Public Vehicle ETA System using Machine Learning

Inspiring Excellence

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Declaration

We, hereby declare that this thesis is based on results we have found ourselves. Materials of work from researchers conducted by others are mentioned in references.

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ABSTRACT

Traffic Jam impact our day to day life in more ways than we can think of. Our system aims to work on that particular problem to reduce the number of vehicles on the road by encouraging more people to get on public transport to make public transport more efficient for the people who are less keen on taking them due to time delays. Our system uses regression analysis on a data set collected on a specific route to estimate the arrival time of a public transport at a desired travel time. This gives the user a clear idea of the time required to travel between points and thus can utilize their time in an efficient way by not having to wait for a transport. The system uses a compiled data set to analyze historical data and then use regression analysis to predict the arrival time for particular location of the user.

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CHAPTER 1

Introduction

Public vehicle is the mass transport system for a lot of people in our country. As our country is a developing one, a few hours in the job sector will help to progress our country. Also time is very important for students. Due to heavy traffic in our country people waste a lot of time waiting for buses in the road. So we have aimed to develop a system which will help people to get a predicted time for the certain route a bus will take to reach. Through this, people will know when to wait for bus and rather than wasting time in waiting, these hours can be utilized in a more productive way increasing efficiency for the person.

1.1 Motivation

Public transport is a very common way for many of us in our country. From office to university or college even schools or markets, for all the destination, most of us use public transports. Our population is growing and so is the number of vehicles in the road. As a result we have to wait a long time in the road to wait for a bus to come. As a student time is very precious to us. Sometimes we need to wait 5 minutes sometimes it’s more than an hour. All these precious moments are doomed in waiting while it could have been used for very important things. So we felt motivated to give people a way to roughly presume the time that will be needed before the next transport arrives and we wanted to do it through algorithmic and IoT based approach. But with time, deep research work and field work has made us feel that our country Bangladesh is not that much modernized to develop a IoT based Public Vehicle Tracking System. Within time, we have moved from IoT to Machine Learning based system. Most of the time we collected raw data manually and used at least four prediction algorithms to figure out the best output or ETA (Estimated Time Arrival).

1.2 Goals

Our Thesis work mainly focuses on the traffic condition of current Bangladesh Dhaka city. The target was to make full utilization of our public transport system. If the public transport system can be made efficient and produce an effective means of transportation, people will be less inclined towards using private transports. This would benefit the environment as well as reducing traffic jams in the country, keeping these goals in mind, we have developed a system to provide an estimated public transport arrival time at a designated stoppage and also a total time duration taking into account traffic data of the route, of travel to reach destination stoppage.

1.3 Problem Statement

The fact that helped us to work on ETA prediction of Public Vehicle using Machine Learning was the huge traffic jam that occurs regularly in our major cities. Everyday a huge amount of working hours are wasted only due to traffic jam. To reach the destination on time someone has to wait hours to get into a public transport. Delay arrival time of public transport is the main reason of this waiting. This delay occurs because of short amount of public vehicles and traffic jam also. Other than this, it is very hard to assume which is the feasible time to get out to reach a destination on time. During dealing with emergency situation, uncertainty of traffic condition is one of the major facts. People losing valuable lives and hours for this composite situation. Here, comes our solution to predict the ETA of public transport and we also developed a webpage which will display the predicted time to reach the destination.

1.4 Solutions and Methodology

In the above stated circumstances, we came up with the idea of ETA prediction of Public Transport. Our first proposed solution was IoT based which later we had to change because of unavailability of IoT based system here in our major cities. Then, we moved to prediction based solution for which we implemented Machine Learning. We used four different prediction algorithms and compared their outputs among them to get the best prediction result. We tried to develop a free system for all the public those who use public transport on a regular basis. Moreover, in the Literature Review section we have given a brief idea about the previous used or proposed solutions. Unfortunately, again and again we had to face obstacles for lack of digital tracking system availability. To get to original prediction time we decided to go manually. We collected data manually from Point A (Start Point, Khilgaon; Khidmah Hospital) to Point B (Interval point, Abul Hotel), Point C (Interval point, Rampura Bridge), Point D (Interval point, Badda Link Road), Point E (Interval point, Gulshan-1), Point F (Interval point, BRAC University), Point G (Interval point, Mohakhali Rail-Gate), Point H (Interval Point, Prime Minister's Office), Point I (Interval point, IDB Bhaban; Aagargaon). Not only this we have divided the transport movement time according to On pick hour, Off pick Hour, Low pressure, High pressure etc. Then we had to prepare dataset according to our modified Azure model and input the data into the model. We used the model in different algorithms which gave us different results. Then we sorted the results manually and chose the best prediction time focusing on accuracy rates.

1.5 Thesis Contribution

To bring out the best ETA Estimated Time of Arrival we had to go through numerous researches and tried different algorithms in different data sets. Our first attempt was based on IoT but eventually we faced lots of barriers and had to move to Machine Learning based ETA of Public transport. Now, our latest result is best and most solid accurate result comparison with all the other prediction algorithm output results. We are also using a web page to predict the arrival time of the nearest Public Transportation to the selected stoppage and also the time required to reach the required destination.

1.6 Thesis Outline

The outline of this thesis paper is as follows:

CHAPTER 01 explains the motivation, entire idea and the problem statement of this system.

CHAPTER 02 explains all the related previous works which are considered as literature review.

CHAPTER 03 explains the model structure, data collection process and the system overview.

CHAPTER 04 explains the result and analyzes the evaluation of the proposed models.

CHAPTER 05 concludes the entire thesis work and defines the future scope regarding the research.

CHAPTER 2

LITERATURE REVIEW

2.0 TRAVEL TIME PREDICTION MODELS

Throughout the years a few expectation models have been produced that has prompted estimating movement states such an activity stream and travel time. The significance of the transient travel time forecast has expanded strikingly (Smith and Demetsky, 1995). An assortment of expectation models, for example, verifiable information based models, relapse models, time arrangement models and neural system models, have been created throughout the years. The five most generally utilized models incorporate recorded information based models (Williams and Hoel, 2003; Jeong , 2004), time arrangement show (Thomas, Weijermars, and Van Berk, 2010; Al-Deek, H, M, and M, 1998), relapse models (Jeong , 2004; Ramakrishna, Y., P. Ramakrishna, V. Lakshmanan, and R. Sivanandan, 2006), Kalman separating model (Chien, S.I.J., Ding, Y., Wei, and C., 2002; Shalaby and Farhan, 2004) and machine learning models (Bin et al 2006, Yasdi 1999, Jeong 2004). (Kirby et al 1997, Zheng et al 2006) be that as it may, talked about that no single indicator has been produced that presents itself to be all around acknowledged as the best, and constantly, and compelling activity state estimating model for realtime movement task. Half and half models, e.g. a mix of Kalman sifting and neural system (Chien et al 2002, Chen et al 2004), a mix of time arrangement and Kalman separating (Thomas, Weijermars, and Van Berk, 2010) additionally drew much consideration. A few characterizations of expectation strategies have been recommended by specialists. The concentration will be given to their application in movement time forecast, generally for travel vehicles.

2.1 Historical Data Based Models

These expectation models gives the present and future transport travel time from the chronicled travel time of past adventures on a similar day and age. The present movement condition is expected to stay stationary. (Williams and Hoel 2003) called attention to that the marvel that movement conditions take after ostensibly reliable day by day and week after week designs prompts a desire that recorded midpoints of the conditions at a specific time and day of the week will give a sensible figure of future conditions in the meantime of day and day of the week (Shalaby and Farhan, 2004). In this manner, these models are solid just when the movement design in the zone of intrigue is moderately steady, e.g. provincial regions.

2.2 Regression Models

These models anticipate and clarify a reliant variable with a numerical capacity shaped by an arrangement of autonomous factors (Chien et al 2002). Dissimilar to recorded information based forecast models, these can work palatably under temperamental movement condition. Relapse models normally measure the concurrent impacts of different elements, which are free in the vicinity of one and another, influencing the needy variable. (Patnaik et al 2004) proposed an arrangement of multilinear relapse models to assess transport entry times utilizing the information gathered via programmed traveler counter (APC).

They utilized separation, number of stops, abide times, loading up and landing travelers and climate descriptors as autonomous factors. They demonstrated that the models could be utilized to appraise transport landing time at downstream stops. Be that as it may, this approach is solid when such conditions can be set up. (Jeong 2004) and (Ramakrishna et al 2006) likewise created multilinear relapse models utilizing diverse arrangements of information sources. The two examinations showed that relapse models are surpassed by different models. One incredible preferred standpoint of multilinear relapse demonstrate is that it uncovers which inputs are less or more vital for forecast. For instance, (Patnaik et al 2004) found that climate was not an imperative contribution for their model. Additionally (Ramakrishna et al 2006) discovered that transport prevent stay times from the starting point of the course to the present transport stop in minutes and convergence delays from the beginning of the course to the present transport stop in minutes are less essential sources of info. When all is said in done, the pertinence of the relapse models is restricted on the grounds that factors in transportation frameworks are profoundly between associated (Chien et al 2002)

.2.3 Time Series Models

These models assume that the exogenous factors acting upon the dynamical system either remain constant, or can be measured and accounted for in the model, if they vary in time. In terms of traffic, they assume that the historical traffic patterns will remain the same in the future. As has been indicated on (Chien et al 2002), the accuracy of time series models is a function of the similarity between the real-time and historical traffic patterns. Variation in historical travel time data or changes in the relationship between historical and real-time travel time data could significantly cause inaccuracy in the prediction results. To the author's knowledge, these models have not been used for prediction of bus travel time so far. However, they have been used and indicated to be effective for link travel time and traffic volume predictions either alone or in combination with other models, e.g. Kalman filtering (Al-Deek et al 1998, Thomas et al 2010).

2.4 Kalman Filtering Models

It has been used extensively for predicting bus arrival time (Chen et al 2004, Vanajakshi et al 2009, Wall and Dailey 1999, Chien et al 2002, Yang 2005). Chen and Chien (2002) and Wall and Dailey (1999) used Kalman filtering techniques to predict auto travel time. The Kalman filtering model has the potential to adapt to traffic fluctuation with time-dependent parameters (Chen and Chien 2002). These models are effective in predicting travel time one or two time periods ahead, but they deteriorate with multiple time steps (Park and Rilett 1999). Park and Rilett compared neural network models with other prediction models including Kalman filtering techniques to predict freeway link travel time. While the average mean absolute percentage error (MAPE) of neural network models changed from 8.7 for one time period to 16.1 for 5 time periods, that of Kalman filtering changed from 5.7 to 20.1 (Park and Rilett 1999).

2.5 Machine Learning Models

Machine learning methods present some advantages with respect to statistical methods: they are able to deal with complex relationships between predictors that can arise within large amounts of data, are able to process non-linear relationships between predictors and are able to process complex and noise data (Ricknagel 2001). These models can be used for prediction of travel time, without explicitly addressing the (physical) traffic processes (Hoogendoorn and Van Lint 2008). However, they are location-specific solutions, requiring significant efforts in input- and model selection for each specific application, via for instance correlation analysis, or genetic algorithms or trial-and-error procedures. Results obtained for one location are (typically) not transferable to the next, due to location-specific circumstances (geometry, traffic control, etc.). Artificial Neural Network (ANN) and Support Vector Regression methods are presented under these categories.

2.6 Artificial Neural Network Models

Much research has been on predicting bus arrival time using ANNs because of its ability to solve complex non-linear relationships (Chen et al 2004, Ramakrishna et al 2006, Jeong 2004, Chien et al 2002, Park et al 2004). Compared to the previously discussed models, ANNs can be developed without specifying the form of the function, while the restrictions on the multicollinearity of the explanatory variables can be neglected. Chien developed an enhanced Artificial Neural Network model to predict dynamic bus arrival time using Back-Propagation algorithm (Chien et al 2002).

On another study, Chen developed a methodology for predicting bus arrival time using data collected by Automatic Passenger Counter (APC) (Chen et al 2004).Their model consisted of an Artificial Neural Network (ANN) model to predict bus travel time between time points and a kalman filter based dynamic algorithm to adjust the predicted arrival time using bus location information. The ANN was trained with four input variables, day-of-week, time-of-day, weather and segment; and produced a baseline estimate of the travel time. The dynamic algorithm then combined the most recent information on bus location with the baseline estimate to predict arrival times at downstream time points. The algorithm not only explicitly considered variables influencing the travel time but also updated it using the real-time APC data. The authors indicated that their model was powerful in modelling variations in bus-arrival times along the service route. It was observed that the dynamic algorithm performed better than the corresponding ANN model because it incorporated the latest bus-arrival information into the prediction. The ANN model also performed better than the timetable. (Jeong and Rilett 2004) also proposed an ANN model for predicting bus arrival times and demonstrated its superior performance as compared with the historical data based and multi-linear regression models. Historical data based model gave superior results, as compared to the multiple linear regression. The authors have tested 12 training and 14 learning functions and the best functions were chosen for the prediction purpose.

The advantage of their models was that traffic congestion, schedule adherence and dwell times at stops were considered as inputs for the prediction. (Ramakrishna et al 2006) developed a Multiple Linear Regression (MLR) model and an Artificial Neural Network (ANN) model for prediction of bus travel times using GPS-based data. These models were applied to a case study bus route in Chennai city, India. It was indicated that Artificial Neural Network model performed better than Multiple Linear Regression model.

In general, ANN models have the ability to capture the complex non-linear relationship between travel time and the independent variables. These models have been proved to be effective for the provision of satisfactory bus arrival time information. They could be very useful in prediction when it is difficult or even impossible to mathematically formulate the relationship between the input and output. Though the learning and testing process is inherently delicate and is slow to converge to the optimal solution (Hagal et al 1996), it is still possible to do an off-line training and adapting ANNs to real-time condition if the inputs are chosen carefully.

2.7 Support Vector Machines

Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. While other machine learning techniques, such as ANN, have been extensively studied, the reported applications of SVM in the field of transportation engineering are very few. Support vector machine and support vector regression (SVR) have demonstrated their success in time-series analysis and statistical learning (Chun-Hsin et al 2003). Since support vector machines have greater generalization ability and guarantee global minima for given training data, it is believed that support vector regression will perform well for time series analysis. (Bin et al 2006) proposed Support Vector Machine (SVM) as a new neural network algorithm to predict the bus arrival time. They pointed out that unlike the traditional ANN, SVM is not amenable to the over fitting problem, and it could be trained through a linear optimization process. This study predicted the arrival time based on the travel time of a current segment and the latest travel time of the next segment. The authors built separate models according to the time-of-day and weather conditions.

The developed model was tested using off-line data of a transit route and exhibited advantages over an ANN based model methods. These models have been developed for prediction of travel time on highways, e.g. (Chun-Hsin et al 2003). They compared their proposed SVR predictor to other baseline predictors, the results showed that the SVR predictor can reduce significantly both relative mean errors and root mean squared errors of predicted travel times. However, (Bin et al 2006) indicated that when SVM is applied for solving large-size problems, a large amount of computation time will be involved. In addition, the methods for selecting input variables and identifying the parameters should be further researched.

2.8 Dynamic Models

Different researchers have different opinions on dynamic models, and as a result different algorithms are proposed in the dynamic models.

