour) ahead prediction. Similarly, two-step ahead prediction of ten and fifteen minutes interval of dataset indicated are 2*ten minutes and 2*fifteen minutes advanced prediction. The prediction error slightly increases while interval time increases due to the number of train samples is reduced at ten and fifteen-minute intervals prediction. Ten and fifteen minute's interval train data are 983 and 660 instances respectively. Moreover, in multi-step ahead prediction train sequences are prepared by next day initial sequences of data after 8:00 PM due to lack of 24 hours data.

That's why the model weights are updated and learned according to the next day targeted travel time at the end of the day based on prediction step(s). The model train and prediction performance degraded due to the dataset gap between two days. In this case, predicted errors increase in the last couple of sequences while making the multi-steps ahead prediction. It will be avoided by considering 24 hours data collection for making accurate multi-step ahead predictions. One step ahead prediction is affected by the next day initial one sequence data. That's why one-step-ahead prediction accuracy is higher compared to multi-step prediction. Also, multi-step ahead prediction required more train data set as well as 24 hours.

Table-7.2, Multi-step ahead travel time prediction accuracy

Step	Minutes	Training Data	Validated Data	Neuron	Epoch	MRE (%)	MAE (Sec)	RMSE (Sec)
1	5	1309	643	49+49	180	5.84	58.42	77.61
2	5	1309	642	46+46	129	5.86	59.90	81.05
3	5	1309	641	44+44	180	6.29	65.03	87.93
4	5	1309	640	42+42	180	6.60	66.97	88.15
5	5	1309	639	41+41	181	6.90	70.93	96.55
6	5	1309	638	39+39	135	6.63	68.07	93.14
7	5	1309	637	38+38	350	6.60	67.17	89.53
8	5	1309	636	36+36	305	7.15	73.69	99.54
9	5	1309	635	35+35	234	8.75	91.12	122.61
10	5	1309	634	34+34	171	7.76	80.49	109.50
11	5	1309	633	33+33	254	8.58	90.09	119.97
12	5	1309	632	32+32	498	8.31	88.10	115.54
1	10	659	323	25+25	75	7.49	76.28	108.58
2	10	659	322	23+23	388	7.98	80.92	109.99
3	10	659	321	22+22	225	7.80	80.86	111.18
4	10	659	320	21+21	307	9.86	103.80	139.03
5	10	659	319	20+20	242	10.48	111.26	151.14
6	10	659	318	19+19	179	10.93	114.14	149.21
1	15	442	217	16+16	123	8.49	85.83	115.70
2	15	442	216	16+16	214	9.02	90.91	116.79
3	15	442	215	15+15	210	10.22	101.93	128.57
4	15	442	214	14+14	225	9.18	93.49	120.01

Table-7.2 indicates that the lowest three types of error like MRE 5.84%, MAE 58.42 (sec) and RMSE 77.61 (sec) for the five minutes interval data compared to ten and fifteen minutes intervals of data. Other's steps prediction errors gradually increased due to smaller train dataset and training sequences problem for the 8:00 AM - 8:00 PM dataset which is biased by next day data. In addition, travel time prediction accuracy stable at five minutes intervals compare to others because urban traffic patterns frequently changed with the time interval.

The model prediction accuracy also depends on the input features or observations and the number of hidden neurons. More hidden neurons consumed more training time, and high accuracy whereas a small number of hidden neurons indicate fast training and low accuracy. In this context, considering better performance and accuracy, the hidden neurons are adjusted using equation-10 for getting optimum performance.

The model's other two errors mean absolute and root mean square is relatively small at five minutes intervals of data from one step to twelve-step ahead of travel time prediction. Also, ten and fifteen minute's intervals of data MAE and RMSE are comparatively small for frequently changes urban traffic patterns. These errors will be reduced while using the 24-hour training dataset and smaller time intervals.

The developed model simulated a maximum one hour ahead travel time prediction whereas twelve-step ahead at five minutes, six-step ahead at ten and four-step ahead at fifteen minutes interval dataset. The twelve-step ahead travel time prediction graph is shown in Fig-7.2.

The experiment performed based on their previous travel time historical information including adjacent roads, VIP movement status and weather information. Each step prediction accuracy is most higher like 94% and closed to next-step ahead prediction until seven-step and after eight-step, to last step ahead prediction error gradually increased. The prediction error increased while increasing the number of steps due to the lack of 24-hour training data.

The prediction travel time accuracy reducing after 8:00 PM in each step due to unavailable sequential train dataset. After 8:00 PM, the model trained by next day morning sequence of data whose actual travel time was small. The prediction accuracy will be improved more while training the model with 24 hours continue dataset. So that, the developed two-layer stacked LSTM network is suitable for predicting time series or sequential data one-step or multiple steps ahead with higher prediction accuracy.

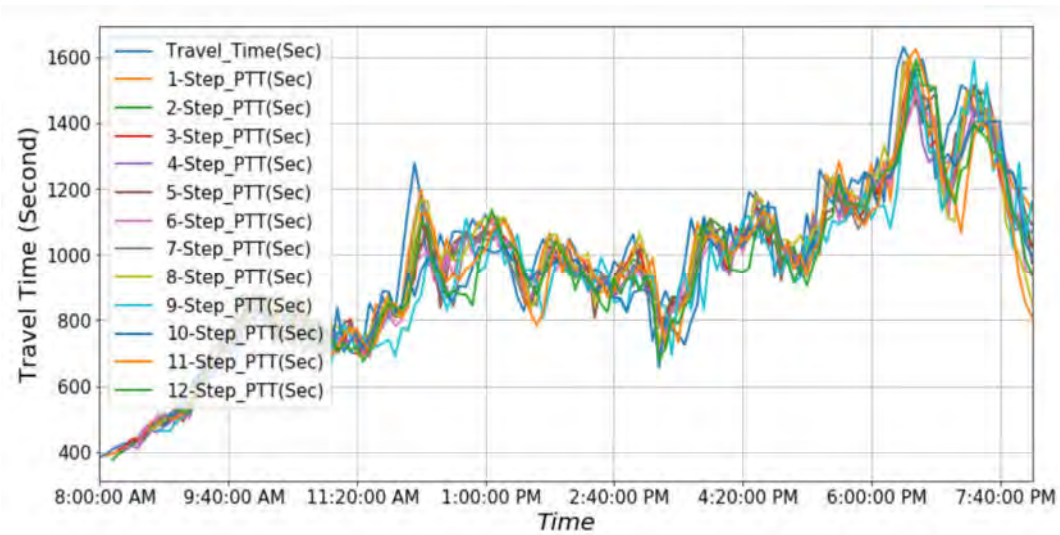

Fig-7.2, Twelve-step ahead travel time prediction at five minutes

The model prediction accuracy is measured in terms of mean relative error (MRE). If the prediction (%) MRE is smaller then the model prediction accuracy will be higher. The twelve-step ahead prediction MRE at five minutes intervals graph is shown in Fig-7.3. According to this graph, the mean relative error is all-time minimum from one-step to seven-step and increasing with the number of predicted steps are increasing.

The model predicted a smaller travel time compared to actual travel time after 11:30 AM and similar at 3:00 PM and the 6:30 PM also. It will be minimized through 24 hour travel time dataset employing during training and increasing the training dataset also.

The model prediction error all time remained below 20% from 8:00 AM to 8:00 PM from one-step to seven-step ahead prediction. The model prediction performance and accuracy evaluated in different angles based on the three types of errors in Eq. 11-13. The mean relative error is calculated by using Eq.13.

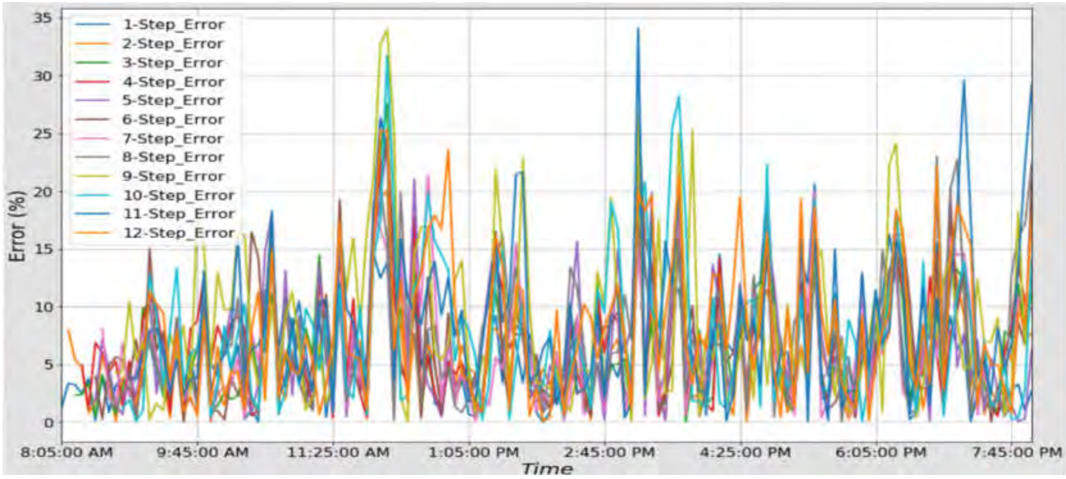

Fig-7.3, Twelve-step ahead prediction error (MRE) at five minutes

Subsequently, the developed model simulated one hour ahead prediction using a ten-minute interval of the dataset for finding the interval dependency. The developed model performance analysis with the ten-minute interval of data set and the result is shown in Fig-7.4 through the six-step ahead prediction. Model prediction accuracy is stable and higher like 93% from one-step to three-step although the interval span is ten minutes and accuracy reduce 3% from four-step to last-step. The model prediction accuracy decreases while increasing the interval span. The urban traffic frequently changes their travel pattern due to lack of traffic rule and number of traffic as well as the limited capacity of the road. Moreover, the trained data also reduced while employed ten-minute intervals for simulating. Total 983 data are employed during training and it also impacted the prediction accuracy.

