Reseach Paper

TRAVEL TIME PREDICTION IN PUBLIC TRANSPORTATION

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ABSTRACT

Today, travel time prediction is essential for passengers who can easily access information and want to be able to plan their journeys as well as their daily activities. Travel time varies due to some unpredictable external factors especially in big cities. Therefore this paper proposes a powerful but simple Machine Learning (ML) model by using data collected by GPS devices. The model uses a Multiple Linear Regression algorithm that learns from historic data and predicts future data for each bus stop interval by considering external factors such as; weather condition, peak hours, busy week days and busy days of year. A simulation model was developed to validate the model. Then the simulation model was compared to average of historic data and real data. Results show that the prediction model outperforms the average model and calculates closest travel times to the real data.

Index Terms: Travel time prediction, multiple linear regression

TOPLU ULAŞIM ARAÇLARINDA ULAŞIM SÜRESİNİN TAHMİNİ

ÖZET

Günümüzde toplu ulaşımda, otobüsün ulaşım süresinin tahmini, bilgiye kolayca erişebilen ve günlük aktivitelerini planladıkları gibi yolculuklarını da planlamak isteyen yolcular için oldukça önemlidir. Büyük şehirlerde otobüslerin varış süresi bazı öngörülemeyen dış faktörler nedeniyle çeşitlilik göstermektedir. Bu nedenle bu çalışma, GPS cihazları ile toplanan veriyi kullanarak, güçlü ancak sade bir Makine Öğrenmesi tekniği sunmaktadır. Teknik, geçmiş veriden öğrenerek ve hava durumu, yoğun saatler, haftanın yoğun günleri ve yıllın yoğun günleri gibi etkenleri göz önünde bulundurarak her durak aralığı için gelecek verisini tahmin eden Çoklu Doğrusal Regrasyon algoritmasını kullanmaktadır. Tekniği doğrulamak amacı ile bir simulasyon modeli oluşturulmuştur. Simulasyon modeli geçmiş verinin ortalaması ve gerçek veri ile kıyaslanarak modelin doğruluğu ölçülmüştür. Sonuçlar tahmin tekniğinin ortalama modeline göre daha iyi performans gösterdiğini ve gerçek veriye en yakın tahmini yaptığını göstermiştir.

Anahtar Kelimeler: Ulaşım süresi tahmini, çoklu doğrusal regrasyon

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1. INTRODUCTION

Efficient time management has become an indispensable requirement in today's busy world. Every day, new technologies are developed to provide time efficiency for individuals. People demand easily accessible, affordable and reliable public transportation. Therefore travel time prediction has an utmost importance by providing time saving and personal planning in public transportation, hence increases customer satisfaction as a part of comprehensive Passenger Information Systems (PIS).

Istanbul is a commercial and historical center of Turkey with thousands of years of history. It is a transcontinental city connecting Europe to Asia via 3 bridges and 2 underground tunnels. With a population over 15 million, the city hosts an average of 9 million visitors every year. Public Transportation (PT) in this colorful and vibrant city is carried out by various modes such as bus, subway, tram, ferry, minibus and taxi. Bus transportation constitutes 30% of PT and the transportation operator Istanbul Elektrik Tramvay ve Tünel İşletmeleri Genel Müdürlüğü (IETT) operates bus transportation in Istanbul since 1871 starting business with horse drawn trams. Today IETT operates bus and metrobus transportation and has about 7000 buses, 6000 drivers and 5 million daily journeys. IETT installed screens onboard in every bus and 933 smart bus stops in the city to display current location and expected arrival time of the buses to prevent time loss in PT. Additionally, a mobile app helps individuals to plan their journey and view predicted travel times of the buses.

Predicting travel time is a challenging process for Istanbul since it directly depends on the number of vehicles in traffic and there are various factors determining the number of vehicles. First of all, during school periods more vehicles join traffic because while schools are located in central points of the city, the settlement is towards the outside of the city. Therefore, students need to be transported to the city center by shuttle buses and public transportation. Second, every day of week shows different characteristics as a result of local bazaars, weekend events and workdays. For example, when local bazaars set up, pedestrian traffic increases dramatically. Next, in mornings and evenings there is too much traffic as people go to work and get back home, these times called peak hours and during peak hours number of vehicles in traffic are maximum. Last, weather conditions have a huge impact on traffic flow. When it is rainy, less people go out thereby less traffic occurs in some parts of the city. When building a prediction model for Istanbul, these 4 major factors need to be considered. Moreover, the effect of the factors might change according to different parts of the city. This inconsistency causes obstacles in the prediction and indicates the need of a stronger model.