Elhenawy et al. [1] developed a data clustering and genetic programming approach for modeling and predicting the dynamic travel times along freeways. Chen et al. [2] proposed a dynamic algorithm integrating the ANN model and Kalman filter-based algorithm, because the history data-based models had difficulty in dealing with dynamic traffic conditions. Results showed that this dynamic model was powerful in predicting bus arrival times along the service route. Yu et al. [3] proposed a hybrid model which was based on SVM and Kalman filtering technique to predict bus arrival times, which performed better than the ANN-based methods. Liu et al. [4] predicted urban arterial travel times with state space neural networks (SSNN) and Kalman filters. The Kalman filters algorithm was applied to train the SSNN model, which was different from that of Chen et al.'s [5] method. Chen et al. proposed an integrated bus rapid transit (BRT) vehicle travel time prediction model. This model used the SVM and Kalman filter algorithm to dynamically predict travel times. The Kalman filter algorithm was applied to adjust the bus travel times predicted by SVM. The prediction results of the proposed model outperformed the Kalman filter model, but it lacked the results comparison with that of SVM model. Besides, BRT vehicles (buses) operate on exclusive rights-of-way or bus lanes [6], which totally differs from the buses in the normal bus transit systems.

However, only Yu et al. [7] addressed the importance of buses on road with multiple bus routes. By integrating bus travel times of different bus routes on the same road segments, the estimation accuracy of traffic conditions could be improved. The limitation of Yu's research is that no dynamic model was introduced and only peak hours were studied. It needs further study in this specific case of buses sharing the same road segments and bus stops.

In summary, previous researches have been conducted on the research field of bus travel/arrival time prediction for a single bus route, but few researches addressed the case of buses on road with multiple bus routes, which is worth further research in order to improve the prediction accuracy. The previous researches only used the information of the same bus route to predict the bus travel/arrival times, but the integration of bus information of multiple bus routes was not included in these studies. Although Yu et al. [7] made some contributions to this problem, no dynamic model was developed in the study and whether a dynamic model could further improve the prediction accuracy remained unknown. Since studies in recent years proved that SVM and ANN models outperformed other models in prediction accuracy, in this study five models, including pure ANN, pure SVM, pure Kalman, ANN-Kalman (ANN-Kalman model refers to the model based on ANN and Kalman filtering-based algorithm), and SVM-Kalman (SVM-Kalman model is short for the model based on SVM and Kalman filtering-based algorithm) models, are proposed for bus travel time prediction on road with multiple bus routes.

2.9 Travel time distribution

Travel time distribution is a result of the fluctuations in traffic demand and supply (Van Lint et al 2003, (Tu, 2008). Travel times are the result of traffic flow operations, which in turn are attributed to the interaction between traffic demand and traffic supply characteristics. These characteristics are categorized as below:

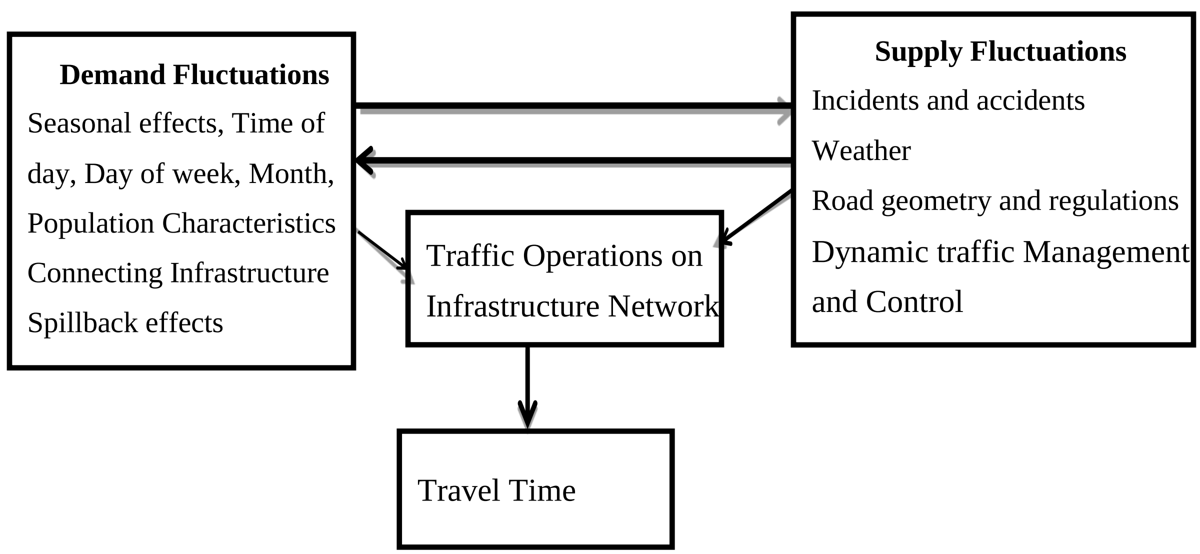


Figure 2.9.1 Overview of factors influencing the distribution of travel times (Tu 2008, (Zegeye&Nall, 2014)

To improve the reliability of traffic information and increase the accuracy of travel time predictions, the knowledge of travel time variability is valuable. Therefore, a reduction in travel time variability reduces the uncertainty in decision-making about departure time and route choice as well as the anxiety and stress caused by such uncertainties. As far as these fluctuations continue to exist, one will frequently experience variability in travel time irrespective of the type of vehicle. Predicting travel time along certain roadways or routes can be challenging due high degree of variability which in turn may result in less reliable travel time information.

Very few studies have concentrated on quantifying sources of uncertainties making travel time unreliable. Asakura has categorized the sources of travel time fluctuations in to three factors which are from demand side such as day to day traffic variation, supply side such as road closure due to accidents and external factors such as adverse weather effects and natural disaster (Asakura 2006). Most of the studies in the literature used deterministic approach to model travel time variation under the influence of various factors from supply side and demand side of the system.

Ruimin examined travel time variability under the influence of time of day, day of week, weather effect and traffic accident [21]. In that study, the author quantified sources of travel time parameters with the help of multiple linear regressions with one way interaction models. The results of his study is summarized in the table below

	Independent Variables	Adjusted R Square
Morning peak	Day of week, time of day, weather, incident and all interaction terms	0.56
	Time of day, day of week, weather, incident	0.55
	Time of day, day of week	0.53
Afternoon peak	Day of week, time of day,weather, incident and all interaction terms	0.50
	Time of day, day of week, weather, incident	0.43
	Time of day, day of week	0.25

Table 1: Independent traffic peak variables

Ruimin thus concluded from the above findings that day of week and time of day effects have more significant influence on morning peak travel times than on afternoon peak travel times. Whereas effects like rain and incidents, contribute more variability to the afternoon travel times than the morning travel times. Therefore, almost half travel time variability in morning peak is caused by demand related variations, while the 25% of the travel time variability in afternoon peak results from the capacity related variations. This is consistent with the traffic situation of the study site.

Ruimin however stated that his research was more focused on the day-to-day instead of time-to-time travel time variability thus to mean that the day-to-day travel time variability measures the change of travel times for the same trip at the same time from day-today, while time-to-time travel time variability emphasizes the change of travel times of the same trip on the same day from time to time. This study has further recommended that travel time data across a longer time period than the one-month used are needed to separate out the effect of time of day and day of week.

In another study, Van identified the main causes of unreliability of travel times for Netherlands urban roads. According to his study, 74 % of unreliability in the travel time is mainly due to internal factors of the traffic. The remaining is due to weather (8 %), road works (14 %), accidents (3 to 12 %) and combination factors (2 %) (Van Zuylen, 2004).

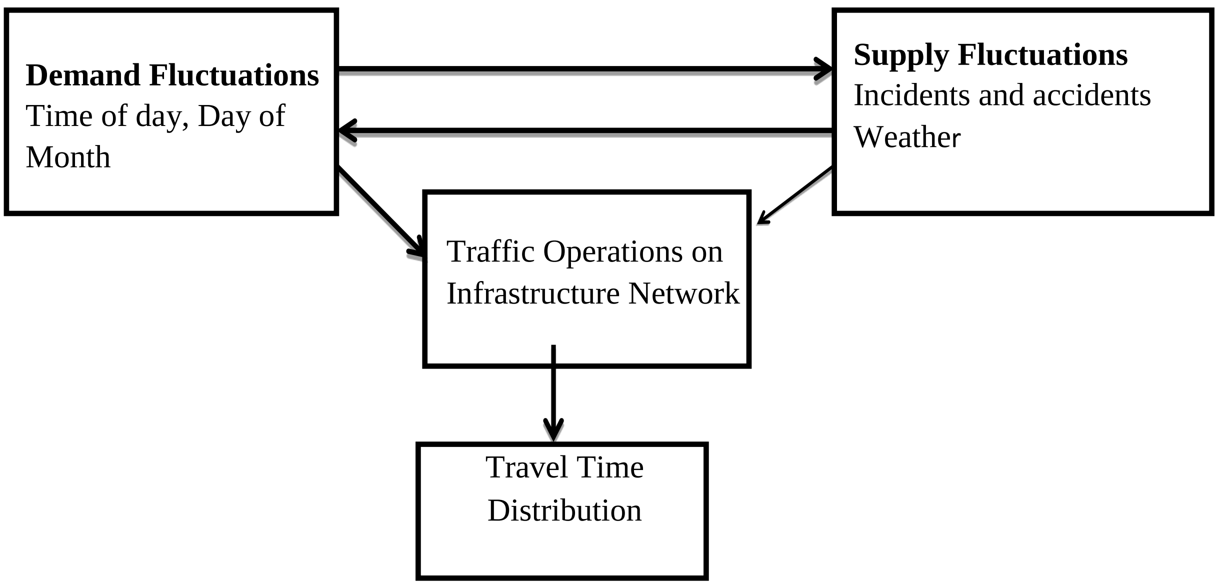
From Tu's research recommendations this research proposed a travel time distribution model that is suitable under the following conditions:-

I. The model is suited for all motorways under all conditions,

II. Modeling the reliability of individual travel times, using monitoring data from single vehicles,

III. Modeling reliability of travel times on urban road networks. (Tu, 2008)

The proposed SVR travel time conceptual framework for this research is shown in the diagram



below:

Figure 2.9.3 The SVR based conceptual framework for travel distribution model

The travel time distribution framework has been reduced to reflect only the factors that the research focused on or have significant effect on travel time during the period of study. The rest of the factors are treated as constants and data collected under the influence of those factors were not considered in developing the prediction model algorithm. This model can be justified by the fact that the population characteristics, seasonal effects, cultural factors, connecting infrastructure and spillbacks a part of the demand fluctuations as indicated in Tu's model can be treated as impact variables and in most cases they largely remained constant during the period and section of study. Under supply fluctuations, road geometry and dynamic traffic management and control as constant as well were treated as constant.

2.10 Microsoft Azure Machine Learning Studio

Microsoft Azure Machine Learning Studio is a web platform to experiment with various machine learning algorithm. This platform has various experiment which were contributed by other researchers. It is very easy to operate and it provides various facilities. It is a cloud based platform where users can run experiment for research involving Computer Science for free and also use the cloud and other facilities to store their website data for a fee.

CHAPTER 3

Proposed Models and Data Collection

3 Design of our Public Vehicle ETA System using Machine Learning

For understanding the design of our proposed model and researched work, it is very important to understand the concept. That is why, we want to demonstrate a real life situation to comprehend our proposed model.

3.1 Real Life Example of Our proposed Public Vehicle ETA System using Machine Learning

In our country there is no data regarding tracking any public vehicle. People have to wait for hours for a bus to come. Also many people cannot determine the best time to go somewhere without facing huge traffic. Our system will give solution to all these problems. Firstly, our system will be able to provide an estimation time in a particular route of a particular vehicle and this will help people to save time. For example, a person using our system may find that the next public transport will arrive after 40 minutes due to heavy traffic and so he will be able to save quite some time in other works rather than waiting outside for the bus. This is one aspect of our system.

Secondly, this system can predict ETA time of public transport in a given time frame so whenever a person want to know which time of the day is better for him to go to a certain destination without traffic, our system will predict the time needed based on previous values and provide the person with a prediction that will help him to determine his departure time without facing heavy traffic.

Thirdly, this system can be used to evaluate the high traffic areas in particular routes to be able to avoid them in case of emergency, for example and ambulance with a patient may try to determine the most time effective route and use our system to get the time needed to reach the destination using different route. This may save a few lives.

3.2 Design of Our Proposed System

Our system is a machine learning algorithm based system where we have used hand picked data for 877 various scenario starting from Khidmah Hospital to IDB Bhavan in Mirpur. The routes were named from Node 0 to Node 8. We have done our simulation from Khidmah Hospital to BRAC University as a one way route covering the existing points in between the route. We have chosen to use this route particularly as it covers a heavy traffic zone. Also it is a busy route due to a lot of offices and corporate houses and BRAC University situated in this route. The functionality are described below.

3.2.1 Data Collection

The process of data collection of our system spanned from December, 2017 to March, 2018. The data was collected manually and entered into a workbook. The time span provided us with a total of 876 data sets in total for the complete route. The start node categorized as Khidmah Hospital, Khilgaon and the end point categorized as IDB Bhaban, Aagargaon. The window of data collection was set as 24 hours but the concentration of data was most during the hours of 8:00am in the morning till 8:30pm at night.

3.2.1.1 Data Collection Methodology

The data collection was completed using 47 individuals, who regularly use public transport in the route of analysis during various hours of the day. The class of individuals participating as contributors mainly contained students and a few job holders. They willingly decided to contribute travel time data of their travel at any moment of time on the specified route using public transport.

3.2.1.2 Data Entry

The collection of data was completed manually, the data received was entered into a datasheet at the end of the day in the form of travel time required to reach various points. The last column of the workbook displayed total points, the first one the serial no. of the data set and the other eight displayed the time to travel between the points.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Khidmah_	Total(0_1)	Abul_hote	Total(0_1_	Rampura_	Total(0_1_	Badda_Lin	Total(0_1_	Gulshan_1	Total(0_1_	BRAC_Uni	Mohakhal	PMO_IDB_	Total_Trip_
2	25	25	30	55	45	100	37	137	15	152	0	0	0	621
3	18	18	26	44	40	84	27	111	17	128	0	0	0	513
4	20.55	20.55	45	65.55	33.2	98.75	17	115.75	10	125.75	16	13	22	603.1
5	16	16	40	56	37	93	20	113	12	125	11	10	0	549
6	60	60	50	110	120	230	30	260	20	280	0	0	0	1220
7	6	6	7	13	10	23	12	35	12	47	5	7	8	191
8	10	10	8	18	15	33	10	43	5	48	0	0	0	200
9	22	22	12	34	20	54	20	74	12	86	10	0	0	366
10	24	24	16	40	40	80	22	102	5	107	0	0	0	460
11	16	16	10	26	33	59	15	74	10	84	12	0	0	355
12	80	80	40	120	0	120	0	120	0	120	0	0	0	680
13	30	30	26	56	48	104	18	122	9	131	15	22	30	641
14	10	10	5	15	18	33	10	43	5	48	0	0	0	197
15	25	25	10	35	22	57	17	74	10	84	7	12	16	394
16	25	25	30	55	45	100	37	137	15	152	0	0	0	621
17	18	18	26	44	40	84	27	111	17	128	0	0	0	513
18	20.55	20.55	45	65.55	33.2	98.75	17	115.75	10	125.75	16	13	22	603.1
19	16	16	40	56	37	93	20	113	12	125	11	10	0	549
20	60	60	50	110	120	230	30	260	20	280	0	0	0	1220
21	6	6	7	13	10	23	12	35	12	47	5	7	8	191
22	10	10	8	18	15	33	10	43	5	48	0	0	0	200
23	22	22	12	34	20	54	20	74	12	86	10	0	0	366
24	24	24	16	40	40	80	22	102	5	107	0	25	18	503
25	16	16	10	26	33	59	18	77	14	91	16	0	0	376
26	80	80	40	120	35	155	27	182	10	192	0	0	0	921
27	30	30	26	56	48	104	18	122	9	131	15	22	30	641
28	10	10	5	15	18	33	10	43	5	48	0	0	0	197
29	25	25	10	35	22	57	17	74	10	84	7	12	16	394
30	25	25	30	55	45	100	37	137	15	152	0	0	0	621
31	18	18	26	44	40	84	27	111	17	128	0	0	0	513
32	20.55	20.55	45	65.55	33.2	98.75	17	115.75	10	125.75	16	13	22	603.1
33	16	16	40	56	37	93	20	113	12	125	11	10	0	549
34	60	60	50	110	120	230	30	260	20	280	0	0	0	1220
35	6	6	7	13	10	23	12	35	12	47	5	7	8	191
36	10	10	8	18	15	33	10	43	5	48	0	0	0	200

Figure 3.2.1 a: Data in excel sheet

This chart some of the values stored in our datasets excel files. All the data were collected manually. These data were used in our evaluation using four major prediction algorithm such as Poisson, Linear, Neural Network and Ordinal Regression.