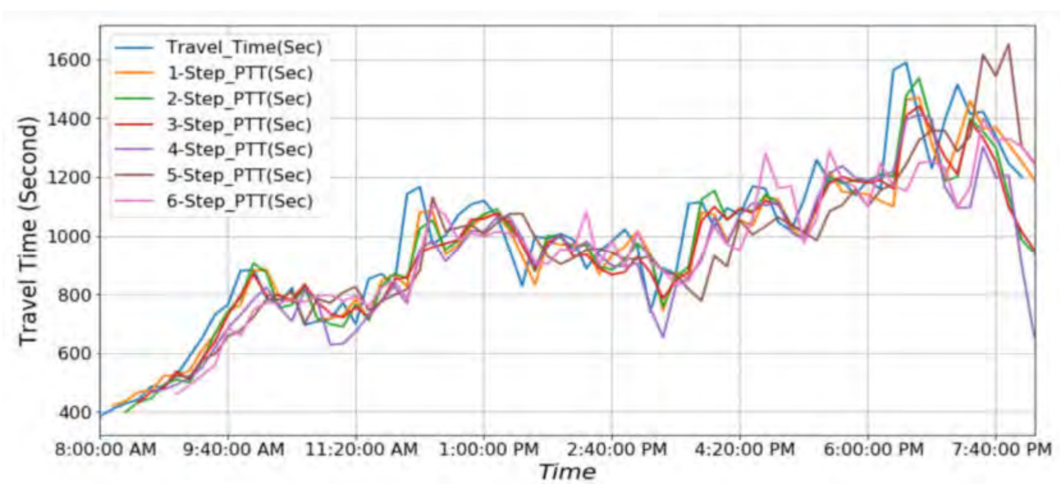

Fig-7.4, Six-step ahead travel time prediction at ten minutes

For ten minutes interval dataset, the mean relative error is shown in Fig-7.5. The developed model generated a maximum error of 25 % for one to three-step ahead prediction and other steps maximum error is 32%. Most of the interval time prediction error remains below 15% and will be stable all time while considering a more sequential continue training dataset. The model prediction accuracy depends on previous interval travel time. For the ten-minute interval, prediction accuracy is a maximum of 90% even in urban traffic. Urban traffic is generally unpredictable due to traffic patterns are unstable or unpredictable.

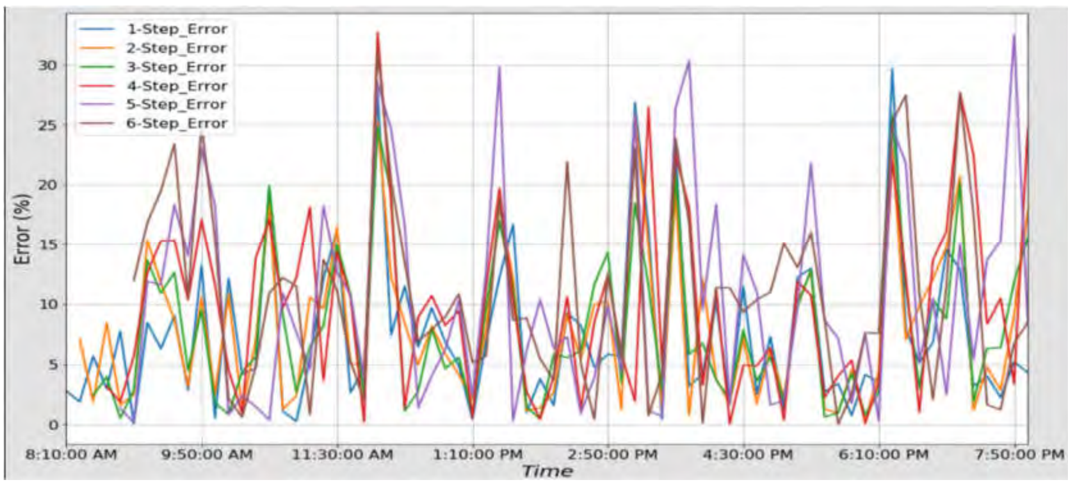

Fig-7.5, Six-step ahead prediction error (MRE) at ten minutes

Finally, one hour ahead travel time predicted using fifteen minutes interval of data set and maximum predicted four steps (one hour) outcomes are shown in Fig-7.6. The model prediction accuracy range is 90% ~92% and of all times close and stable to an actual prediction. The model performed better even for large time span intervals in the urban road networks. The model under fitting shown in the F.g-7.6 due to training datasets is already decreased.

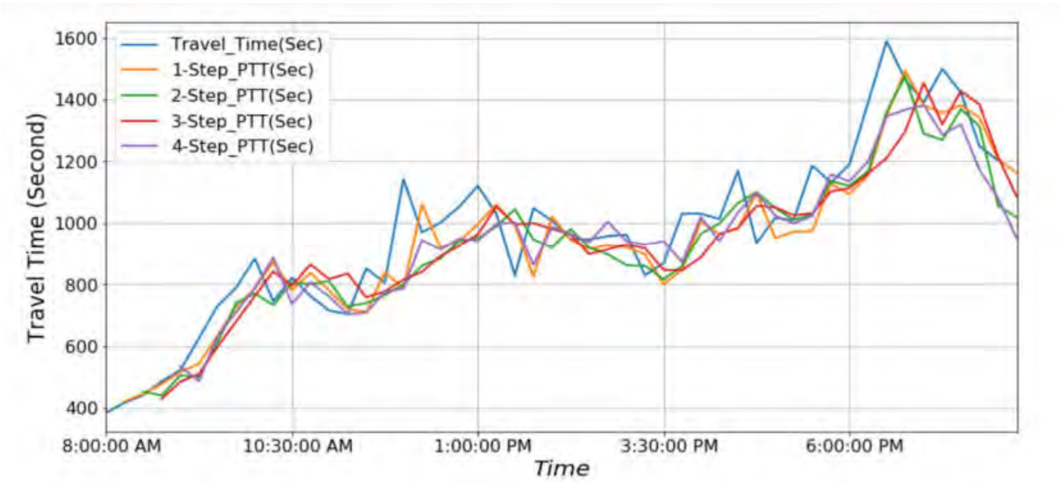

Fig-7.6, Four-step ahead prediction at fifteen-minute

Fifteen-minute steps ahead prediction mean relative error graph is shown in Fig-7.7. The highest error generated is 32% through all steps prediction at 12 O' clock while the model predicted smaller than an actual prediction. The error level in each step is closed to each other's although the average prediction error is 8%~10%. The accuracy will be increased while increasing the training dataset. Moreover, the data set time span increases in the fifteen minutes intervals and traffic patterns are also deferred in the urban roads. The developed LSTM or sequential model prediction performance will be best while considering smaller time span datasets and sufficient data.

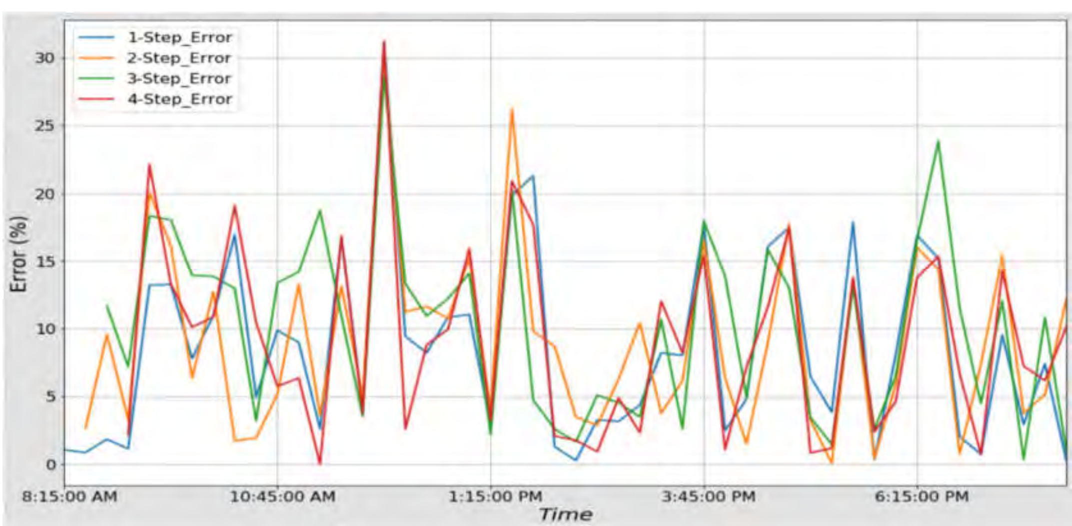

Fig-7.7, Four-step ahead prediction error (MRE) at fifteen-minute

The developed model for five, ten and fifteen-minute intervals prediction mean relative error (MRE) graph is shown in Fig-7.8. Model prediction accuracy performance depends on mean relative error (MRE). The prediction accuracy will be higher while MRE will be smaller. In this travel time prediction research, MRE is smaller at the 5-minute intervals and higher at the 15-minute interval of the dataset. The model prediction accuracy is decreasing while increasing the number of steps ahead prediction. The model one hour ahead predictions accuracy is above 89% to 92%.

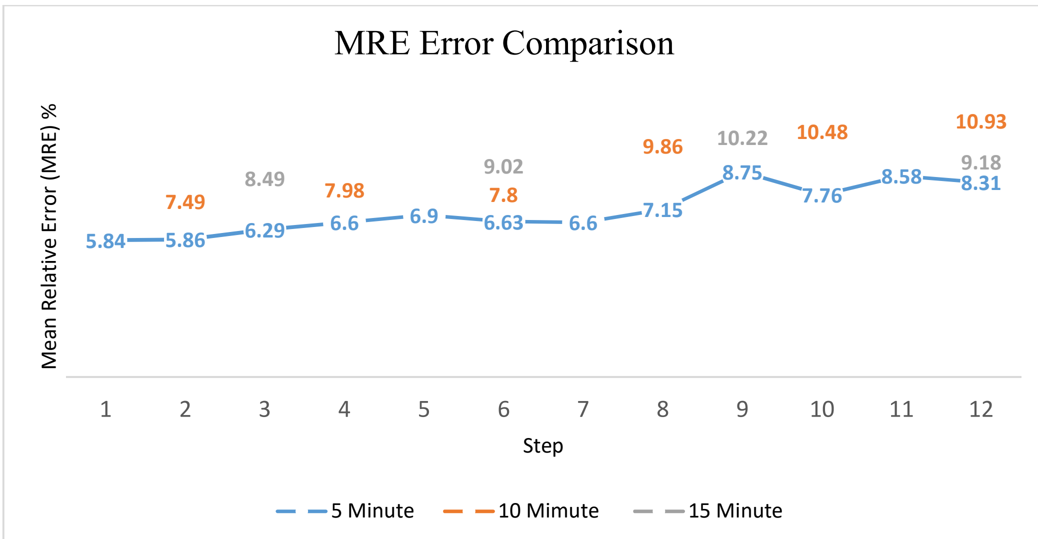

Fig-7.8, prediction error (MRE) comparison at the different time interval

Also, the travel time prediction model mean absolute error and root mean square error (RMSE) at five, ten and fifteen-minute intervals is shown in Fig-7.9. The mean absolute error (MAE) is a measure of the average difference between actual and prediction travel time and always considers a positive (non-negative) value in second.