3.2.1.3 Data Filtering and Sorting

Firstly, all the data were entered into the workbook and after the collection time ended, we filtered and sorted the data to organize them into the required structure for using in the selected prediction algorithms

3.2.1.4 Data Transformation

The data set was transformed into various combinations for making it readable for the algorithms. One example of transformation can be given as, division of the dataset to display distance and time total to reach all the places from one certain point, making a total of nine (9) workbook for one single point.

3.2.1.5 Data Sheet Selection

We manually collected all the data and saved them in a notebook but to be able to process them through various Machine Learning prediction algorithms, we needed to insert them certain files such as excel or csv. In Microsoft Azure Machine Learning studio, the experiment are done with data files in .csv format. So we selected .csv (Comma Separated Values) format so that our system can easily read the data from the data set continuously and run prediction algorithms.

3.2.1 Web Page for Tracking User Location

3.2.1.1 Front End Design

In this web page the location of the user will be automatically recorded. Also the user will input his destination which will be sent to the cloud service we are using. This web page was developed simply using simple HTML5 and CSS3 and JavaScript. These designs are only for user interface. No prediction algorithm is running inside the JavaScript.

Figure 3.2.1 b: Front page of the website

This is the front page of our website. When user hovers mouse cursor over the “LOCATION” or “DESTINATION” bar, the drop down menu comes up and the user can choose his location and destination. Then the webpage fetches data from the cloud and show the user the ETA.

Figure 3.2.1 c: Hovering Mouse on “Location” bar

User hovers mouse on the location bar and drom down menu comes up with the location names.

Figure 3.2.1 d: Location is chosen

After choosing the location from menu, chosen location is shown in the page.

Figure 3.2.1 e: Destination is chosen

The same process follows for destination bar. User can see the chosen location and destination.

Figure 3.2.1 f: “GO” button connects to cloud

This little “GO” button is to see the results. The “GO” button gives permission to PHP to connect to the cloud and fetch data.

Figure 3.2.1 g: Predicted outcome.

After pressing the "GO" button the ETA is shown in the next page.

3.2.1.2 Back End Design

The backend was developed through PHP5. This web page only serves the duty to provide our cloud server with the user data such as location, time and destination point. No simulation or manipulation is being done here for security reasons. The web page sends these data to the cloud server which is Microsoft Azure Web Services. Our algorithm and parent database are kept in Azure. The webpage is a user friendly medium for users to access our services.

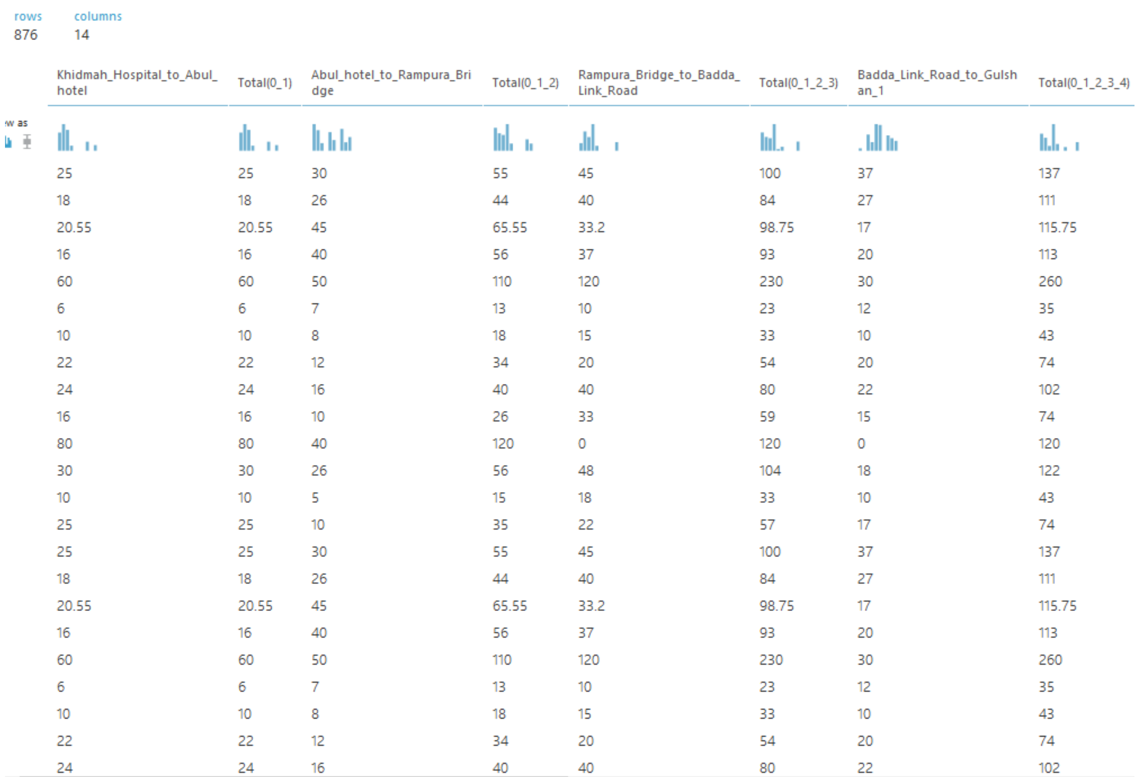
3.2.2 Send User Data to the Cloud Server

3.2.2.1 Sending User Data to the Cloud

The data is send though internet to our cloud server. It is used only for input purpose to get a result. No extra information is recorded. Our webpage will only send the user location, time slot and destination information to our cloud and no additional data will be gathered without the consent of the user for ethical purposes.

3.2.2.2 Choosing the Relevant Rows and Columns in Dataset

The data we get from the webpage is sent to our cloud service in Azure Machine Learning Studio where the system analyzes the dataset for the user required field. For example if a user is in BaddaLink Road and wants to know the nearest public vehicle's arrival time, our system will try todetermine the location of the public vehicle and then it will run queries along with the time of the incident and analyze the dataset.



rows 876 columns 14

Khidmah_Hospital_to_Abul_hotel	Total(0_1)	Abul_hotel_to_Rampura_Bridge	Total(0_1_2)	Rampura_Bridge_to_Badda_Link_Road	Total(0_1_2_3)	Badda_Link_Road_to_Gulshan_1	Total(0_1_2_3_4)
25	25	30	55	45	100	37	137
18	18	26	44	40	84	27	111
20.55	20.55	45	65.55	33.2	98.75	17	115.75
16	16	40	56	37	93	20	113
60	60	50	110	120	230	30	260
6	6	7	13	10	23	12	35
10	10	8	18	15	33	10	43
22	22	12	34	20	54	20	74
24	24	16	40	40	80	22	102
16	16	10	26	33	59	15	74
80	80	40	120	0	120	0	120
30	30	26	56	48	104	18	122
10	10	5	15	18	33	10	43
25	25	10	35	22	57	17	74
25	25	30	55	45	100	37	137
18	18	26	44	40	84	27	111
20.55	20.55	45	65.55	33.2	98.75	17	115.75
16	16	40	56	37	93	20	113
60	60	50	110	120	230	30	260
6	6	7	13	10	23	12	35
10	10	8	18	15	33	10	43
22	22	12	34	20	54	20	74
24	24	16	40	40	80	22	102

Figure 3.2.2 a: Data in cloud with relevant columns

This chart shows some of the data that are stored in our Microsoft Azure Cloud where all these data are processed using the mentioned algorithm and prediction values are gathered. the excel file of the dataset was given as input database and the cloud server converted it as mentioned above in the picture to use for regression analysis using Ordinal, Linear, Neural Network and Poisson regression analysis.

16	16	10	26	33	59	18	77
80	80	40	120	35	155	27	182
30	30	26	56	48	104	18	122
10	10	5	15	18	33	10	43
25	25	10	35	22	57	17	74
25	25	30	55	45	100	37	137
18	18	26	44	40	84	27	111
20.55	20.55	45	65.55	33.2	98.75	17	115.75
16	16	40	56	37	93	20	113
60	60	50	110	120	230	30	260
6	6	7	13	10	23	12	35
10	10	8	18	15	33	10	43
10	10	8	18	15	33	10	43
25	25	30	55	45	100	37	137
16	16	40	56	37	93	20	113
60	60	50	110	120	230	30	260
18	18	26	44	40	84	27	111
24	24	16	40	40	80	22	102
16	16	10	26	33	59	18	77
80	80	40	120	35	155	27	182
30	30	26	56	48	104	18	122
10	10	5	15	18	33	10	43
25	25	10	35	22	57	17	74
25	25	30	55	45	100	37	137
18	18	26	44	40	84	27	111
20.55	20.55	45	65.55	33.2	98.75	17	115.75

Figure 3.2.2 b: Data in cloud with relevant columns

This chart shows some of the data that are stored in our Microsoft Azure Cloud where all these data are processed using the mentioned algorithm and prediction values are gathered.

3.2.2.3 Running the Algorithms

The algorithms we used for analyzing were Linear Regression, Neural Network Regression, Poisson Regression and Ordinal Regression. All of these algorithms read 20% data from dataset and based on the Mean Absolute Error, Root Mean Squared Error, Relative Absolute Error and Relative Squared Error which leads to the determination of co-efficient and use to it predict ETA for the rest 80% values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y'_i - Y_i) \wedge 2 \ \ldots\ldots\ldots\ldots\ldots \ (1)$$

$$RMSE = \sqrt{\sum \frac{(Y_{pred} - Y_{ref})^2}{N}} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

These are the formulas used to find coefficient of determination among the given data sets in order to find the predicted values. The regression analysis was done on our datasets.

These predicted values are sorted out accordance to the time slot. The above

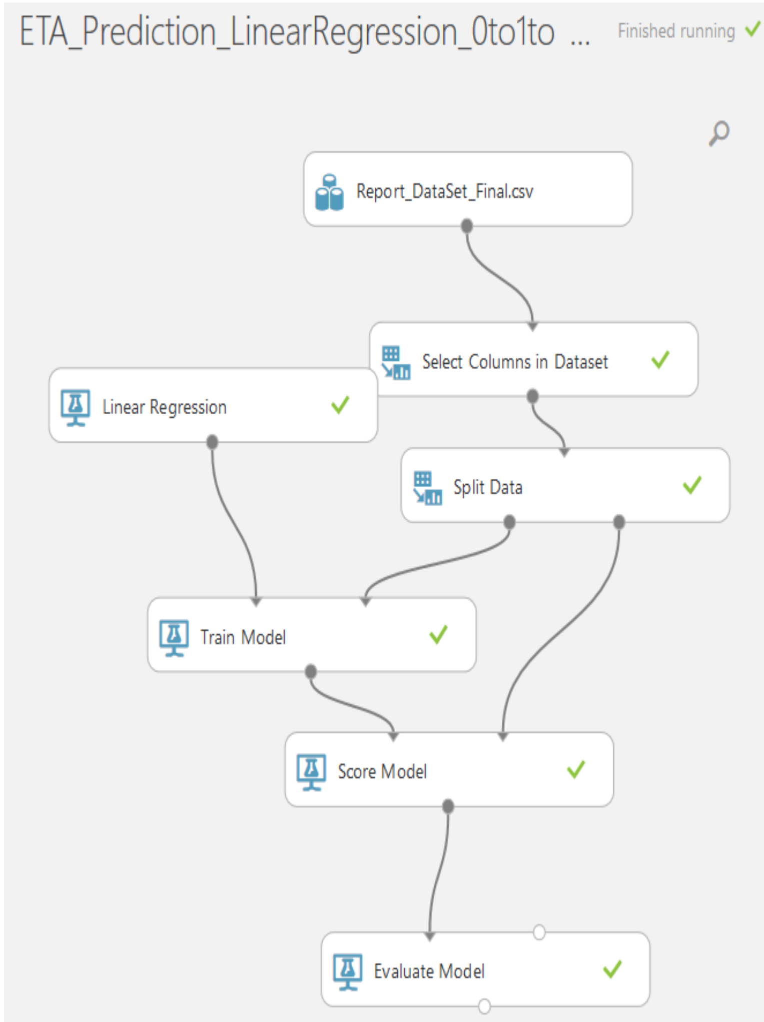


Figure 3.2.2 c: Linear regression flow chart model used in cloud

This is the flowchart for linear regression. Here the data is taken from our datasets and then the columns needed for analysis is chosen. Next, the data is split into 1:9 where the linear regression analyses 10% data for error. Next linear regression analyses the rest 90% data in the trained section. Later, prediction is made in scored data sheet. Lastly the evaluation is for graph and comparison evaluation.

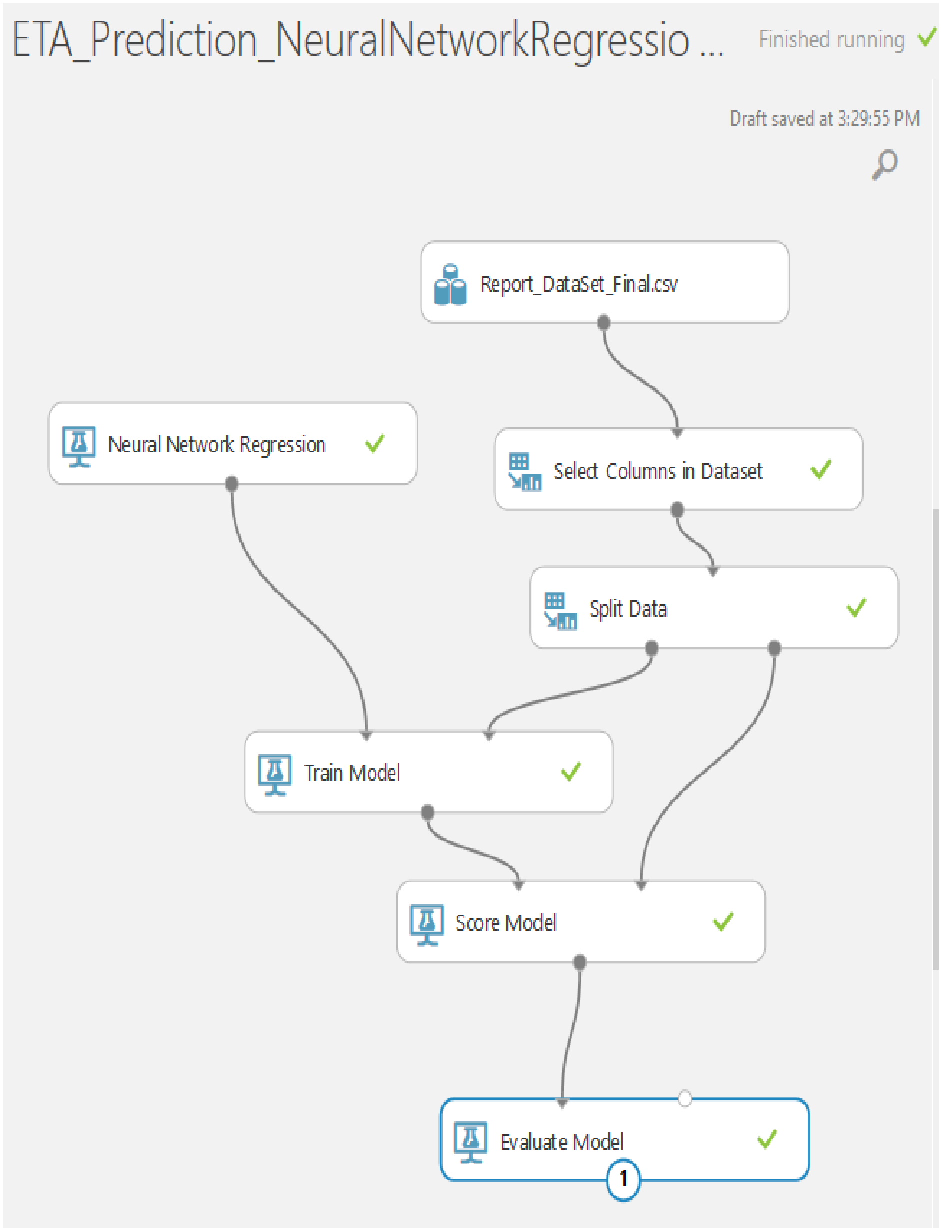


Figure 3.2.2 d: Neural network regression flow chart model used in cloud

This is the flowchart for neural network regression. Here the data is taken from our datasets and then the columns needed for analysis is chosen. Next, the data is split into 1:9 where the linear regression analyses 10% data for error. Next neural network regression analyses the rest 90% data in the trained section. Later, prediction is made in scored data sheet. Lastly the evaluation is for graph and comparison evaluation.

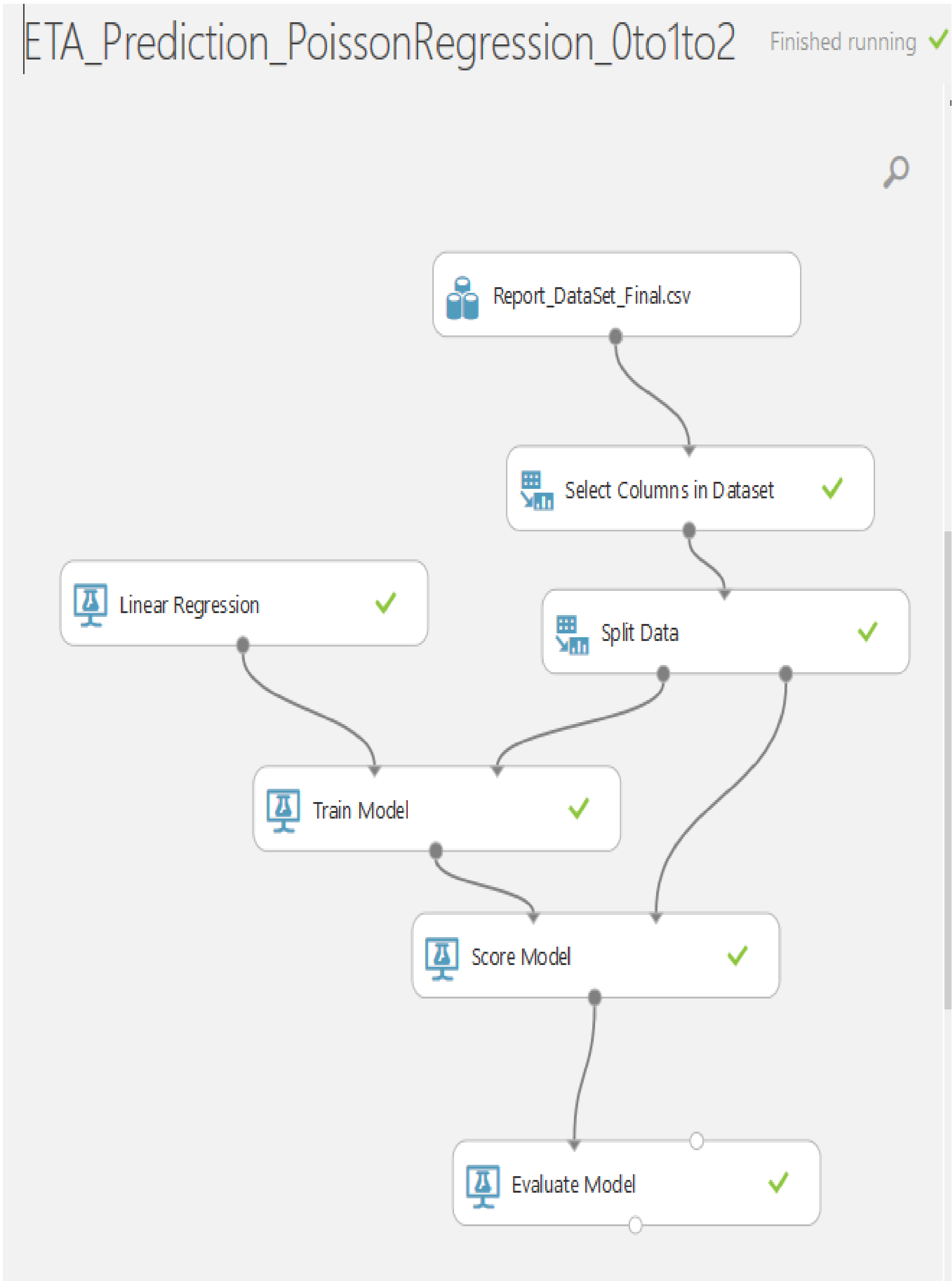


Figure 3.2.2 e: Poisson regression flow chart model used in cloud

This is the flowchart for poisson regression. Here the data is taken from our datasets and then the columns needed for analysis is chosen. Next, the data is split into 1:9 where the linear regression analyses 10% data for error. Next poisson regression analyses the rest 90% data in the trained section. Later, prediction is made in scored data sheet. Lastly the evaluation is for graph and comparison evaluation.

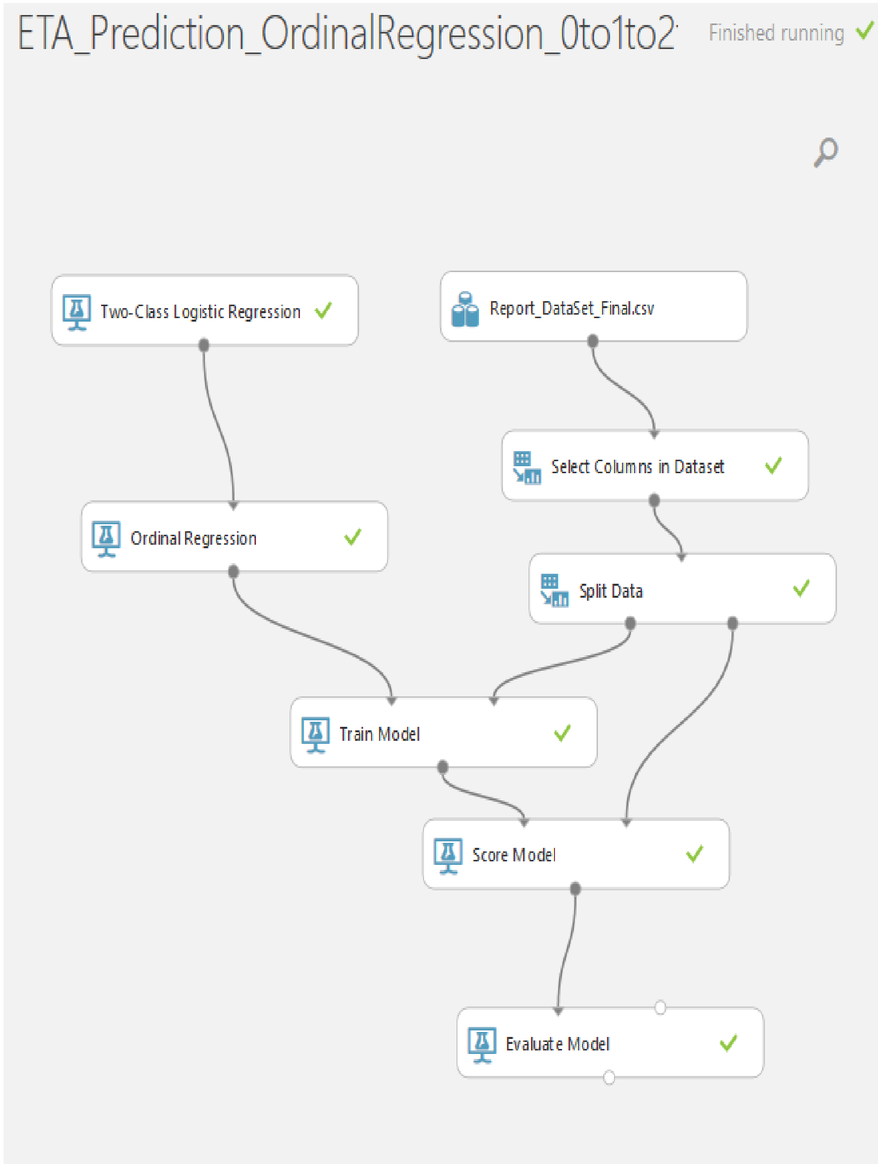


Figure 3.2.2 g: Ordinal regression flow chart model used in cloud

This is the flowchart for ordinal regression. Here the data is taken from our datasets and then the columns needed for analysis is chosen. Next, the data is split into 1:9 where the linear regression analyses 10% data for error. Next linear regression analyses the rest 90% data in the trained section. Later, prediction is made in scored data sheet. Lastly the evaluation is for graph and comparison evaluation.

3.2.3 Return the Result to the User through the Web Page

3.2.3.1 Send Data to the Web Page Used for Queries by the User

After the algorithm is done with processing and analyzing and prediction of data, the system searches for the predicted value for the user defined time slot. This data is stored in the cloud and sent to the ip address where the user is using the webpage.

3.2.3.2 Show the Predicted Result

The predicted value is sent to the webpage and then the PHP framework catches it and then shows the predicted value as an output for predicted ETA. The data is shown as HH:MM (Hour:Minute)

3.3 Case Study

Case study is a detailed overview of the data set. The way data was collected is discussed previously. The case study we used was during the busiest time in those route which is from 8am to 5pm. This case study helped us to do some narrow focus on the particular data set to get detailed information about the data in whole. Also this case study is done for public buses only that use the route from Khidmah Hospital to BRAC University during the hours 8am to 5pm.

3.3.1 Units of Analysis for the Research

Units of analysis is very important for a detailed research. The reason buses were chosen was due to the fact that a lot of people use bus for profession and study. In the context of our country, buses are the main medium of mass transportation. So a detailed overview on these vehicles will allow us to understand the situation of the traffic jam in the route by comparing the predicted ETA in different time.

3.3.2 The Routes under Study

We took data for the public buses that pass through Khidmah Hospital, Abul Hotel, Rampura Bridge, Badda Link Road, Gulshan 1, BRAC University, Mohakhali Railgate, PMO (Pirime Minister Office) and IDB Bhavan. Each of the location, i.e, Khidmah Hospital, Abul Hotel,

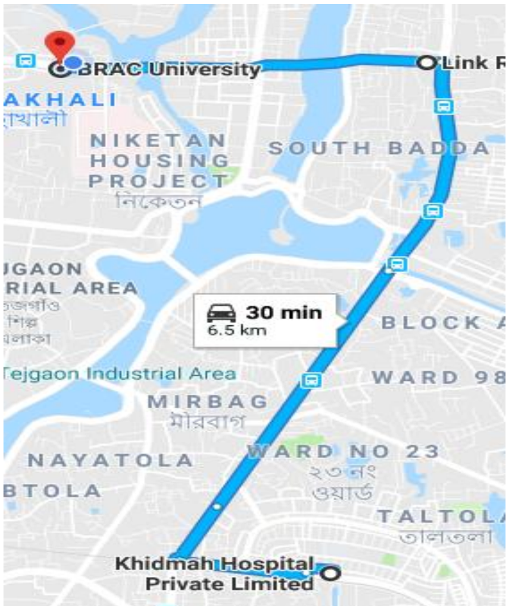


Figure 3.3.1 a: Google map view of the routes used for the research

Rampura Bridge etc were named as node 0, node 1 etc.

Location Name	Node
Khidmah_Hospital	0
Abul_Hotel	1
Rampura_Bridge	2
Badda_Link_Road	3
Gulshan_1	4
BRAC_University	5
Mohakhali Railgate	6
PMO	7
IDB Bhavan	8

Figure 3.3.1 b: Excel table showing route name with node value

This is the chart for renaming the points of traffic. Khidmah is our first point and is named as route 0. IDB Bhavan is the last point and renamed as route 8. Others are also renamed respectively. When we analyzed the data, we took the time from one point to another, i.e. route 0 to route 1 for our evaluation.

3.3.3 Traffic and ETA

The buses will pass through traffic. We do not need the traffic data used by google-traffic api because it only focuses on the traffic duration. However, it does not calculate the time while the user using Google-traffic api keeps the net connection of his phone off. Our data set simply takes

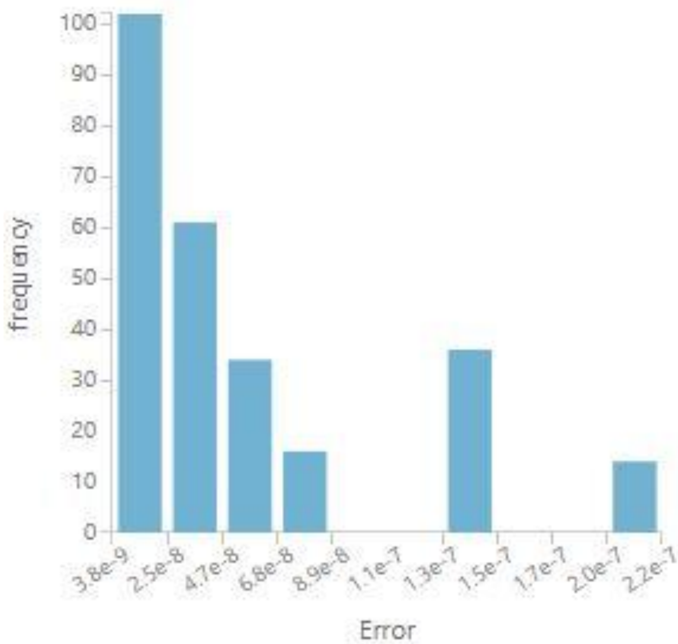


Figure 3.3.3: Frequency of ETA against Error

the time which the bus needed to pass from one node to another and it calculates all the necessary waiting time it takes starting traffic delay to the delay for stopping and let in and out passengers and also the delay for narrow roads. This research is done in the context of our country where rules and regulations in the road regarding maintenance of lanes is not feasible.