It's lower at the five-minute intervals for one hour ahead prediction and higher at the ten-minute intervals for one ahead prediction of five, ten and fifteen minutes' intervals data. RMSE is the square root of the average of squared errors. The effect of each error on RMSE is proportional to the size of the squared error. RMSE is always non-negative, and lower RMSE is better than a higher one. The RMSE error is smaller at five minutes and higher at ten-minute interval data.

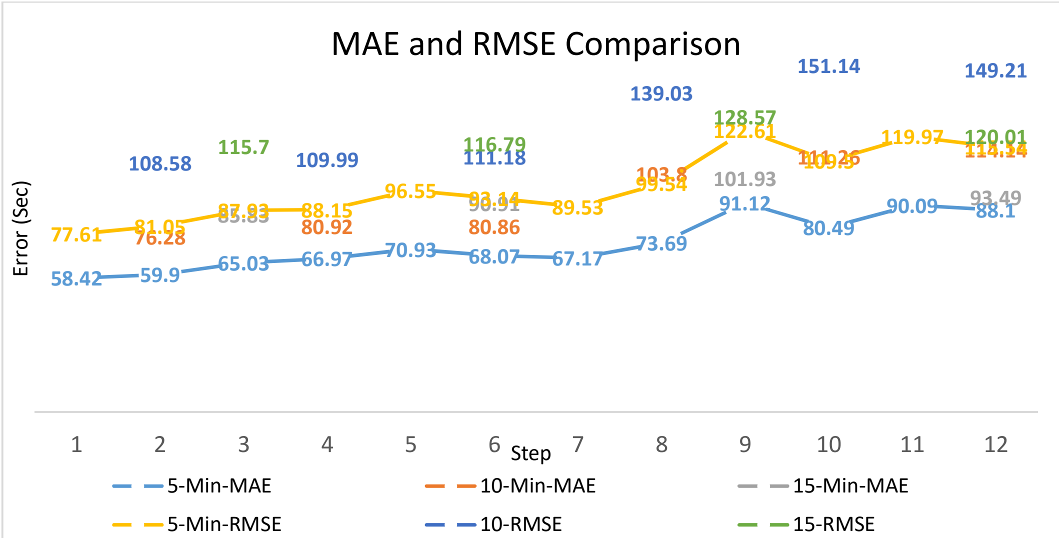

Fig-7.9, One hour ahead prediction (MAE & RMSE)

Higher prediction variance causes RMSE error to increase in each sequence. Both linearly increases from one-step to last-step within one hour at five, ten and fifteen-minute intervals dataset. Both errors increase while increasing the step due to a decrease in the training data. Also, required 24 hours continue dataset for training to reduce the MAE and RMSE. It means that prediction accuracy decreases while the number of steps are increasing. These two can be overcome by adding more sequential data set during training the model.

The model travel time prediction accuracy depends on various properties like the number of training data, road properties, vehicle types, time intervals, traffic controlling and traffic patterns. In urban road networks, traffic pattern prediction is difficult due to insufficient traffic policy and controlling systems. Always varies the traffic patterns from the previous step and unstable at all times. In this situation, the developed model prediction accuracy is high even one hour ahead of prediction. The model ensures accuracy range 94.16% to 89.07% for one hour ahead prediction through the various steps. Model prediction accuracy will be increased more while investigating 24 hours more data for training and validation. The travel time prediction model will be helpful for the traveller, rider, travel planer, logistic, driver, ubar, pathao and other services to find out the shortest travel time or help to avoid traffic for reaching the desired destination in the urban roads network. Also, It will be helpful for the economy of the country and increase productivity.

Finally, we calculate the actual prediction accuracy of the model by employing Google Map provided travel time accuracy which dataset is considered as an input. The research investigated the Google Maps provided travel time accuracy is 91.19% compared to field-level travel time. The model's actual travel time prediction accuracy will be calculated by multiplying model predicted accuracy with the average field-level predicted travel time accuracy. Suppose the model is one step ahead travel time prediction accuracy is 94.16% at five minutes and the average Google Map provided travel time accuracy is 91.19%. So that, the model actual travel time prediction accuracy is calculated by using model predicted accuracy multiply with the Google Map provided travel time accuracy. The developed model one step ahead actual prediction accuracy will be (94.16*91.19)% =85.86% while using the Google Maps provided travel time data as input. The model prediction performance also depends on the usages input data accuracy. Developed model prediction accuracy is higher compared to Google Maps provided travel time due to Maps provided traffic information accuracy is 91% instead of 100%. Google Maps provided travel time accuracy increases through the travel or crowdsourced users, internet and Google Maps enable smartphone using. If the training and test data accuracy is 100%, then the model prediction accuracy will be higher. The model prediction accuracy can be improved through high accuracy train and test dataset and more amount of dataset. According to this investigation, the two stacked LSTM model travel time prediction accuracy is high.

The model predicted travel time representation on Google Maps is shown in Fig-7.10. The Google Maps provided traffic information represented by four colours in Bangladesh like green, orange, red and dark-red according to the traffic density or traffic speed for any road section. Several investigations have been performed to find out the current travel time colour code. In this context, continue two days 3 hours observations are performed and found the speed range 0 to 3.50 mile/hr represent the dark-red (traffic gridlock; heavy vehicles are present on-road) colour on the Maps, range 3.51 to 4.50 mile/hr represent red (traffic delays; compared light vehicles are present on-road), range 4.51 to 5.50 mile/hr represent orange (medium traffic; few traffic is present) and greater than 5.50 mile/hr represents the green colour (no traffic delay; there is no traffic are present that means freeway).

The green colour indicates the road section is free while dark red indicates heavy traffic on the road section. Considering the Google Maps prediction speed at 8:05 AM is 14.35 mile/hr and the model predicted speed 14.00 mile/hr for HTG road section of an interval in respect to predicted travel time. The colour code will be green for Google Maps and the model predicted output colour will be the same. Both predicted outcome is shown in the same graph as their prediction outcomes are in the same range of speed.

Fig-7.10, Model-predicted output represent on Google Maps

7.3 Traffic Flow Prediction Model

The final experiment is performed on three road sections for predicting the multi-step ahead traffic flow through model-1 (Sainik club, centre to west, CTW), model-2 (Sainik club, centre to north, CTN) and model-3 (Army stadium, south to north, STN) road section. The CTW (140-meter length) road section is considered low traffic flow demand for multi-step ahead traffic flow prediction at five-minute intervals data (3:00 PM to 7:00 PM). The CTN (140-meter length) is considered high traffic flow demand and the STN (318-meter length) road section is considered freeway traffic flow for multi-step ahead traffic flow prediction by employing five-minute intervals of the dataset (8:00 AM to 12:00 PM and 3:00 PM to 7:00 PM). The CTW road section is a little bit busy compared to the CTN road section traffic flow and STN road is fully free-flow traffic.

In this experiment, total of 1801 and 1344 instances are used for these three models train and validation at five-minute time intervals considering traffic speed data. Each model is separately trained, validated and tested for optimum prediction accuracy. The CTW road section multi-step ahead traffic speed prediction model through a five-minute interval train and test loss graph is shown in Fig-7.11. CTW road section is a restricted road and only limited types of traffic are allowed. The limited vehicles are rickshaws, motorcycles, cars and authorized buses only.

The traffic flow patterns deferred each time in this road section due to the number of motorcycles, cars and rickshaw movements being random and unplanned. However, the model train and test loss indicated that the model was properly trained for better prediction accuracy and performance. The model's prediction can be better when train and validation loss will be zero. In the real-time application model, train loss is zero quiet impossible.

Also, the LSTM model suffering from under-fitting and as well as over-fitting which causes model prediction accuracy can differ. If the training loss is much greater than the validation or test loss then the model fall in over-fitting and the model indicate poor prediction performance while predicting. On the other hand, if the training loss is much less than validation or test loss then the model suffers from under-fitting; it will also indicate poor performance while predicting. Overfitting and underfitting both are impacted in model prediction accuracy.

The model will be the best fit while train and test loss in the same line and closed to each other. According to Fig.7.11, the model is best fitted for predicting the vehicle's traffic speed for this road section. The model train and test loss slightly deferred while predicting multi-steps ahead. The reason behind each step target (traffic speed) value is more variance compare to the next step due to lower train dataset, higher interval span and unstable traffic patterns also.

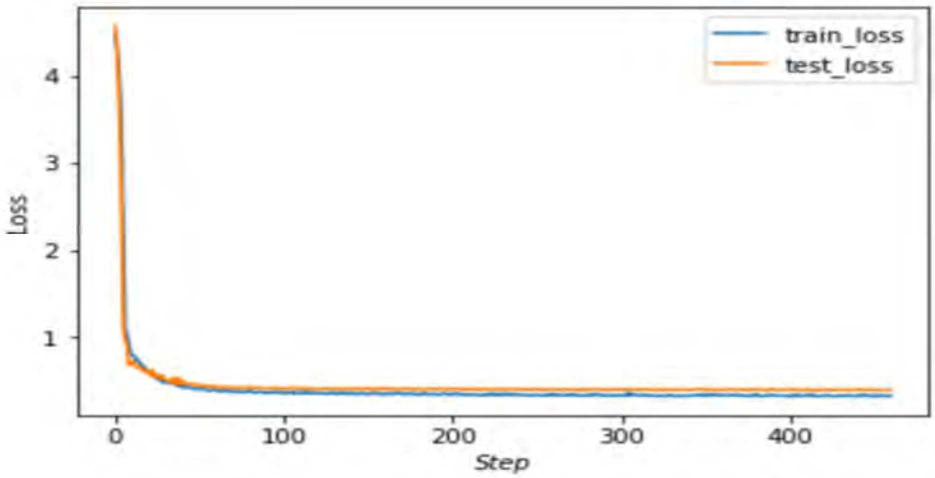

Fig-7.11, Train and test loss of traffic speed

The model-1 or CTW road section is considered for multi-step ahead traffic flow prediction analysis on the five-minute interval of the dataset. This analysis primarily employed traffic speed data as model input and predicted traffic speed according to the training and test flowchart. Secondly, we employed these predicted traffic speeds to the time-dependent correlation algorithm to obtain the target outcome traffic flow for each sequence of input. Time-dependent correction equations are developed by field-level collected traffic flow and traffic speed that was collected from Google Maps. Both data collection was in the same interval and at the same time.

The model-1 traffic flow prediction performance is analyzed by using one-month historical traffic data including various features; day, month, hour, minute, holiday, weekday, road properties, weather conditions, adjacent road speed and space mean speed or traffic speed. The model simulated through 52, 50 and 48 hidden neurons as per equation-10, 128 batch size and optimize epochs for five minutes time interval of traffic speed. The CTW road section evening hour traffic patterns is shown in Fig-7.12. The non-motorized vehicle (NMV), bus and CNG flows stable at all times whereas motorcycle (MC) and car flow uncertainly change in each time span. After 6:00 PM car and motorcycles are rapidly increased due to it's the shortest and jam-free return path for Gulshan and Mohakhali areas traffic.

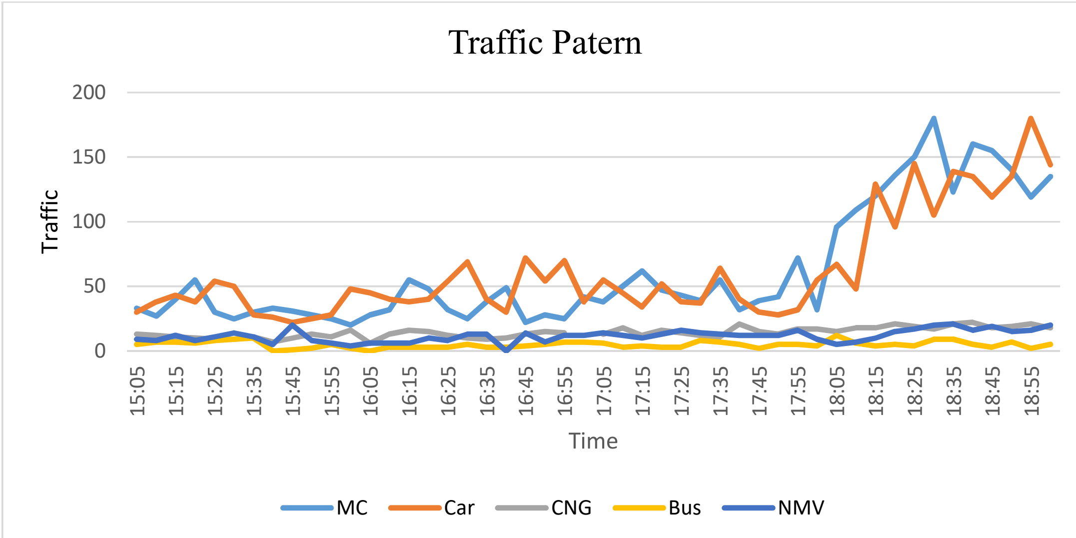

Fig-7.12, CTW road section traffic flow patterns

Developed model-1 predicted one-step, two-step, three-step ahead traffic flow prediction result is shown in Table-7.3. Here, one-step-ahead prediction (y_{t+1}) indicates previous one-step observation analysis (x_t). Similarly, two-step (y_{t+2}) and three-step (y_{t+3}) ahead predictions are indicated previous (x_t , x_{t+1}) and (x_t , x_{t+1}, x_{t+2}) steps analysis. Five minutes interval of traffic data and three-step ahead prediction indicates fifteen minutes ahead prediction of traffic flow. The model predicted traffic speed mapped to traffic flow using sequences of time-dependent correlations developed by field-level collected data.

Table-7.3, Traffic speed and flow prediction on CTW road traffic-evening

Step	Cell	Trained Instance	Traffic Speed			Traffic Flow		
			MRE	MAE	RMSE	MRE	MAE	RMSE
1	26+26	900	7.84	0.34	0.43	12.18	17	24
2	25+25	900	7.78	0.35	0.46	12.14	17	24
3	24+24	900	7.97	0.35	0.41	14.09	19	27

According to the Table-7.3, model-1 mean relative error range is 7.78 %~ 7.97% for traffic speed whereas 12.14% ~ 14.09% for traffic flow prediction through 1-step to 3-steps ahead. The mean relative error is small and stable in traffic speed and comparatively 4% -6% higher while predicting traffic flow.

This is because, while mapping predicted traffic speed to predicted traffic flow using half an hour or six consecutive time-dependent correlation equations, the traffic flow deferred with the same traffic speed and small changes in the prediction speed causes traffic flow changes comparatively more. Sometimes observed the weak correlations among these time, speed and flow variables. The model traffic flow prediction is linearly related to the predicted traffic speed. The traffic flow prediction error is increasing while increasing traffic speed prediction. The model prediction accuracy is small and stable in both speed and flows prediction in this interrupted road section and maximum flow prediction accuracy is 88% approximate. Moreover, model-1 mean absolute error (traffic flow/ 5 minute) and root mean square error (traffic flow/ 5 minute) for traffic speed prediction is small due to actual and prediction difference is small. Similarly, traffic flow mean absolute error and root mean square error is comparatively small in terms of the number of traffics although higher numbers of unplanned traffic flow happened on this road section. A higher number of unplanned traffic flows created from one interval to another interval through the motorcycle, car and traffic signal as well. Moreover, this road is interrupted by a train signal.

Subsequently, the model-1 traffic flow prediction graph is shown in Fig-7.13 in order to understand the flow prediction accuracy over a defined time. The graph indicates a maximum three-step or fifteen-minute ahead traffic flow prediction status. Also, the graph indicated the traffic flow number of vehicles per five minutes from 3:00 PM to 7:00 PM. This road section handles more traffic during evening hours due to the number of vehicles are returned within this time. As per the traffic flow graph Fig-7.13, prediction accuracy remaining close to each other even in a higher number of traffic flow at evening hours. The model predicted a smaller traffic flow near 5:00 PM compares to the actual prediction. It happened due to time-dependent weak correlation equations. All other time, flow and speed relations are strong with their time and prediction flow also very closed and stable. Also, the unwanted traffic flow causes model traffic flow prediction accuracy to slightly degrade in some steps. The model three step ahead prediction is closer to the actual prediction in all-time except after 5:00 PM in a day. This road is restricted and only limited vehicles movement exists in this road section.

Also, it is the best return path for Mirpur from Gulshan, Mohakhali and others areas motorcycle and cars vehicles. That's why unexpectedly, traffic flow increased after 5:00 PM each day as per the traffic data.

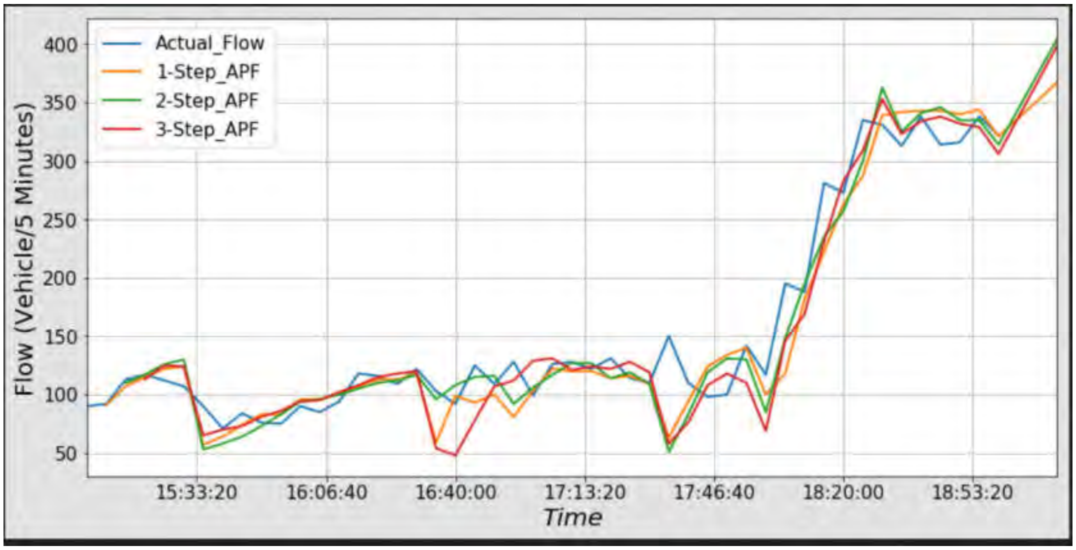

Fig-7.13, CTW road section multi-step traffic flow prediction

The model-1 prediction error will be minimized by avoiding unwanted traffic flow created train signal and applying traffic existing policy. So that, traffic flow will be stable and model prediction also will be stable. The absolute mean relative error range is between 0 to 65% and maximum error happened near 5:00 PM for weak correlation for this day. All other time, interval relative errors are comparatively small. The maximum relative error occurred in two-step and the minimum at one step ahead of traffic flow prediction.

Moreover, their average prediction difference between actual to predicted is nearby in each step. Interval to interval more traffic flow pattern variation causes model prediction error also increased. The model-1 traffic flow prediction accuracy is comparatively higher even frequently updated or unwanted traffic flow patterns existing in this road section. The model traffic flow prediction error increased max 6% approximate by comparing to the traffic speed prediction. And it's introduced by time-dependent correlation equations while obtaining traffic flow with respect to the predicted traffic speed.

Consequently, model-2 is developed for multi-step ahead traffic flow prediction through the five-minute intervals average traffic speed data of CTN road section in Sainik club intersection. The CTN road section length is 140 meters and more demanding or busy due to the highest numbers of traffic flow existing each day. This analysis basically how performed the model while traffic flow higher and nearly stable. The CTN road section traffic flow pattern is shown in Fig-7.14.

The highest numbers of traffic generated by the MC and car at all times and their flow pattern is almost similar. Morning traffic flow is higher than evening traffic. Bus, CNG and NMV are smaller in number and their flow is also stable at all times. Morning hour traffic slightly increases due to office hour start and most of the office located with this adjacent road. Moreover, the sum of the two roads section traffic flow is considered for analysis. The NMV flow is lowest in this road section. The average traffic speed range is 1.52 miles/hr. to 9.28 mile/hr. in each day from morning to evening. The CTN road section is considered the highest traffic flow demand road in this research.