3.4 Estimation Model Development

3.4.1 Linear Regression

Linear regression is a well-known algorithm from statistics which was recently developed to be used in machine learning for predicting values. It is used to find relation between scalar dependent variables. This is widely used for various machine learning prediction system. In linear regression, linear predictor functions are used for prediction and the parameters for these functions are taken from the trained dataset.

Due to this, it is quite easy and time effective to use linear regression when evaluating a lot number of dataset. Besides the result comes in form of a linear model very close to the train dataset. The best advantage of linear regression is the execution time. It is very fast and so whenever huge amount of data is used for training set, linear regression can be used for getting very fast result compared to other regression models.

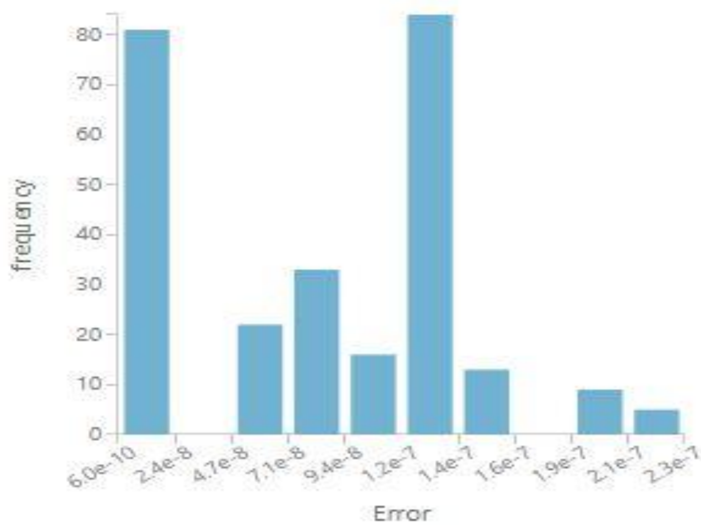


Figure 3.4.1: Frequency of ETA against Error in a linear regression model

This chart shows the error evaluation done by linear regression for predicting values. This is not the comparison done over the prediction values. This is the error marginality for original values and later this data was used to predict the predicted values.

3.4.2 Ordinal Regression

Ordinal regression is another model for machine learning prediction. It is used for predicting ordinal variables. Ordinal values exist on an arbitrary scale and the relative ordering between different values is significant in this regression model. This regression analysis is used when data is in a ranked form such as good for less ETA and bad for more ETA. Ordinal regression is often used in social sciences as well as information retrieval. When it is used in machine learning, it is also called ranked regression model. The often used model for ordinal regression is latent variable model but other models, i.e. PRank is also used from time to time for relevant field of work.

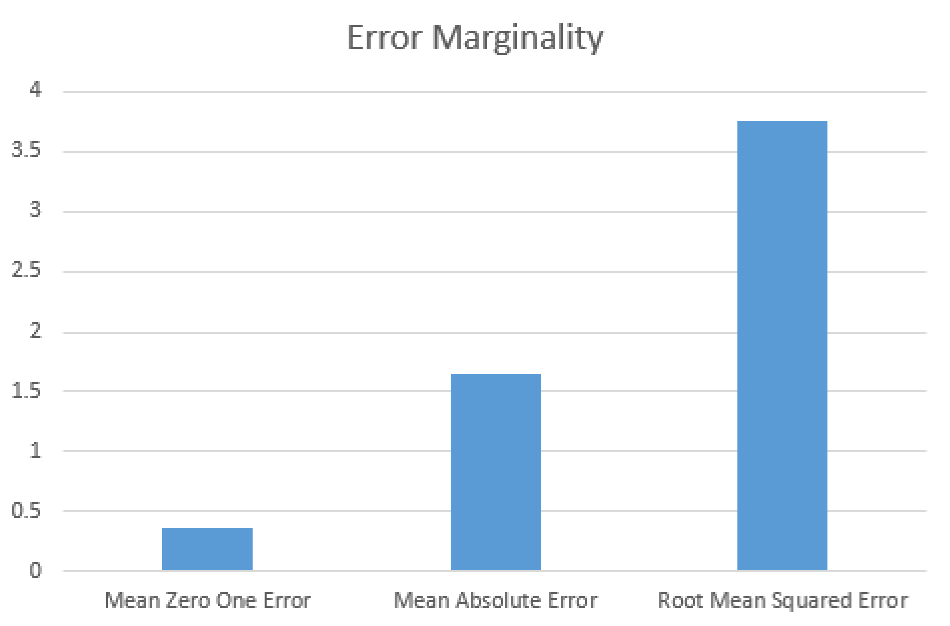


Figure 3.4.2: Error modeling through ordinal regression for ETA

This chart shows the error evaluation done by ordinal regression for predicting values. This is not the comparison done over the prediction values. This is the error marginality for original values and later this data was used to predict the predicted values.

3.4.3 Neural Network Regression

Neural network regression comes from mathematics. It uses various radial basis function and the output is always the combination of radial basis function of the inputs and neuron parameters. The advantage of neural network regression is the accuracy of the predicted dataset though the drawback is the long runtime it takes to execute. This model have been used in various machine learning prediction system and sometimes due to the extreme values the predicted results fluctuate compared to the original data. However for small database this does not pose as a threat but when big data is used, this becomes a big issue.

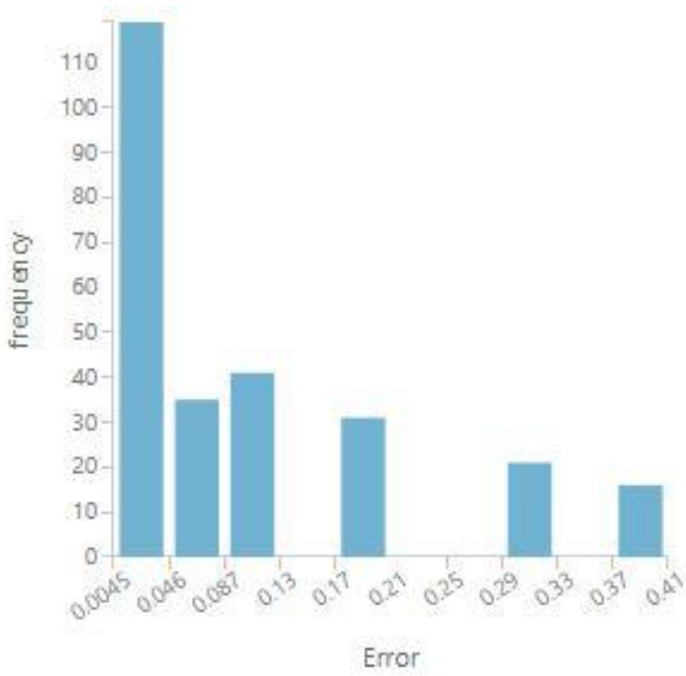


Figure 3.4.3: Error modeling through neural network regression for ETA

This chart shows the error evaluation done by neural network regression for predicting values. This is not the comparison done over the prediction values. This is the error marginality for original values and later this data was used to predict the predicted values.

3.4.4 Poisson Regression

Poisson regression is a generalized linear model form of regression analysis used to model count data and contingency tables. A Poisson regression model is sometimes known as a log-linear model, especially when used to model contingency tables. This is used for getting event counts, i.e. how many times may the extreme values occur as an anomaly in the dataset.

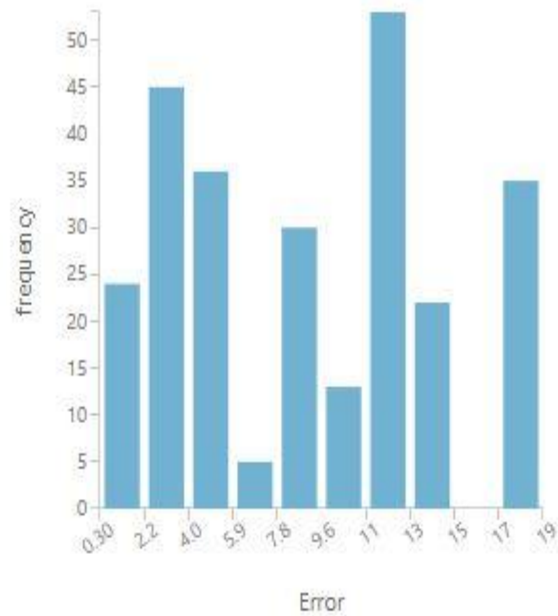


Figure 3.4.4: Error modeling through poisson regression for ETA

This chart shows the error evaluation done by poisson regression for predicting values. This is not the comparison done over the prediction values. This is the error marginality for original values and later this data was used to predict the predicted values.

Chapter 4

Model Evaluation and Result Analysis

4.1 Introduction

The main purpose of the previous chapter was to build a prediction model in line with our research objectives. In this chapter the focus is to evaluate the performance of the developed model. Since data was used, a statistical measure of accuracy is defined and used. The implication of this statistical measure to our model accuracy is then discussed. This measure is then applied in comparing the accuracy of the different prediction models developed in this research study and from literature. The accuracy of the developed model on different partitions of data is later compared and discussed. Their search results are then analyzed and the research findings presented. The results obtained in this study are then compared to other results obtained from literature. The findings will seek to answer the research questions that guided the study.

4.2 Model Performance

It is important to evaluate the developed prediction models in terms of prediction accuracy. The SVR model has been evaluated for its performance and compared with that of linear regression travel time model. The accuracy of the developed model is further compared with the values obtained from literature. Root Mean Square Error (RMSE) is one of the most widely used statistical measures. RMSE measures how much error there is between two sets of paired data. RMSE compares a predicted value and an observed value. In this research we compare the predicted value to the observed value. Root mean square error takes the difference for each predicted value and observed value. This is how RMSE is calculated. Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response, and is the most important criterion for fit if the main purpose of the model is prediction.

$$RMSE = \sqrt{\sum \frac{(Y_{pred} - Y_{ref})^2}{N}} \text{ ....(3)}$$

Below are the images of statistical error report of various algorithm conducted on the total route, from Khidmah Hospital to BRAC University.

Mean Absolute Error	0
Root Mean Squared Error	0.000001
Relative Absolute Error	0
Relative Squared Error	0
Co-efficient of Determination	1

Figure 4.2 a: Statistics report of error for linear regression

This chart shows the error evaluation done by linear regression for predicting values. This is not the comparison done over the prediction values. This is the error marginality for original values and later this data was used to predict the predicted values. Here it is seen that root mean square error is almost 0 and co efficient of determination is 1.

Mean Absolute Error	**0.040932**
Root Mean Squared Error	**0.062806**
Relative Absolute Error	**0.000821**
Relative Squared Error	**0.000001**
Co-efficient of Determination	**0.999999**

Figure 4.2 b: Statistics report of error for neural network regression

This chart shows the error evaluation done by neural network regression for predicting values. This is not the comparison done over the prediction values. This is the error marginality for original values and later this data was used to predict the predicted values. Here it is seen that root mean square error is almost 0.06 and co efficient of determination is 0.99.

Mean	**5.6018**
Median	**5.6018**
Min	**5.6018**
Max	**5.6018**
Standard Deviation	**NaN**
Unique Values	**1**
Missing Values	**0**
Feature Type	**Numeric Feature**

Mean Absolute Error	0.07353275

Figure 4.2 c: Statistics report of ordinal regression

This chart shows the error evaluation done by ordinal regression for predicting values. This is not the comparison done over the prediction values. This is the error marginality for original values and later this data was used to predict the predicted values. Also the mean, median, min and max values that are essential for ordinal regression is also mentioned here. These values were used for analysis.

Root Mean Squared Error	0.09608864
Relative Absolute Error	0.000147513
Relative Squared Error	0.0000019054
Co-efficient of Determination	0.980946

Figure 4.2 d: Statistics report of error for poisson regression

This chart shows the error evaluation done by poisson regression for predicting values. This is not the comparison done over the prediction values. This is the error marginality for original values and later this data was used to predict the predicted values. Here it is seen that root mean square error is almost 9.6 and co efficient of determination is 0.98. Though this data may seem very accurate this may fluctuate due to big data model.

We can see that linear regression gives us the best co-efficient of determination which is 100%. Other algorithms also gives us results close to 99%. The drawback is traffic data keeps changing and so the database will be huge. When too many data are in the train module, the execution time will increase rapidly. This will lead to delay. In neural network, one advantage is its very fast. So when the dataset gets massive, it will be feasible to use neural network regression to get a fast and swift analysis.

4.3 Model Prediction Time Compared to the given datasets

The prediction algorithm developed was subjected to the 10% test data that was not used in training to be able to predict the arrival time of trucks. The summary tables below display all the results that were achieved form the test results.

We are going to compare the prediction time for Khidmah Hospital to BRAC University for each of the algorithm. The prediction was done based on 20% data in train module which means the algorithms read 20% of the data and then predicted for the rest 80%.

4.3.1 Ordinal Regression Analysis and Prediction

Khidmah to BRACU	Predicted Values
152	152
125	125.75
192	280
192	280
152	152
280	280
84	84
107	107
91	86
125	125.75
128	125.75
280	280
47	48
192	280
128	125.75
125	125.75
107	107
47	48
48	48
107	107
192	280

Figure 4.3.1 a: A portion of the predicted values by Ordinal Regression for route Khidmah to BRAC University

This chart shows the predicted values gathered through ordinal regression in respect to the original data sets. This predicted values are almost accurate but whenever extreme data occurred, the prediction got a bit fluctuated due to using mean, median, max and min values.