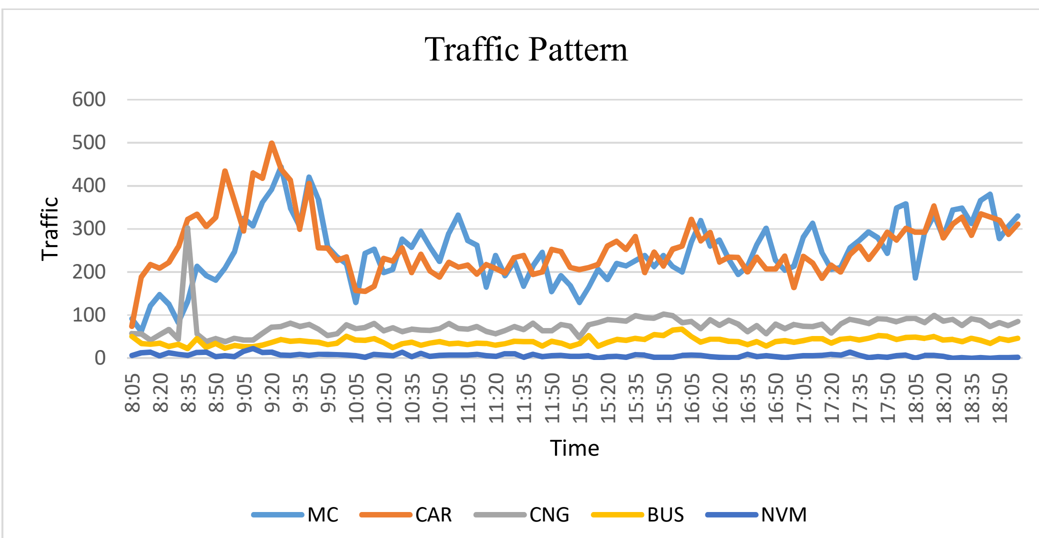

Fig-7.14, CTN road section traffic flow patterns

This (CTN) road section's one to three steps ahead of traffic and speed traffic flow prediction at five-minute intervals investigation is shown in Table-7.4. Total 2688 instances and adjacent roads impact are considered for traffic speed prediction. The model train and validation loss is the best fit as similar to the earlier model and more number of training and validation dataset employed compared to the previous model.

The model hidden neurons required the higher compared to the previous model due to the higher number of training dataset usages for this model. The road section is slightly interrupted by the intersection u-turn lane. Also, two roads traffic (From Mirpur and Mohakhali) are flow in this road and its causes all time exists the traffic.

Table-7.4, Traffic speed and flow prediction on CTN road traffic

Step	Train	Cell	Time Interval	Traffic Speed			Traffic Flow		
				MRE	MAE	RMSE	MRE	MAE	RMSE
1	1801	60+60	5	9.32	0.65	0.82	8.82	54	81
2	1801	56+56	5	9.34	0.64	0.82	8.76	54	81
3	1801	53+53	5	8.99	0.60	0.77	8.25	52	78

According to Table-7.4, the model predicted mean relative error (MRE) range 8.99%~9.34% during predicted traffic speed and 8.25% ~ 8.82% for traffic flow prediction. Model traffic flow prediction error differs approximately 1% from predicted traffic speed. The model traffic speed prediction and traffic flow prediction error is stable in each step and also more closely predicted in each step. The model flow prediction accuracy is higher compare to speed prediction because this road section is uninterrupted and has stable flow all times from morning to evening. Also time, speed and flow correlations are strong compare to the previous model-1. The model mean absolute and root mean square error is small and stable in each step prediction although a higher number of traffic movements exists in this road section. The maximum fifteen-minute ahead traffic flow prediction accuracy is 91% approximate which is high for urban road networks, especially in Bangladesh. Also, the average absolute error is 54 vehicles whereas the average of 626 vehicles flow exists in each interval. Car, Bus and Motor Cycle are the most traffic in this road and their flow is almost stable. The model prediction accuracy will be increased through the 24/7 higher number of the trained datasets.

The model-2 for CTN road section's maximum three-step ahead traffic flow prediction at five-minute intervals graph is shown in Fig-7.15. Model three-step ahead prediction performance is higher from morning to evening hours. The higher number of traffic flows existed in the morning hour; then degrade and up and down over the time as spike and traffic flow increased at the evening hour. Three steps or fifteen-minute ahead prediction status graph indicates that every step's prediction is much closed to the next step prediction at all times.

Sometimes, the model-2 under and over predicted due to a small predicted traffic speed difference caused more or less traffic flow generated while mapping through the time-dependent correlation equations. The traffic flow prediction accuracy is stable and closed to each step even higher traffic flow in this road section in all day.

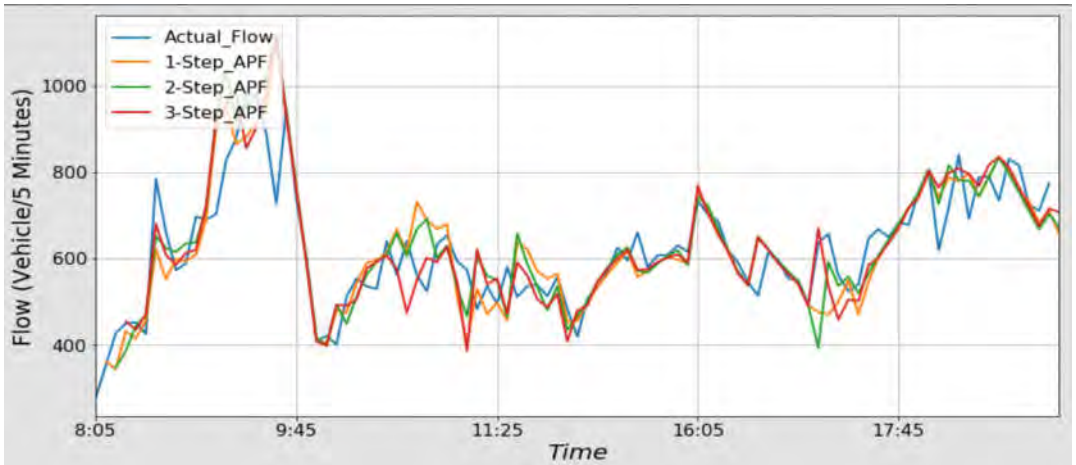

Fig-7.15, CTN road section multi-step traffic flow prediction at five minutes

Moreover, CTN road section traffic flow is managed by three signalized traffic which is introducing a little bit of unwanted traffic flow for few times in a day. At the morning hour, the model over predicted the traffic flow due to the higher number of traffic and frequently changed the pattern whereas all other times in a day, flow prediction is stable even three steps ahead of prediction. The over prediction can be addressed by employing 24 hours dataset for training and validating. The developed model overall prediction performance is stable, smaller prediction error and is high at a five-minute interval dataset even three-step ahead prediction.

The model-2 mean relative error details graph shown in Fig-7.16 for from morning to evening for obtaining the developed model performance. The model traffic flow predicted error at morning hour exceeds 50% for all steps due to higher unwanted traffic and frequently changes their flow pattern and all others times remained below 30% as well as smaller prediction error. Also, all times and three steps ahead model prediction are stable. The model three steps ahead of traffic flow prediction error maximum introduced 53% and minimum near about 0%.

The average model flow prediction error is small and accuracy is high also stable. The developed LSTM deep network model performed better in stable traffic flow road section and higher number of traffic flow existed in all time.

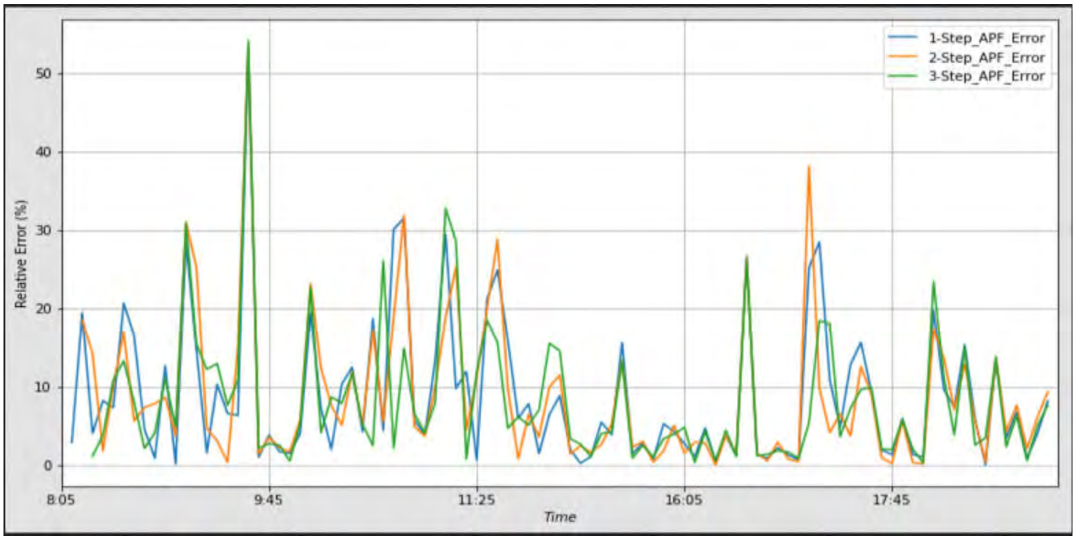

Fig-7.16, CTN road section multi-step traffic flow relative error at five minute

The final traffic flow prediction experiment is performed by the developed model-3 on the army stadium road section (STN) for multi-step traffic flow prediction at five-minute intervals. The STN road section average traffic speed range is 25.41 miles/hr. ~ 32.33mile/hr. in a day and it's considered for free flow or freeway traffic in the urban road network in this study. The previous two roads traffic flow is interrupted traffic because these roads section managed by traffic signals whereas STN road section is signal free road. The signalized road section average traffic speed frequently changes with the time interval and the non-signalized road section traffic flow speed is almost the same from one interval to another interval.

The STN road section traffic flow pattern is shown in Fig-7.17. The motorcycle (MC), car, CNG and bus are the main traffic sources in this road section. Car is the highest number of traffic and motorcycle also closed to the car. Bus and CNG traffic flow patterns are stable whereas motorcycle & car flow pattern varies all times in this road section. The traffic flow pattern in this road section is fully different from the above two road sections due to there is no signal for controlling the traffic flow.

The traffic flow speed is near about 30 miles/hr. and always stable from morning to evening. Uninterrupted and higher traffic speed causes this road section to consider free-flow traffic.

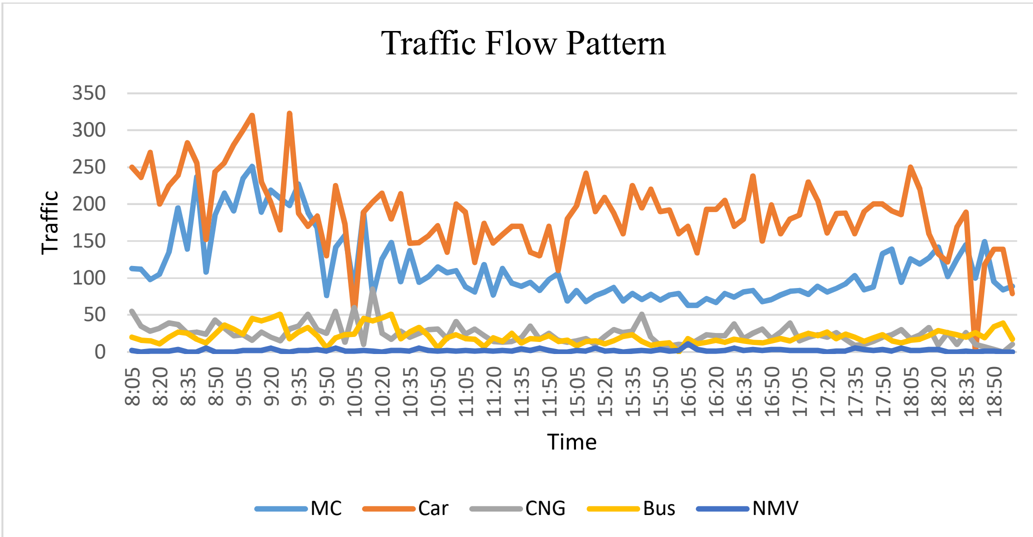

Fig-7.17, STN road section traffic flow pattern

This research investigated the developed model-3 prediction performance on the freeway or free-flow traffic (high speed) and its experimental multi-step ahead prediction result shown in Table-7.5. The developed model multi-step prediction mean relative error range 2.76%~ 2.94% for average traffic speed and 8.82%~9.02% for traffic flow. The developed model average prediction accuracy is higher and stable than other's road sections for multi-step ahead traffic speed prediction. The model hidden neurons required higher compared to the above two models due to the higher number of training datasets and a smaller number of feature usages.

Table-7.5, Traffic speed and flow prediction on STN road freeway traffic

Step	Train	Cell	Time Interval	Traffic Speed			Traffic Flow		
				MRE	MAE	RMSE	MRE	MAE	RMSE
1	1801	82+82	5	2.87	0.83	1.03	8.82	27	38
2	1801	75+75	5	2.76	0.79	1.00	9.02	27	38
3	1801	69+69	5	2.94	0.83	1.05	8.9	27	36

Model-3 traffic flow prediction accuracy is also 91% approximate which is high comparatively for three-step or fifteen-minute ahead traffic flow prediction although all types of traffic flow patterns are different in each step.

Moreover, model mean absolute error and root mean square is stable and small. Model prediction error defers 5% from speed to traffic flow mapping. In the free flow road section, the same traffic average speed existing in few couples of intervals but the number of traffic flow changes over the time interval. As the traffic speed in this road section is higher and small variation of traffic speed cause huge vary the traffic flow prediction while mapping with time-dependent correlation equations. So that, the model overall performance is higher while investigating freeway or free-flow traffic flow where the traffic speed is also higher. This road is fully uninterrupted by the traffic signal. That's why all times traffic speed remain much closed.

The model five-minute interval traffic flow of multi-step ahead prediction graph is shown in Fig-7.18. The traffic flow is frequently updated from morning to an evening within a specific range. Sometimes the same speed remains but traffic flow changes. The model is three-step ahead of traffic flow prediction very closed to each other in each step. The model performed better all day at five-minute intervals even three-step ahead prediction. The actual flow pattern and predicted flow pattern slightly changes for high traffic speed. It is created by the time-dependent correlation equations due to small average variation speed causes number traffic flow changed over time. So that, the model multi-step ahead traffic flow prediction accuracy is high and stable in the freeway traffic. Also, three-step ahead traffic flow prediction steps are near about the same in the freeway road section.

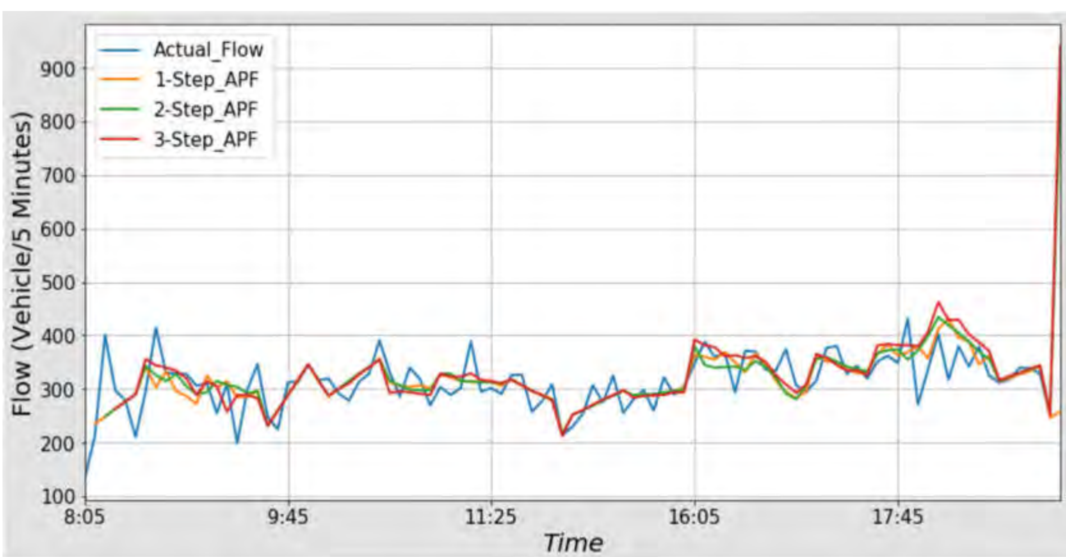

Fig-7.18, STN road section multi-step traffic flow prediction at five minute

Subsequently, the model-3 multi-step ahead traffic flow prediction performance in terms of mean relative error at five-minute intervals is shown in below Fig-7.19. The model mean relative errors are similar at each time and smaller in maximum interval except few intervals at the morning and the evening hours. Such error is basically introduced by time-dependent mapping equations. It can be mitigated by establishing a strong correlation with time, speed and flow. In the free flow road section traffic speed variation in each interval is small and their traffic flow variation is also small.

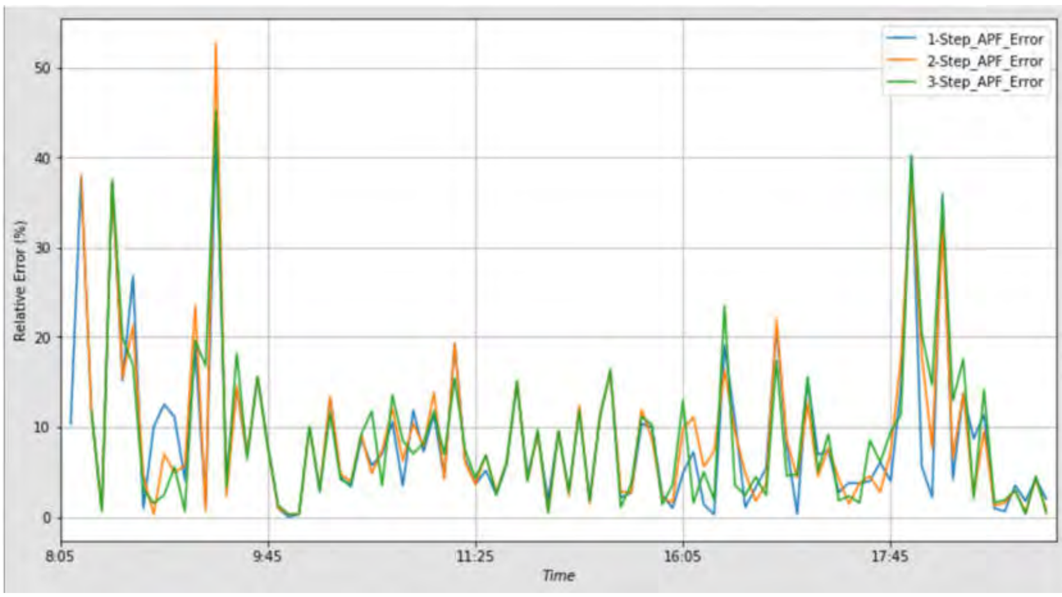

Fig-7.19, STN road section multi-step traffic flow prediction MRE at five minute

7.4 Traffic Flow Prediction Limitation

In this research, traffic flow models are developed on three road sections on the single-day traffic flow data collection. Time-dependent correlation developed on actual traffic speed and traffic flow. Other six days traffic flow data of this road section is required for developing time-dependent correlation because traffic flow patterns are different from one to another day(s). The time-dependent correlation will be performed better while developing day-wise speed-to-flow relations. Real traffic flow data collection is so troughed for seven days in a week that’s why developed the model on the single day where the traffic flow was regular and the day was sunny. There is no unwanted interruption for traffic flow in these road sections.

The developed models will be performed similarly while considering individual day's time-dependent correlations. Moreover, the number of vehicle flows always changes from one day to another day in our developing country. If a similar number of vehicles are flowing every day in a week then the developed models can be used for single-day time-dependent correlation equations.

7.5 Travel Time Prediction Model Validate With Google Maps

Developed travel time prediction is validated with Google Maps prediction for one-hour advanced prediction. Google Maps advanced predicted results show up using a range of values instead of single. Whereas the developed model advanced predicted result is single which closed to actual travel time. Google Maps is providing only real-time traffic information in specific values which is already experimenting with 91% accuracy in respect to actual traffic information. Google Map also predicted values always show up through the range of values considering the previous historical data only. In our developed model, considering various factors like current adjacent roads status, weather forecasting and VIP movement are also for getting the best prediction accuracy. Developed model travel time prediction accuracy is observed around 95 % in each step. The developed model prediction result is validated with the Google Maps shown in detail in Appendix-II for one-hour advanced prediction through the five-minute interval of data. According to Appendix-II, developed model prediction accuracy is higher and specific compared to Google Maps advanced prediction system.

7.6 Travel Time and Traffic Flow Prediction Accuracy Comparison

The developed model accuracy performance compare with the existing developed model is an important part of the researcher. The travel time and traffic flow prediction play a vital role in ITS. In the meantime, so many researchers introduced various models to help the transportation system, drivers, riders, logistics department and travel planners. These models traffic data sources, data collection procedures and their developed model structure are different. We developed model usages datasets that are fully separated from existing all models and nobody usages such data type of data for travel time or traffic speed or traffic flow prediction.