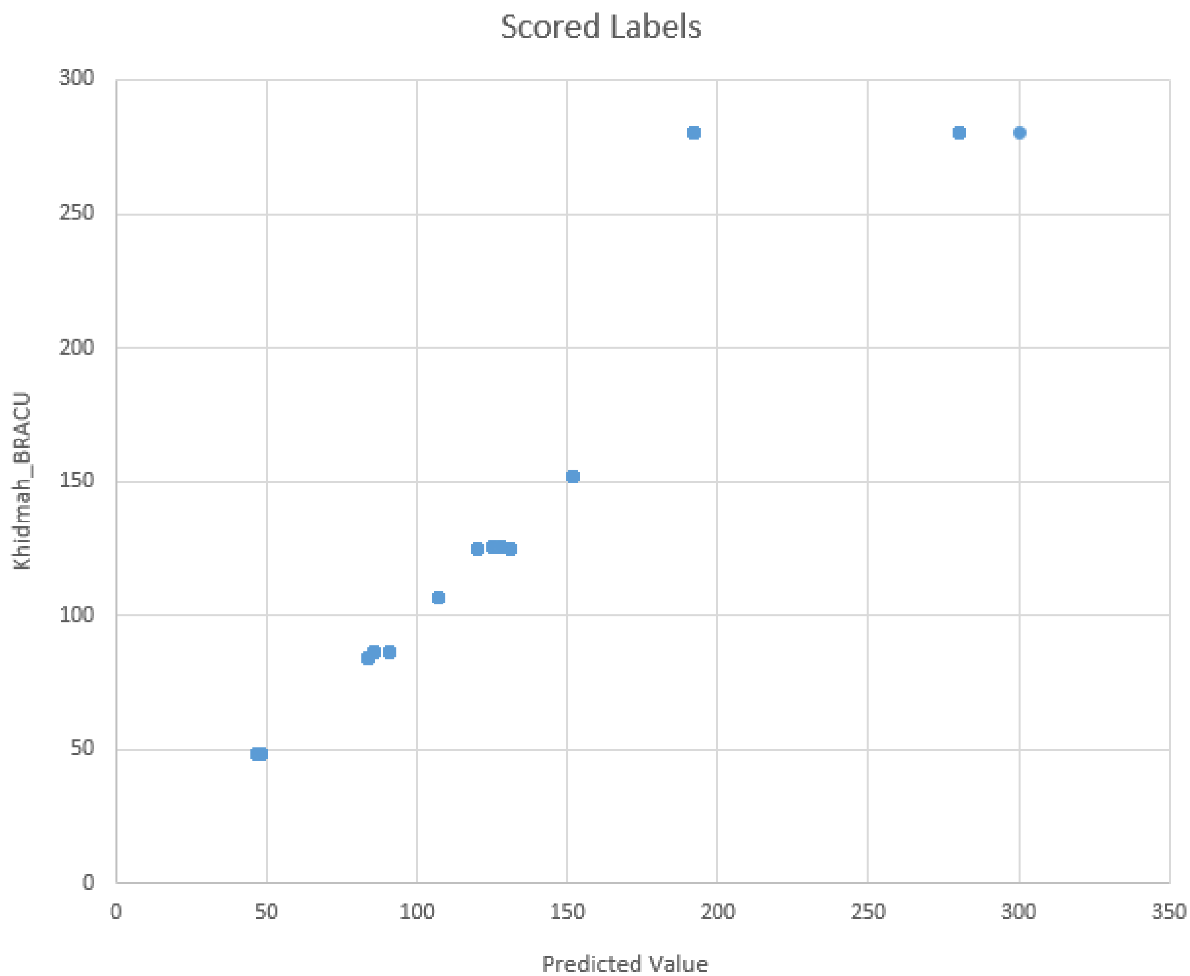


Figure 4.3.1 b: Scored Label by ordinal regression against real datasets (Total)

This graph shows the predicted values against the original dataset. We can see that almost all the points emerge on each other though some fluctuated. This is due to the way ordinal regression is done with mean, median, max and mean values.

Mean	**128.576**
Median	**125**
Min	**48**
Max	**280**
Standard Deviation	**72.7875**
Unique Values	**8**

Missing Values	**0**
Feature Type	**Numeric Score**

Figure 4.3.1 c: Statistical data of the prediction done by Ordinal Regression

These are the mean, median, max, mean and standard deviation gathered through ordinal regression on the original data sets. This data was then used to predict the values. Here we can also see some unique values which were gathered during extreme traffic conditions. This is to clarify that we took all data in condition.

Khidmah to Rampura	Predicted Values
56	56
120	120
55	56
56	56
13	15
110	120
44	44
120	120
13	15
110	120
110	120
44	44
56	56
26	26
56	56
110	120
18	18
26	26
35	34
120	120
13	15
44	44
26	26
110	120

Figure 4.3.1 d: A portion of the predicted values by Ordinal Regression for route Khidmah to Rampura Bridge

This graph shows the predicted values for the route Khidmah to Rampura Bridge through ordinal regression. Almost all the values are accurate as no extreme data occurred.

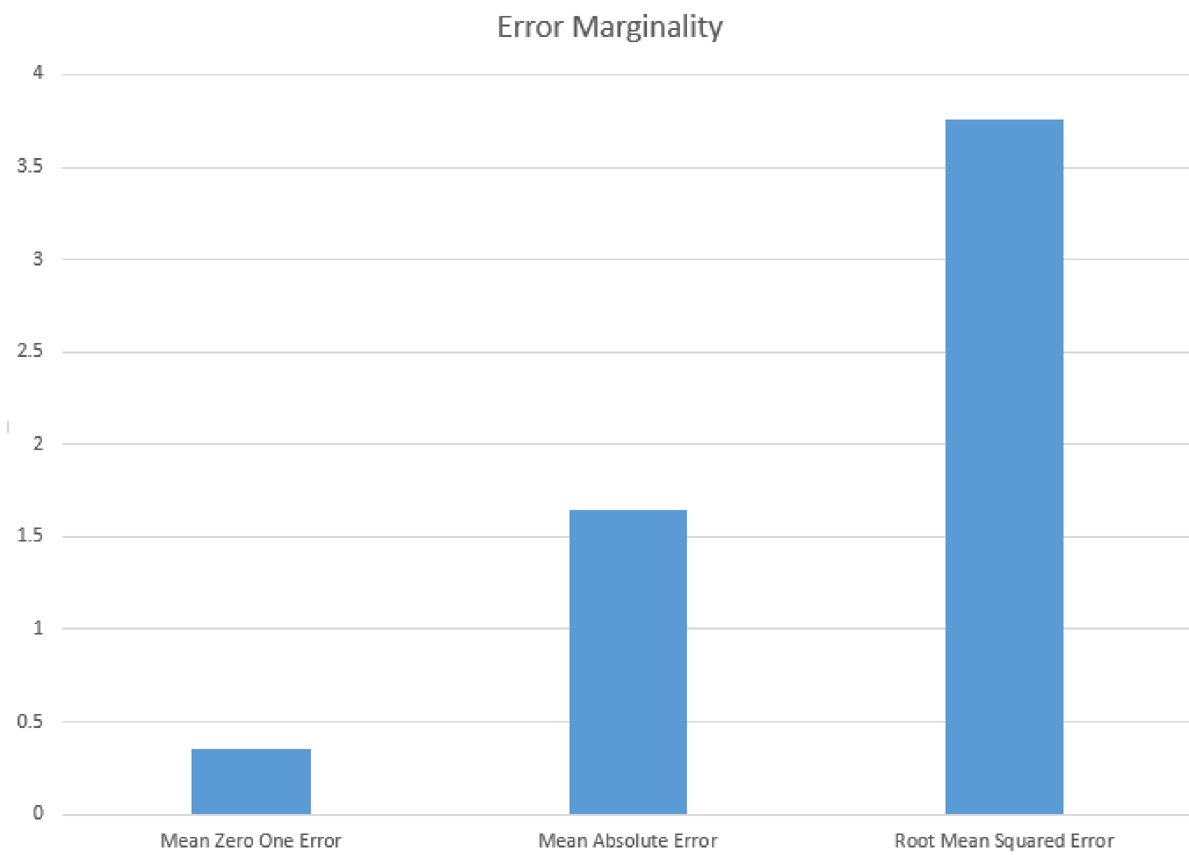


Figure 4.3.1 e: Error marginality by Ordinal Regression for route Khidmah to Rampura Bridge

This is the error chart used in ordinal regression for the route Khidmah to Rampura Bridge. Based on this error values, the final prediction was made.

4.3.2 Linear Regression Analysis and Prediction

Khidmah to BRACU	Predicted Values
131	131.0000005
120	120.0000002
152	151.9999997
131	131.0000005
47	46.9999995
280	279.9999998
128	127.9999993
192	191.9999996
47	46.9999995
280	279.9999998
280	279.9999998
128	127.9999993
125	125
91	90.99999957
131	131.0000005
280	279.9999998
48	48.00000067
84	84.00000019
84	83.99999989
192	191.9999996
47	46.9999995

Figure 4.3.2 a: A portion of the predicted values by Linear Regression for route Khidmah to BRAC University

This chart shows the predicted values gathered through linear regression in respect to the original data sets. This predicted values are almost accurate and even extreme traffic condition or the extreme data have given almost accurate prediction.

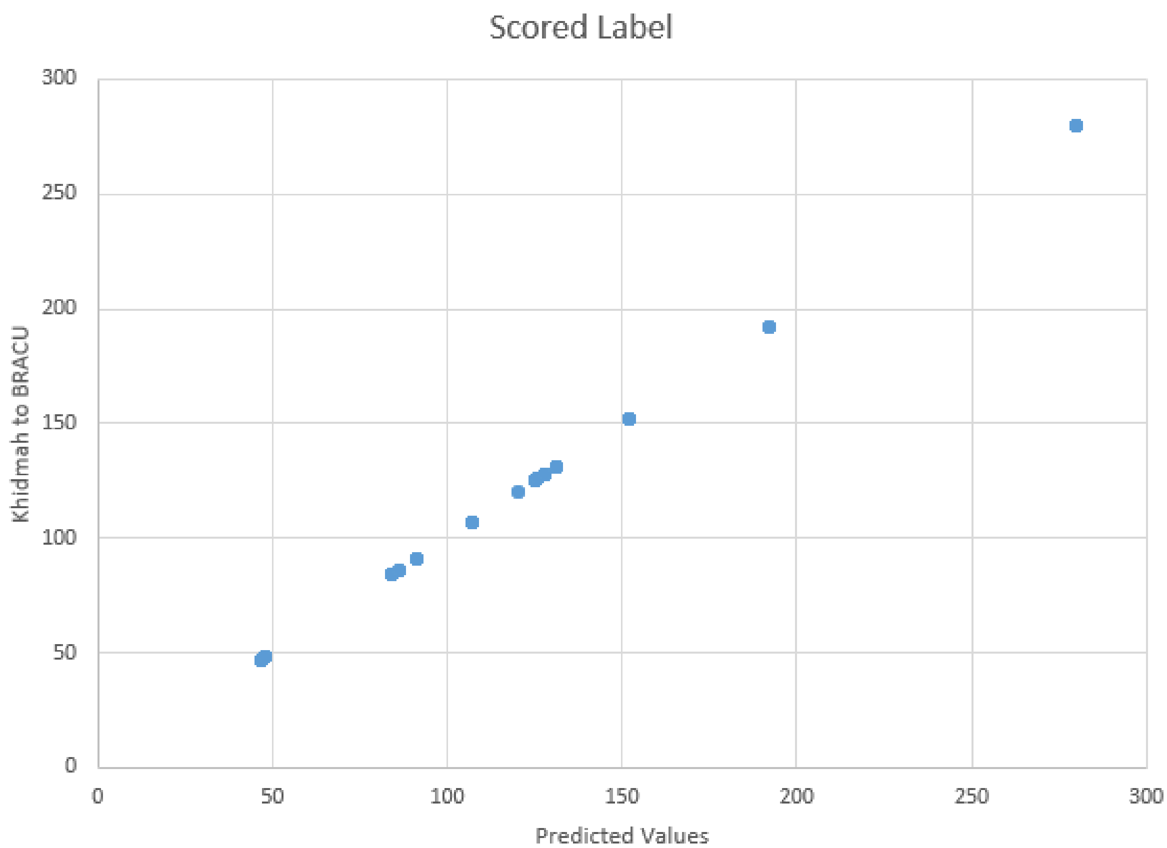


Figure 4.3.2 b: Scored Label by Linear regression against real datasets (Total)

This graph shows the predicted values against the linear regression analyzed dataset. We can see that almost all the points emerge on each other and no fluctuation was noted. Linear regression gives almost 100% accurate prediction.

Mean	**125.1427**
Median	**125**
Min	**47**
Max	**300**
Standard Deviation	**66.5427**
Unique Values	**17**
Missing Values	**0**
Feature Type	**Numeric Score**

Figure 4.3.2 c: Statistical data of the prediction done by Linear Regression

These are the mean, median, max, mean and standard deviation gathered through linear regression on the original data sets. This data was then used to predict the values. Here we can also see some unique values which were gathered during extreme traffic conditions. This is to clarify that we took all data in condition.

Khidmah to Abul Hotel	Predicted Values
18	18.00000007
10	10.00000015
25	25
30	29.99999994
22	22.00000003
16	16.00000009
10	10.00000015
10	10.00000015
20.55	20.55000004
24	24.00000001
24	24.00000001
30	29.99999994
18	18.00000007
60	59.99999963
24	24.00000001
80	79.99999943
25	25
60	59.99999963
25	25
10	10.00000015
22	22.00000003
18	18.00000007

Figure 4.3.2 d: A portion of the predicted values by Linear Regression for route Khidmah to Abul Hotel

This graph shows the predicted values for the route Khidmah to Abul Hotel through linear regression. Almost all the values are accurate as no extreme data occurred.

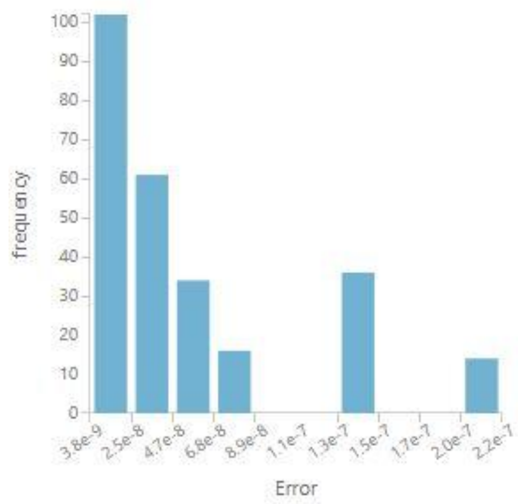


Figure 4.3.2 e: Error marginality by Linear Regression for route Khidmah to Abul Hotel

This is the error chart used in linear regression for the route Khidmah to Abul Hotel. Based on this error values, the final prediction was made.

4.3.3 Neural Network Regression Analysis and Prediction

Khidmah to BRACU	Predictd Values
152	151.0375366
125	124.3328934
192	191.6608276
192	191.6608276
152	151.0375366
280	279.6973267
84	83.50312042
107	106.4920731
91	89.80635834
125	124.3328934
128	127.3734512
280	279.6973267
47	47.07892227
192	191.6608276
128	127.3734512
125	124.3328934
107	106.4920731
47	47.07892227
48	47.73221207
107	106.4920731
192	191.6608276
125	124.3328934
280	279.6973267
125.75	125.0701523
84	82.37541962
280	279.6973267

Figure 4.3.3 a: A portion of the predicted values by Neural Regression for Khidmah to BRAC University

This chart shows the predicted values gathered through neural network regression in respect to the original data sets. This predicted values are almost accurate and even extreme traffic condition or the extreme data have given almost accurate prediction.

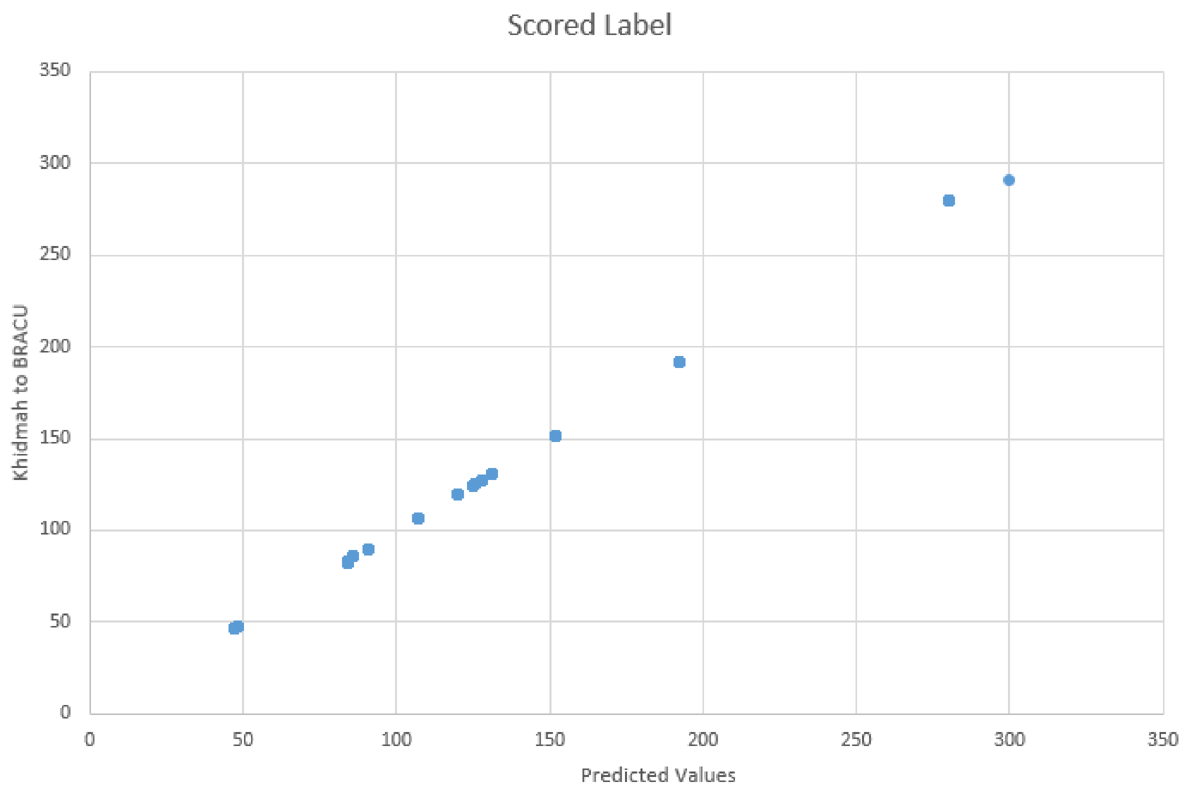


Figure 4.3.3 b: Scored Label by Neural regression against real datasets (Total)

This graph shows the predicted values against the neural network regression analyzed dataset. We can see that almost all the points emerge on each other and no fluctuation was noted. Linear regression gives almost 100% accurate prediction.

Mean	**124.6439**
Median	**124.3329**
Min	**47.0789**
Max	**290.8882**
Standard Deviation	**66.4936**
Unique Values	**17**
Missing Values	**0**
Feature Type	**Numeric Score**

Figure 4.3.3 c: Statistical data of the prediction done by Neural Regression

These are the mean, median, max, mean and standard deviation gathered through neural network regression on the original data sets. This data was then used to predict the values. Here we can also see some unique values which were gathered during extreme traffic conditions. This is to clarify that we took all data in condition.

Khidmah to Badda	Predicted Values
104	103.899231
120	120.0580902
100	99.95449829
104	103.899231
23	23.41442871
230	230.009491
84	84.068573
155	155.0948029
23	23.41442871
230	230.009491
230	230.009491
84	84.068573
93	93.03626251
59	58.9954567
104	103.899231
230	230.009491
33	32.68928909
59	58.9954567
57	57.18807602
155	155.0948029
23	23.41442871
84	84.068573
59	58.9954567
230	230.009491
59	58.9954567
155	155.0948029
120	120.0580902
230	230.009491
230	230.009491

Figure 4.3.3 d: A portion of the predicted values by Neural Network Regression for route Khidmah to Badda Link Road

This graph shows the predicted values for the route Khidmah to Badda Link Road through neural network regression. Almost all the values are accurate as no extreme data occurred.

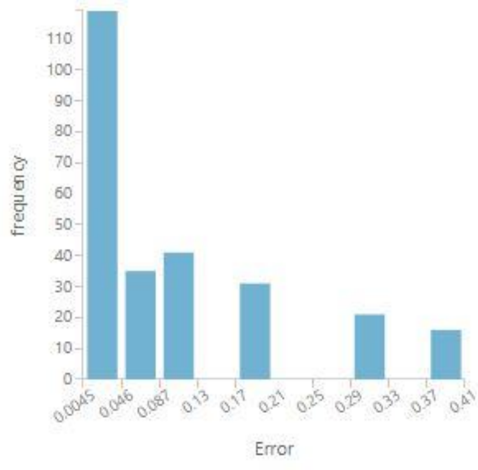


Figure 4.3.3 e: Error marginality by Neural Network Regression for route Khidmah to Badda Link Road

This is the error chart used in neural network regression for the route Khidmah to Badda Link Road. Based on this error values, the final prediction was made.

4.3.4 Poisson Regression Analysis and Prediction

Khodmah to BRACU	Predicted Values
152	151.9999993
125	124.9999998
192	191.9999985
192	191.9999985
152	151.9999993
280	279.9999995
84	83.99999939
107	107.0000044
91	90.99999811
125	124.9999998
128	127.9999972
280	279.9999995
47	46.99999771
192	191.9999985
128	127.9999972
125	124.9999998
107	107.0000044
47	46.99999771
48	48.00000228
107	107.0000044
192	191.9999985

Figure 4.3.4 a: A portion of the predicted values by Poisson Regression from Khidmah to BRAC University

This chart shows the predicted values gathered through poisson regression in respect to the original data sets. This predicted values are almost accurate and even extreme traffic condition or the extreme data have given almost accurate prediction.

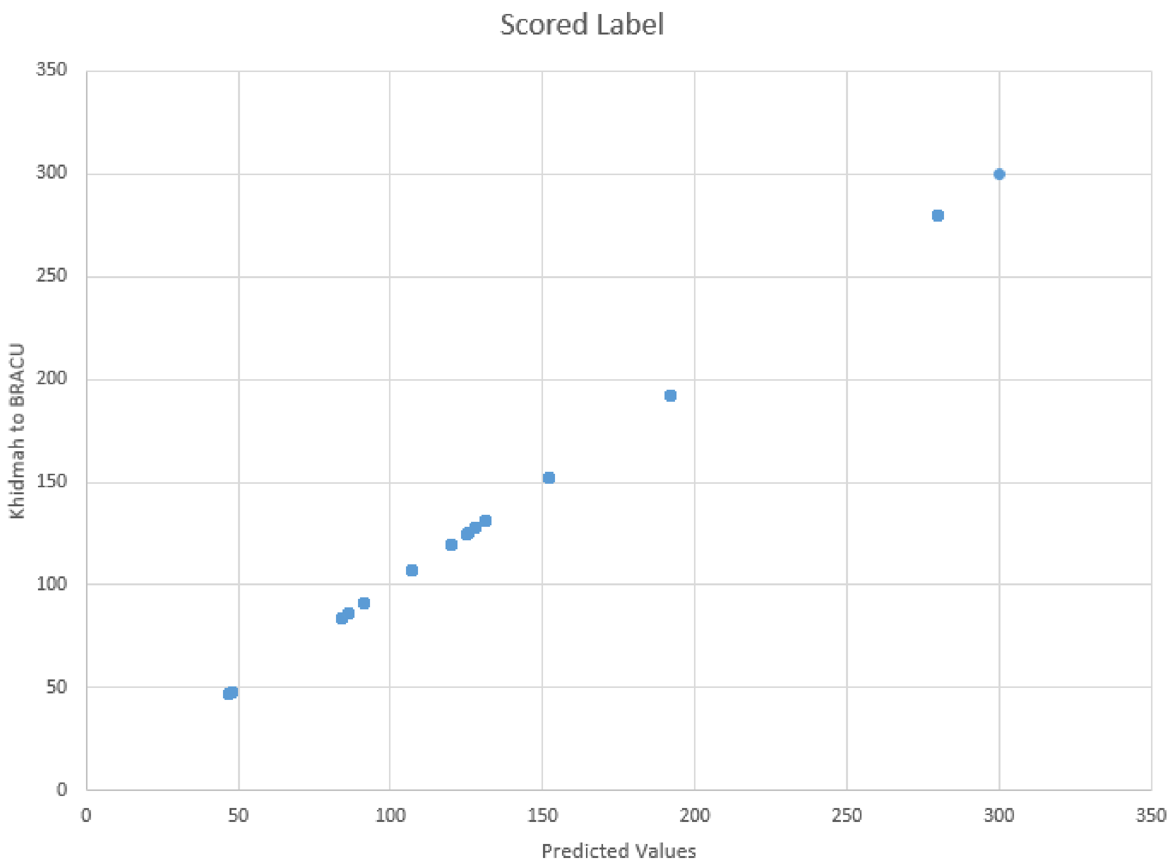


Figure 4.3.4 b: Scored Label by Poisson regression against real datasets (Total)

This graph shows the predicted values against the Poisson regression analyzed dataset. We can see that almost all the points emerge on each other and no fluctuation was noted. Linear regression gives almost 100% accurate prediction.

Mean	124.6439
Median	124.3329
Min	47.0789
Max	290.8882
Standard Deviation	66.4936
Unique Values	17
Missing Values	0

Feature Type	Numeric Score

Figure 4.3.4 c: Statistical data of the prediction done by Poisson Regression

These are the mean, median, max, mean and standard deviation gathered through Poisson regression on the original data sets. This data was then used to predict the values. Here we can also see some unique values which were gathered during extreme traffic conditions. This is to clarify that we took all data in condition.

Khidmah to Gulshan 1	Predicted Values
122	100.8643329
120	111.5777957
137	135.3476572
122	100.8643329
35	53.2193172
260	260.042367
111	103.9873517
182	184.7108197
35	53.2193172
260	260.042367
260	260.042367
111	103.9873517
113	113.1060851
77	69.5297873
122	100.8643329
260	260.042367
43	54.6577847
74	66.57174647
74	69.92524028
182	184.7108197
35	53.2193172

Figure 4.3.4 d: Predicted values by Poisson Regression for route Khidmah to Gulshan 1

This graph shows the predicted values for the route Khidmah to Gulshan 1 through poisson regression. Almost all the values are accurate as no extreme data occurred.

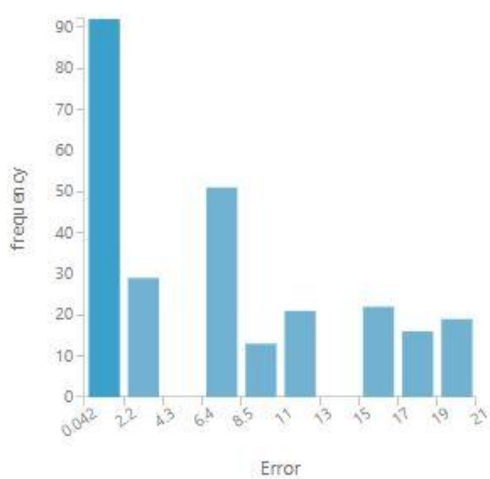


Figure 4.3.4 e: Error marginality by Poisson Regression for route Khidmah to Gulshan 1

This is the error chart used in neural network regression for the route Khidmah to Gulshan 1. Based on this error values, the final prediction was made.

4.3.5 Comparative Analysis

4.3.5.1 Comparative Analysis based on Error Marginality

After using Poisson, Linear, Ordinal and Neural Network, we have gathered various statistical data. When we are using regression, the statistical data of the error is very important. The comparative error data of all 4 algorithms is given below:

Category	Linear Regression	Neural Network Regression	Poisson Regression
Mean Absolute Error	0	**0.040932**	0.07353275
Root Mean Squared Error	0.000001	**0.062806**	0.09608864
Relative Absolute Error	0	**0.000821**	0.000147513
Relative Squared Error	0	**0.000001**	0.0000019054
Co-efficient of Determination	1	**0.999999**	0.980946

Figure 4.3.5 a: Comparison table of error marginality of Poisson, Neural and Linear

This chart shows us the mean absolute error, root mean squared error, relative absolute error and relative squared error. This error data is a must whenever prediction is done using machine learning.

Mean absolute erroris a measure of difference between two continuous variables. Whenever we are trying to predict datasets we need to measure the difference of two continuous variable in our data in order to predict the next value. From the table, we can see that linear regression has 0 mean absolute value that is because linear regression always finds the linear relation between the values. As mean absolute error is a great way to compare forecasts with the eventual outcomes.

So linear has the best accuracy in terms of mean absolute error. Neural Network has 0.04 and Poisson has 0.07.

Root-mean-square erroris a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. This is used when the prediction algorithm is done with the prediction and try to analyze the accuracy. Linear aces the best accuracy again in terms of Root mean square error. It is almost 0 or 0.000001. Neural and Poisson has 0.6 and 0.9 respectively.

The relativeabsolute error is the magnitude of the difference between the exact value and the approximation. Linear has 0 relative absolute error, the best one. Neural and Poisson has 0.0008 and 0.0001 respectively.

The relative squared error takes the total squared error and normalizes it by dividing by the total squared error of the simple predictor. This is done to analyze the overall error measurement of the predicted values. Linear has 0 while Poisson and linear both has 0.000001.

The coefficient of determinationis the proportion of the variance in the dependent variable that is predictable from the independent variable. This is all the same for all 3 algorithms.

By analyzing the statistical error data, we can see that linear has the best outcome.

4.3.5.2 Comparative Analysis based on Statistical data

Whenever regression analysis is done, some statistical data are produced. These data are very important as the whole regression analysis depends on this statistics. The final prediction is done based on the analysis of these statistical data.

Category	**Ordinal Regression**	**Linear Regression**	**Neural Regression**	**Poisson Regression**
Mean	**128.576**	**125.1427**	**124.6439**	124.6439

Median	**125**	**125**	**124.3329**	124.3329
Min	**48**	**47**	**47.0789**	47.0789
Max	**280**	**300**	**290.8882**	290.8882
Standard Deviation	**72.7875**	**66.5427**	**66.4936**	66.4936
Unique Values	**8**	**17**	**17**	17
Missing Values	**0**	**0**	**0**	0
Feature Type	**Numeric Score**	**Numeric Score**	**Numeric Score**	Numeric Score

Figure 4.3.5 b: Comparison table of statistics data of Poisson, Neural, Linear and Ordinal Regression

Mean is the traditional mean used in the statistics. The mean value provided in the chart is the mean of the data collected for the route Khidmah to BRACU. We can see that almost all 4 algorithms have the same mean value. As the equation of mean is always the same for all 4 algorithms, the value is almost same.

Median is also the same as mean. It has a universal equation. So all 4 algorithms have almost the same value for median.

The most important item in this chart is the standard deviation. The standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values. This is important to analyze the data in order to come up with a prediction that has great accuracy. From the chart, linear has 72.78% standard deviation which is very good. This means linear regression is able to predict the outcome with great accuracy. Other three algorithms such Poisson, Neural Network and Ordinal, these three algorithms have 66-67% standard deviation. This is also good but not as accurate as linear. As standard deviation counts the dispersion, it is also clear that, linear regression is able to find out more extreme situation or data regarding traffic compared to Ordinal, Poisson and Neural Network. Though all four algorithms show great accuracy, when we will deal with massive data or big data with a lot of variance, then the small difference of standard deviation will determine the greater accuracy.