Although there is no similarity with our developed model, only shown at a glance of existing models structure, data sources and prediction performance. The existing models are developed based on the highway or freeway traffic flow data. These models data collection procedures are also different and data sources are also different. Moreover, their developed model's structure is also different from our developed model structure. These existing proposed and developed models travel time prediction error range is 5% to 21% for highway data whereas our developed model error is 5.84% to 10.93% for urban traffic data. Similarly, the existing traffic speed prediction model error is 5.6% to 6.22% whereas our developed model traffic speed prediction error is 2.76% to 2.94% for freeway traffic.

The prediction accuracy of our developed model is higher comparatively than the existing models. Also, these existing models data collection processes are costly and time consumed. Our developed model travel time and traffic speed prediction data were collected from Google Map which is reliable, real-time and lost cost. So that, our developed model is a smart, reliable and hassle-free high accuracy model for the urban road network. Its accuracy will be more improved while employing freeway traffic data of developed countries where maintain the traffic policy and traffic rules.

7.7 Developed Model Result Summary

The experimental result showed that Google Maps provided real-time traffic information average accuracy is 91.2% considering the 1251m road section in the urban network. The traffic was regular and the weather was sunny day these data collection days. Accuracy range found 87% to 97% through ten rounds both direction data collection considering all impacts. Google Maps providing real-time traffic information instantly for each road section through crowdsourced, internet-enabled smartphone users and location-sharing services. Its traffic information accuracy increasing day by day with internet-enabled phone users. The Google Maps provided traffic information accuracy is in the urban road networks. Similarly, travel time prediction model prediction accuracy maximum 94% while employing small interval of data and almost stable in each step. Model prediction accuracy decreasing slightly while increasing span or interval travel time like ten and fifteen minutes.

Moreover, the model prediction error in each step is smaller while using a small time span dataset. The experimental result also showed that developed model prediction accuracy range varying 89% ~ 94% for one hour advanced travel time prediction by employing five, ten and fifteen-minute interval data for this selected road. While increasing interval span model prediction error also increasing due to urban traffic are frequently changes their pattern compare to freeway or highway. Also, this road section has eight traffic signals for controlling the traffic on all days. The model prediction accuracy is higher for the urban road network and it will improve more while urban traffic maintains traffic policy, avoid lane violation and sufficient road capacity. Model prediction accuracy also improved by adding more 24 hours more datasets during training and validating. So that, the model can learn accurately by 24 hours data for future prediction. Developed model prediction accuracy also higher than existing models as well as Google Maps predicted travel time. LSTM is suitable for processing time-series data like travel time with high accuracy.

Finally summarized the experimental result of traffic flow prediction models on interrupted and low demand traffic road section. Model-1 traffic speed prediction accuracy maximum 93% whereas traffic flow prediction accuracy 88% approximate. The model prediction performance is good in this road section even it interrupted by two signals and its traffic flow patterns are uncertain and unstable due to frequently train signals. Model-2 developed for high demand traffic flow road section for prediction the multi-step ahead traffic flow. It traffic speed prediction accuracy 92% and also traffic flow prediction accuracy 92% approximate. The developed model performed better due its traffic flow patterns are stable in all day in each step. Also it correlation co-efficient also strong for each time dependent equations.

In the same way, model-3 traffic speed prediction accuracy is 97% whereas traffic flow prediction accuracy is 92% approximately. The model performance is best in this research for flow prediction. This model is performed on freeway traffic where traffic speed is higher and stable. It causes stable traffic flow prediction while mapping with the time-dependent correlations equations.

After several investigations of traffic speed-flow patterns, developed model prediction performance best in free-flow traffic and better prediction in high demand traffic flow road section. Similar performance outcomes are obtained on speed and flow prediction in the high demand road section (model-2). Good performed the developed model on low demand traffic flow (model-1) for traffic flow prediction. Overall prediction performance of these developed models are high by considering the signalized, interrupted and freeway traffic existing road sections. The developed models can be properly and accurately addressed the stable changes in the traffic flow pattern. The signalized or interrupted traffic patterns are frequently changing all the time and it's required a higher traffic patterns dataset for addressing all types of scenarios.

Chapter 8

CONCLUSION

This study investigated the Google Maps provided travel time accuracy, short-term travel time and traffic flow prediction on the differents time interval and road sections. Several experiments are performed manually and developed models for analyzing the Google Maps traffic information accuracy, multi-steps ahead travel time and vehicle flow prediction from morning to evening. At present, Google Maps provided travel time average accuracy is 91.19% in respect to actual travel time. The experiment is performed on Sainik club to Kachukhat road in both directions around 1251m distance for measuring the accuracy. Now a day Google Maps traffic information accuracy increasing through the crowdsourced and IoT. The Google Maps traffic information accuracy is high and real-time road networks. Moreover, such traffic information is reliable, easily accessible 24/7, low cost and a smart data source for model development.

Subsequently, several experiments are performed by developing a travel time prediction model using an LSTM network on a 2.5 km road section. This road section is high demand traffic and busy all times from morning to evening. The developed travel time prediction model error range is 5.84% ~ 10.93% for multi-step or one-hour advanced prediction on several time intervals of data collection. The model prediction error is small (5.84% to 8.58%) and stable while considering a short interval time span. The model predicted error at fifteen-minute intervals is higher comparatively while predicting multi-step due to inadequate train and lack of 24 hours data. Moreover, traffic patterns frequently change cause travel time prediction error to slightly increase while increasing the time span. Short span travel time data should be considered for getting high accuracy for urban and long-span traffic data can be used for highway traffic. Developed model short interval span can address frequently changes traffic pattern easily whereas long interval span is unpredictable. Experimental result shows that, developed LSTM travel time or time series prediction model accuracy and performance is high.

Finally, three categories of traffic flow prediction are performed by separate experiments on three types of road sections like low demand, high demand and free-flow traffic. Developed models traffic flow prediction error range is 8.25% ~14.09% for multi-step ahead prediction using five-minute time interval data. Low demand road (CTW) prediction error range is 12% ~ 14%, error range is 8% ~ 9% at high demand (CTN) and error range is 8% ~ 9% at freeway traffic (STN) respectively. The CTW road section has uncertain traffic flow created by motor vehicles and cars whereas the other two road sections traffic flow is stable all day. Traffic flow prediction is done by a maximum of three steps like fifteen minutes advanced for these road sections. Also, time-dependent correlation causes slightly increasing error while mapped predicted speed to traffic flow. Developed models traffic flow prediction accuracy comparatively higher while predicting freeway and high demand traffic. The traffic flow prediction accuracy will be improved by reducing consecutive sequences for time-dependent correlation equations and also adding 24 hours traffic information.

The above experimental results indicated that developed models overall prediction accuracy and performance are higher compare to existing models. Most of the existing models are studied areas in freeway or highway and developed country traffic information. The developed country always maintains the traffic rules and policy, as well as their road capacity which is sufficient for their existing traffic. But In a developing country like Bangladesh, insufficient road capacity with respect to the number of traffic and lack of traffic rules and policy. That whys, traffic flow patterns are unstable as well as unplanned. Experiments also, shown that models prediction accuracy is high and stable at minimum time interval span and slightly deferred while interval span increasing in busy road sections or frequently updated traffic.

On other hand, model prediction accuracy is high and stable while investigating freeway traffic. The developed model prediction accuracy is higher even in rush hour at five, ten and fifteen minute's time interval sequential data. The developed stacked LSTM deep network model is suitable for processing sequential data or time-series data with high accuracy. The stacked LSTM model is one of the best machine learning models for travel time and traffic flow prediction.

Considering the developed model's accuracy and performance, it may be applied in the following areas:

i. Assist make advanced travel planning.
ii. Select the best route instantly for avoiding traffic congestion.
iii. Help riders, drivers or logistics services make more trips in a day.
iv. Assist traffic control centre for smart traffic policy-making and traffic management systems.
v. Help the transportation road network planning and design.
vi. Help time saving and cost-minimizing which will contribute to the national economy.

Future Work

Travel time and traffic flow models are developed by considering various factors from data collection to perform several experiments for getting higher prediction accuracy. After performing sufficient experiments following scope of works can explore in future:

i. More reliable data sources and parameters can be used to improve prediction accuracy.
ii. A model can be developed for a complete urban road network using 24 hours data.
iii. LSTM models accuracy and performance can be improved by considering sliding window and hybrid models.
iv. Also, considering the full weekday real-time traffic flow data can be the collection for developing a smart traffic flow prediction model for specific road sections.
v. Model developed by using highway traffic data for analysis of the model performance and behaviour.

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APPENDIX-I

Algorithm for Predicted Traffic Speed Mapped into Traffic Flow:

Algorithm for mapping predicted speed into traffic flow using time-dependent correlation equations. The algorithm details are stated in below:

```
#Function of Predicted Traffic Flow
traffic_flow(hour, minute, speed, week_day )
#Algorithm For Time-Dependent Correlations
def traffic_flow (hour, minute, speed, week_day):
#Initial all variables
int h:=0;
int m:=0;
int flow:=0;
float s :=0;
int week_day:=0;

#Assign Variables
Assign h:=int(hour);
Assign m:= int(minute)
Assign s:=float(speed);
Assign day:= int(week_day);

If day equal to 0 then {

        if time between 8:00 to 8:30 then:
        flow:=(a1)+(b1)*h+(c1)*m+(d1)*s;
        return(flow);

        if time between 8:35  to 9:00  then:
        flow:=(a2)+(b2)*h+(c2)*m+(d2)*s;
        return(flow);

        if time between 9:05  to 9:30  then:
        flow:=(a3)+(b3)*h+(c3)*m+(d3)*s;
        return(flow);

        if time between 9:35  to 10:00  then:
        flow:=(a4)+(b4)*h+(c4)*m+(d4)*s;
        return(flow);

        if between 10:05  to 10:30  then:
        flow:=(a5)+(b5)*h+(c5)*m+(d5)*s;
        return(flow);
```

```
if time between 10:35  to 11:00  then:
flow:=(a6)+(b6)*h+(c6)*m+(d6)*s;
return(flow);

if  between 11:05  to 11:30  then:
flow:=(a7)+(b7)*h+(c7)*m+(d7)*s;
return(flow);

if time between 11:35  to 12:00  then:
flow:=(a8)+(b8)*h+(c8)*m+(d8)*s;
return(flow);

if time between 15:05  to 15:30  then:
flow:=(a9)+(b1)*h+(c9)*m+(d9)*s;
return(flow);

if time between 15:35  to 16:00  then:
flow:=(a10)+(b10)*h+(c10)*m+(d10)*s;
return(flow);

if time between 16:05  to 16:30  then:
flow:=(a11)+(b11)*h+(c11)*m+(d11)*s;
return(flow);

if time between 16:35  to 17:00  then:
flow:=(a12)+(b12)*h+(c12)*m+(d12)*s;
return(flow);

if time between 17:05  to 17:30  then:
flow:=(a13)+(b13)*h+(c13)*m+(d13)*s;
return(flow);

if time between 17:35 to 18:00 then:
flow:=(a14)+(b14)*h+(c14)*m+(d14)*s;
return(flow);

if time between 18:05 to 18:30 then:
flow:=(a15)+(b15)*h+(c15)*m+(d15)*s;
return(flow);

if time between 18:35 to 19:00 then:
low:=(a16)+(b16)*h+(c16)*m+(d16)*s;
return(flow);

if time between 6:45PM to 7:00PM then:
flow:=(w12)*speed+(x12)*minute+(y12)*hour+(z12);
return(flow);

}
```