Based on all the experiments we performed and the analysis we went through, linear regression was always better in terms of accuracy and error marginality.

CHAPTER 5

Conclusion and Future Scope

5.1 Conclusions

The model that we have developed uses four machine learning regression algorithm to find the ETA for public vehicles. All four of the algorithms give us almost 100% (99.8%-99.69%) accurate predicted values which is very significant and amusing. This research also shows that all the predicted values are quite close to the original value and so the time frame is quite accurate. Even though, it is our recommendation to use Neural Network Regression Analysis for this model as the database will get bigger with flow of time because of the continuous data collection and so we shall need a faster algorithm to run and provide prediction to the user.

This successful analysis will help to save a lot of time wasted in waiting for public vehicles, i.e. buses. Bangladesh is developing and the population is growing but the roads are getting smaller and vehicle number is also increasing. It is quite impossible to imagine Dhaka city without any traffic jam. People need to utilize their time in more productive works rather than waiting and doing nothing. Our developed model, if it is funded and organized, will passively contribute to the GDP of our country as people will know when to wait for bus and get more time in production and profession.

Due to the heavy traffic jam, many patient have lost their lives inside an ambulance. It is very painful to see someone die due to small reason like traffic. By using our developed model, we can help any ambulance in Dhaka city to find the most time effective route. This will ensure that there is always hope for a patient to reach the hospital in time and get proper medical attention.

Lastly, our model can be financially successful. The Govt. or any private corporation can collaborate with us to cover all the routes of Dhaka city and let people use the benefits through mobile and web application. There is almost 30Million people in Dhaka city and almost 1.5M people use android and ios phones with proper knowledge. They will use our application whenever they need and this will generate enough revenue through InAppsAdvertisement. The Govt. may take very small amount of money as tax for using this model.

5.2 Future Work

We have plans for this research. We wish to expand this system through some future works.

1. If we get proper funding, we shall use this system as an IoT based model where there will be an Iot device in the public transport and it will continuously send data of the transport's location and the time needed to reach one point from another.
2. We shall try to come up with a mobile application that people will use to get predicted ETA for their destination.
3. We plan to use Big Data concept when our database gets more data. It is important to mention that we tried this model with data from New York. We used 2 datasets, one with 60,000 data and the other with 5,459,690 data. We were able to compile the first dataset but could not compile the second one due to huge amount of data. So we want to use big data concept when we get to that point.
4. We plan to cover all of Bangladesh with our model. We shall use Iot device in every corner of our country and one day we shall have enough amount of data to provide people with ETA from any random point to another.

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APPENDIX A
200 entry from the collected data set

Khidmah_Hospital_to_Abul_hotel	Total(0_1)	Abul_hotel_to_Rampura_Bridge	Total(0_1_2)	Rampura_Bridge_to_Badda_Link_Road	Total(0_1_2_3)	Badda_Link_Road_to_Gulshan_1	Total(0_1_2_3_4)	Gulshan_1_to_BRAC_University	Total(0_1_2_3_4_5)	BRAC_University_to_Mohakhali_Rail_Gate	Mohakhali_Rail_gate_to_PMO	PMO_IDB_Bhaban	Total_Trip_duration
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	0.00	0.00	460.00
16.00	16.00	10.00	26.00	33.00	59.00	15.00	74.00	10.00	84.00	12.00	0.00	0.00	355.00
80.00	80.00	40.00	120.00	0.00	120.00	0.00	120.00	0.00	120.00	0.00	0.00	0.00	680.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	197.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	16.00	394.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	25.00	18.00	503.00
16.00	16.00	10.00	26.00	33.00	59.00	18.00	77.00	14.00	91.00	16.00	0.00	0.00	376.00
80.00	80.00	40.00	120.00	35.00	155.00	27.00	182.00	10.00	192.00	0.00	0.00	0.00	921.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	197.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	16.00	394.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00

10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	8.00	12.00	10.00	230.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	25.00	18.00	503.00
16.00	16.00	10.00	26.00	33.00	59.00	18.00	77.00	14.00	91.00	16.00	0.00	0.00	376.00
80.00	80.00	40.00	120.00	35.00	155.00	27.00	182.00	10.00	192.00	0.00	0.00	0.00	921.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	197.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	16.00	394.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	25.00	18.00	503.00
16.00	16.00	10.00	26.00	33.00	59.00	18.00	77.00	14.00	91.00	16.00	0.00	0.00	376.00
80.00	80.00	40.00	120.00	35.00	155.00	27.00	182.00	10.00	192.00	0.00	0.00	0.00	921.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	197.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	16.00	394.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	8.00	12.00	10.00	230.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00

16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	0.00	0.00	460.00
16.00	16.00	10.00	26.00	33.00	59.00	15.00	74.00	10.00	84.00	12.00	0.00	0.00	355.00
80.00	80.00	40.00	120.00	0.00	120.00	0.00	120.00	0.00	120.00	0.00	0.00	0.00	680.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	16.00	394.00
80.00	80.00	40.00	120.00	35.00	155.00	27.00	182.00	10.00	192.00	0.00	0.00	0.00	921.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	197.00
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	25.00	18.00	503.00
16.00	16.00	10.00	26.00	33.00	59.00	18.00	77.00	14.00	91.00	16.00	0.00	0.00	376.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	25.00	18.00	503.00
16.00	16.00	10.00	26.00	33.00	59.00	18.00	77.00	14.00	91.00	16.00	0.00	0.00	376.00
80.00	80.00	40.00	120.00	35.00	155.00	27.00	182.00	10.00	192.00	0.00	0.00	0.00	921.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	197.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	16.00	394.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00

60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	25.00	18.00	503.00
16.00	16.00	10.00	26.00	33.00	59.00	18.00	77.00	14.00	91.00	16.00	0.00	0.00	376.00
80.00	80.00	40.00	120.00	35.00	155.00	27.00	182.00	10.00	192.00	0.00	0.00	0.00	921.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	197.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	16.00	394.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	8.00	12.00	10.00	230.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	22.00	603.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	0.00	0.00	460.00
16.00	16.00	10.00	26.00	33.00	59.00	15.00	74.00	10.00	84.00	12.00	0.00	0.00	355.00
80.00	80.00	40.00	120.00	0.00	120.00	0.00	120.00	0.00	120.00	0.00	0.00	0.00	680.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	16.00	394.00
80.00	80.00	40.00	120.00	35.00	155.00	27.00	182.00	10.00	192.00	0.00	0.00	0.00	921.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	197.00

16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	8.00	191.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	25.00	18.00	503.00
16.00	16.00	10.00	26.00	33.00	59.00	18.00	77.00	14.00	91.00	16.00	0.00	0.00	376.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	30.00	641.00
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	22.00	571.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	0.00	183.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	8.00	208.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	0.00	366.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	25.00	0.00	485.00
16.00	16.00	10.00	26.00	33.00	59.00	18.00	77.00	14.00	91.00	16.00	0.00	0.00	376.00
80.00	80.00	40.00	120.00	35.00	155.00	27.00	182.00	10.00	192.00	0.00	0.00	0.00	921.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	0.00	611.00
10.00	10.00	5.00	15.00	18.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	30.00	227.00
25.00	25.00	10.00	35.00	22.00	57.00	17.00	74.00	10.00	84.00	7.00	12.00	0.00	378.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	16.00	637.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	0.00	513.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	0.00	581.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	22.00	571.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	0.00	581.10
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	8.00	629.00
30.00	30.00	26.00	56.00	48.00	104.00	18.00	122.00	9.00	131.00	15.00	22.00	0.00	611.00
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	0.00	183.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	18.00	218.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	8.00	12.00	0.00	220.00
25.00	25.00	30.00	55.00	45.00	100.00	37.00	137.00	15.00	152.00	0.00	0.00	0.00	621.00
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	30.00	579.00
60.00	60.00	50.00	110.00	120.00	230.00	30.00	260.00	20.00	280.00	0.00	0.00	0.00	1220.00
18.00	18.00	26.00	44.00	40.00	84.00	27.00	111.00	17.00	128.00	0.00	0.00	16.00	529.00
20.55	20.55	45.00	65.55	33.20	98.75	17.00	115.75	10.00	125.75	16.00	13.00	0.00	581.10
16.00	16.00	40.00	56.00	37.00	93.00	20.00	113.00	12.00	125.00	11.00	10.00	0.00	549.00
60.00	60.00	50.00	110.0	120.0	230.00	30.00	260.00	20.00	280.00	0.00	0.00	22.00	1242.00

			0	0									
6.00	6.00	7.00	13.00	10.00	23.00	12.00	35.00	12.00	47.00	5.00	7.00	0.00	183.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00
22.00	22.00	12.00	34.00	20.00	54.00	20.00	74.00	12.00	86.00	10.00	0.00	8.00	374.00
24.00	24.00	16.00	40.00	40.00	80.00	22.00	102.00	5.00	107.00	0.00	0.00	0.00	460.00
16.00	16.00	10.00	26.00	33.00	59.00	15.00	74.00	10.00	84.00	12.00	0.00	10.00	365.00
80.00	80.00	40.00	120.0 0	0.00	120.00	0.00	120.00	0.00	120.00	0.00	0.00	0.00	680.00
10.00	10.00	8.00	18.00	15.00	33.00	10.00	43.00	5.00	48.00	0.00	0.00	0.00	200.00

APPENDIX B
Sample 200 Predicted time value using Linear Regression

Khidmah_Hospital_to_Abul_hotel	Total(0_1)	Abul_hotel_to_Rampura_Bridge	Total(0_1_2)	Rampura_Bridge_to_Badda_Link_Road	Total(0_1_2_3)	Badda_Link_Road_to_Gulshan_1	Total(0_1_2_3_4)	Gulshan_1_to_BRAC_University	Total(0_1_2_3_4_5)	Scored Labels
25	25	30	55	45	100	37	137	15	152	152
16	16	40	56	37	93	20	113	12	125	125
80	80	40	120	35	155	27	182	10	192	192
80	80	40	120	35	155	27	182	10	192	192
25	25	30	55	45	100	37	137	15	152	152
60	60	50	110	120	230	30	260	20	280	280
25	25	10	35	22	57	17	74	10	84	84
24	24	16	40	40	80	22	102	5	107	107
16	16	10	26	33	59	18	77	14	91	91
16	16	40	56	37	93	20	113	12	125	125
18	18	26	44	40	84	27	111	17	128	128
60	60	50	110	120	230	30	260	20	280	280
6	6	7	13	10	23	12	35	12	47	47
80	80	40	120	35	155	27	182	10	192	192
18	18	26	44	40	84	27	111	17	128	128
16	16	40	56	37	93	20	113	12	125	125
24	24	16	40	40	80	22	102	5	107	107
6	6	7	13	10	23	12	35	12	47	47
10	10	8	18	15	33	10	43	5	48	48
24	24	16	40	40	80	22	102	5	107	107
80	80	40	120	35	155	27	182	10	192	192
16	16	40	56	37	93	20	113	12	125	125
60	60	50	110	120	230	30	260	20	280	280
20.55	20.55	45	65.55	33.2	98.75	17	115.75	10	125.75	125.75
16	16	10	26	33	59	15	74	10	84	84
60	60	50	110	120	230	30	260	20	280	280
16	16	40	56	37	93	20	113	12	125	125
10	10	8	18	15	33	10	43	5	48	48
80	80	40	120	35	155	27	182	10	192	192
18	18	26	44	40	84	27	111	17	128	128

10	10	8	18	15	33	10	43	5	48	48
60	60	50	110	120	230	30	260	20	280	280
10	10	5	15	18	33	10	43	5	48	48
25	25	10	35	22	57	17	74	10	84	84
60	60	50	110	120	230	30	260	20	280	280
16	16	10	26	33	59	15	74	10	84	84
18	18	26	44	40	84	27	111	17	128	128
60	60	50	110	120	230	30	260	20	280	280
80	80	40	120	35	155	27	182	10	192	192
25	25	30	55	45	100	37	137	15	152	152
25	25	30	55	45	100	37	137	15	152	152
6	6	7	13	10	23	12	35	12	47	47
20.55	20.55	45	65.55	33.2	98.75	17	115.75	10	125.75	125.75
60	60	50	110	120	230	30	260	20	280	280
6	6	7	13	10	23	12	35	12	47	47
10	10	5	15	18	33	10	43	5	48	48
18	18	26	44	40	84	27	111	17	128	128
18	18	26	44	40	84	27	111	17	128	128
10	10	8	18	15	33	10	43	5	48	48
16	16	10	26	33	59	18	77	14	91	91
10	10	5	15	18	33	10	43	5	48	48
20.55	20.55	45	65.55	33.2	98.75	17	115.75	10	125.75	125.75
25	25	30	55	45	100	37	137	15	152	152
16	16	10	26	33	59	18	77	14	91	91
30	30	26	56	48	104	18	122	9	131	131
16	16	10	26	33	59	15	74	10	84	84
10	10	8	18	15	33	10	43	5	48	48
18	18	26	44	40	84	27	111	17	128	128
60	60	50	110	120	230	30	260	20	280	280
16	16	10	26	33	59	18	77	14	91	91
16	16	10	26	33	59	18	77	14	91	91
6	6	7	13	10	23	12	35	12	47	47
24	24	16	40	40	80	22	102	5	107	107
80	80	40	120	35	155	27	182	10	192	192
10	10	5	15	18	33	10	43	5	48	48
25	25	30	55	45	100	37	137	15	152	152
16	16	10	26	33	59	15	74	10	84	84
25	25	10	35	22	57	17	74	10	84	84
60	60	50	110	120	230	30	260	20	280	280
16	16	40	56	37	93	20	113	12	125	125

80	80	40	120	0	120	0	120	0	120	120
18	18	26	44	40	84	27	111	17	128	128
24	24	16	40	40	80	22	102	5	107	107
16	16	40	56	37	93	20	113	12	125	125
80	80	40	120	35	155	27	182	10	192	192
6	6	7	13	10	23	12	35	12	47	47
10	10	8	18	15	33	10	43	5	48	48
30	30	26	56	48	104	18	122	9	131	131
25	25	30	55	45	100	37	137	15	152	152
25	25	30	55	45	100	37	137	15	152	152
10	10	8	18	15	33	10	43	5	48	48
30	30	26	56	48	104	18	122	9	131	131
25	25	10	35	22	57	17	74	10	84	84
16	16	10	26	33	59	18	77	14	91	91
30	30	26	56	48	104	18	122	9	131	131
22	22	12	34	20	54	20	74	12	86	86
22	22	12	34	20	54	20	74	12	86	86
80	80	40	120	35	155	27	182	10	192	192
18	18	26	44	40	84	27	111	17	128	128
25	25	30	55	45	100	37	137	15	152	152
16	16	40	56	37	93	20	113	12	125	125
16	16	40	56	37	93	20	113	12	125	125
24	24	16	40	40	80	22	102	5	107	107
6	6	7	13	10	23	12	35	12	47	47
60	60	50	110	120	230	30	260	20	280	280
22	22	12	34	20	54	20	74	12	86	86
30	30	26	56	48	104	18	122	9	131	131