APPENDIX-II

Travel Time Prediction Model Validated with Google Maps Prediction:

Developed model's predicted travel time and the Google Maps predicted travel time comparison is stated below:

Date Time	Actual (Sec)	Predicted (Sec)	Maps Predicted Time (Sec)	Model Accuracy
5/6/2019 9:00	522	531	300 ~ 720	1.72
5/6/2019 9:05	546	521	300 ~ 720	4.58
5/6/2019 9:10	588	521	360 ~ 720	11.39
5/6/2019 9:15	625	561	360 ~ 720	10.24
5/6/2019 9:20	651	589	360 ~ 840	9.52
5/6/2019 9:25	669	644	360 ~ 840	3.74
5/6/2019 9:30	730	673	360 ~ 840	7.81
5/6/2019 9:35	716	722	360 ~ 960	0.84
5/6/2019 9:40	763	746	420 ~ 960	2.23
5/6/2019 9:45	789	785	420 ~ 1080	0.51
5/6/2019 9:50	880	801	420 ~ 1080	8.98
5/6/2019 9:55	837	825	420 ~ 1080	1.43
5/6/2019 10:00	883	825	420 ~ 960	6.57
5/6/2019 10:05	809	827	420 ~ 960	2.22
5/6/2019 10:10	788	822	420 ~ 960	4.31
5/6/2019 10:15	745	776	420 ~ 960	4.16
5/6/2019 10:20	763	754	360 ~ 960	1.18
5/6/2019 10:25	803	740	420 ~ 1080	7.85
5/6/2019 10:30	821	728	420 ~ 960	11.33
5/6/2019 10:35	753	767	360 ~ 960	1.86
5/6/2019 10:40	695	798	360 ~ 960	14.82
5/6/2019 10:45	762	746	360 ~ 960	2.1
5/6/2019 10:50	707	750	360 ~ 960	6.08
5/6/2019 10:55	779	744	360 ~ 960	4.49
5/6/2019 11:00	715	745	360 ~ 960	4.2
5/6/2019 11:05	763	705	360 ~ 960	7.6
5/6/2019 11:10	770	729	360 ~ 960	5.32
5/6/2019 11:15	703	707	360 ~ 960	0.57
5/6/2019 11:20	698	720	420 ~ 960	3.15
5/6/2019 11:25	726	675	420 ~ 960	7.02
5/6/2019 11:30	851	703	420 ~ 960	17.39
5/6/2019 11:35	811	760	420 ~ 960	6.29
5/6/2019 11:40	869	819	420 ~ 960	5.75
5/6/2019 11:45	805	849	420 ~ 960	5.47
5/6/2019 11:50	828	837	420 ~ 1080	1.09
5/6/2019 11:55	986	834	420 ~ 960	15.42
5/6/2019 12:00	1142	854	420 ~ 960	25.22

5/6/2019 12:05	1278	956	420 ~ 960	25.2
5/6/2019 12:10	1167	1095	420 ~ 1080	6.17
5/6/2019 12:15	969	1088	420 ~ 1080	12.28
5/6/2019 12:20	971	955	420 ~ 1080	1.65
5/6/2019 12:25	1061	947	420 ~ 1080	10.74
5/6/2019 12:30	1001	871	420 ~ 1080	12.99
5/6/2019 12:35	1069	891	420 ~ 1080	16.65
5/6/2019 12:40	1071	879	420 ~ 1200	17.93
5/6/2019 12:45	1053	877	420 ~ 1200	16.71
5/6/2019 12:50	1107	845	420 ~ 1200	23.67
5/6/2019 12:55	1080	972	420 ~ 1200	10
5/6/2019 13:00	1120	1074	420 ~ 1200	4.11
5/6/2019 13:05	1096	1136	420 ~ 1200	3.65
5/6/2019 13:10	1068	1084	420 ~ 1080	1.5
5/6/2019 13:15	1030	1021	420 ~ 1080	0.87
5/6/2019 13:20	954	1031	420 ~ 1080	8.07
5/6/2019 13:25	869	1010	420 ~ 1080	16.23
5/6/2019 13:30	828	940	420 ~ 1080	13.53
5/6/2019 13:35	921	911	420 ~ 1080	1.09
5/6/2019 13:40	998	879	420 ~ 1080	11.92
5/6/2019 13:45	1048	929	420 ~ 1080	11.35
5/6/2019 13:50	990	995	420 ~ 1080	0.51
5/6/2019 13:55	1010	1040	420 ~ 1080	2.97
5/6/2019 14:00	1007	1006	420 ~ 1080	0.1
5/6/2019 14:05	971	967	420 ~ 1080	0.41
5/6/2019 14:10	986	891	420 ~ 1080	9.63
5/6/2019 14:15	947	953	420 ~ 1080	0.63
5/6/2019 14:20	887	922	420 ~ 1080	3.95
5/6/2019 14:25	956	896	420 ~ 1080	6.28
5/6/2019 14:30	946	849	420 ~ 1080	10.25
5/6/2019 14:35	906	824	420 ~ 1080	9.05
5/6/2019 14:40	980	926	420 ~ 1080	5.51
5/6/2019 14:45	957	879	420 ~ 1080	8.15
5/6/2019 14:50	1021	922	420 ~ 1080	9.7
5/6/2019 14:55	1060	934	420 ~ 1080	11.89
5/6/2019 15:00	962	890	420 ~ 1080	7.48
5/6/2019 15:05	925	937	420 ~ 1080	1.3
5/6/2019 15:10	738	885	420 ~ 1080	19.92
5/6/2019 15:15	829	677	420 ~ 1080	18.34
5/6/2019 15:20	888	714	420 ~ 1200	19.59
5/6/2019 15:25	841	804	420 ~ 1200	4.4
5/6/2019 15:30	869	788	420 ~ 1200	9.32
5/6/2019 15:35	972	838	420 ~ 1200	13.79
5/6/2019 15:40	1109	871	420 ~ 1200	21.46
5/6/2019 15:45	1030	962	420 ~ 1200	6.6
5/6/2019 15:50	1115	1079	420 ~ 1200	3.23

5/6/2019 15:55	1028	1106	420 ~ 1200	7.59
5/6/2019 16:00	1030	1095	420 ~ 1200	6.31
5/6/2019 16:05	953	1075	420 ~ 1200	12.8
5/6/2019 16:10	1095	956	480 ~ 1200	12.69
5/6/2019 16:15	1013	950	480 ~ 1200	6.22
5/6/2019 16:20	1071	946	480 ~ 1200	11.67
5/6/2019 16:25	1190	958	480 ~ 1200	19.5
5/6/2019 16:30	1169	1067	480 ~ 1200	8.73
5/6/2019 16:35	1035	1081	480 ~ 1200	4.44
5/6/2019 16:40	1160	1058	480 ~ 1320	8.79
5/6/2019 16:45	934	1088	480 ~ 1320	16.49
5/6/2019 16:50	1047	999	480 ~ 1320	4.58
5/6/2019 16:55	973	977	480 ~ 1320	0.41
5/6/2019 17:00	1016	917	480 ~ 1320	9.74
5/6/2019 17:05	975	963	480 ~ 1320	1.23
5/6/2019 17:10	1123	905	480 ~ 1320	19.41
5/6/2019 17:15	1010	967	480 ~ 1320	4.26
5/6/2019 17:20	1258	1023	480 ~ 1320	18.68
5/6/2019 17:25	1219	1103	480 ~ 1200	9.52
5/6/2019 17:30	1186	1117	480 ~ 1200	5.82
5/6/2019 17:35	1118	1236	480 ~ 1320	10.55
5/6/2019 17:40	1190	1150	480 ~ 1320	3.36
5/6/2019 17:45	1131	1153	480 ~ 1320	1.95
5/6/2019 17:50	1138	1152	480 ~ 1320	1.23
5/6/2019 17:55	1250	1135	480 ~ 1320	9.2
5/6/2019 18:00	1190	1192	480 ~ 1200	0.17
5/6/2019 18:05	1293	1226	480 ~ 1200	5.18
5/6/2019 18:10	1159	1251	480 ~ 1320	7.94
5/6/2019 18:15	1390	1260	480 ~ 1320	9.35
5/6/2019 18:20	1565	1279	420 ~ 1320	18.27
5/6/2019 18:25	1630	1360	420 ~ 1320	16.56
5/6/2019 18:30	1590	1508	420 ~ 1320	5.16
5/6/2019 18:35	1546	1592	420 ~ 1320	2.98
5/6/2019 18:40	1399	1517	420 ~ 1320	8.43
5/6/2019 18:45	1465	1513	420 ~ 1080	3.28
5/6/2019 18:50	1230	1504	420 ~ 1200	22.28
5/6/2019 18:55	1291	1328	420 ~ 1080	2.87
5/6/2019 19:00	1392	1199	420 ~ 1080	13.86
5/6/2019 19:05	1426	1157	420 ~ 1080	18.86
5/6/2019 19:10	1515	1255	420 ~ 1080	17.16
5/6/2019 19:15	1500	1270	420 ~ 1080	15.33
5/6/2019 19:20	1415	1395	420 ~ 1080	1.41
5/6/2019 19:25	1475	1374	420 ~ 1080	6.85
5/6/2019 19:30	1423	1352	420 ~ 1080	4.99
5/6/2019 19:35	1378	1310	420 ~ 1080	4.93
5/6/2019 19:40	1339	1301	420 ~ 1200	2.84

5/6/2019 19:45	1249	1240	420 ~ 1200	0.72
5/6/2019 19:50	1247	1128	420 ~ 1200	9.54
5/6/2019 19:55	1201	1100	420 ~ 1200	8.41
5/6/2019 20:00	1202	987	420 ~ 1080	17.89
5/6/2019 20:05		938	420 ~ 840	