There are 3 main prediction model types; historical data based models, statistical models and Machine Learning models. Historical data based models calculates current travel time based on average of previous travel times for the same time span. Time Series and Kalman Filter are types of statistical models. Kalman Filter models are used when there is ambiguous data about the system. The models predicts current and future states of the system (Choudhary et al., 2016). Machine Learning models can learn from existing data and predict the future data. Regression and ANN are some of the Machine Learning algorithms. Regression models calculates travel time with a Linear Function formed by some independent variables.

Achar et al. (2020) developed a model that learns the spatial patterns of traffic. They rewrote the predictive model in a linear state space form and applied Kalman Filter. They split the line into sections and used running time of the bus, dwell time and unexpected stoppages to build the model. The model showed 26% better performance than the baseline approaches. The performance of the model is good for both one section and multiple sections.

Some studies targeted multiple prediction models to find better results. Lin et al. (2019) studied 3 models to find the best solution for travel time prediction in Chiayi City, Taiwan. They applied Gradient Boosting Regression Tree, K-Nearest Neighbor and Linear Regression. Traffic data was collected by vehicle detectors, GPS and OBD, and Cellular-Based Vehicle Probe. The results showed that all three models performed well for prediction and Cellular-Based Vehicle Probe provided the best source of data when compared to two others.

Some studies focused on specific types of travel time. For example Hapsari et al. (2018) focused on touristic travelling and developed a regression model to predict visiting time of destinations in Indonesia for tourists. Six parameters were considered in the model to predict the visiting time; access, government, rating, number of reviews, number of pictures, and other information. They compared their model with 4 other popular prediction models; K-Nearest Neighbors, Decision Tree, Support Vector Regression, and Multi-Layer Perceptron. They obtained the least error ratio from Linear Regression model. This model finds total amount of time to reach the destination.

Likewise, Yang (2005) developed a Kalman Filter model for arterial travel time prediction during a graduation ceremony. He used GPS data from test vehicles for a period of 30-45 minutes considering the length of the ceremony. By using Kalman Filter he formulated a recursive procedure that used result of current step to estimate result for next step. The results showed 21.25% error rate and by using a data interpolation method, he reduced the error to 4.40%.

Kwak and Geroliminis (2020) proposed dynamic linear models (DLMs) for speed and time prediction, because DLMs assume parameters are changing in time. They tested the models by using freeway data in California and compared results to the Instantaneous Travel Time Forecaster, K-Nearest Neighbor (k-NN), Support Vector Regression (SVR) and the Artificial Neural Network (ANN). The proposed model showed better performance for short term prediction.

Tan et al. (2008) collected both historical and real-time traffic data from GPS for arrival time prediction. They developed a combination model of historical model and adaptive model and derived a weighted average. Linear Regression algorithm was used for historical model. The algorithm of the combination model worked well with the application.

Another Machine Learning Algorithm is Extremely Randomize Tree. Garcia et al. (2016) concerned about economic losses caused by long travel times and developed a prediction system by using Randomize Trees for Metro Manila where there is no scheduled bus operations. And bus schedules depend on traffic flow, time, vehicle availability and number of passengers. By using 2015 GPS data, they generated number of trees and developed a regression prediction by averaging the total number of the trees. They compared predicted travel time to measured travel time and received R-Squared ($R^{2)}$ between 0.9 and 1. The model was tested on a single route.

Rice and van Zwet (2001) collected data via single loop detectors and suggested a Linear Regression Model affirming that there is a linear relationship between future travel time and current travel time. Their model showed better performance than Principal Components and Historical Mean and lower than NN.

Pan et al. (2012) developed a self-learning algorithm based on historic data collected by GPS sensors. The historic speed data was classified according to seasons, holidays, and peak hours and recorded into a database. Location of the bus was also recorded periodically. Then a BP neural network was used to train the data and to correct the speed based on the average historic travel time. A BP Network is a system with one input layer, one output layer and some hidden layers that is used to train the network. When number of layers increases, accuracy of results increases also. However this makes the network more complicated and training time longer. After extracting distance between stops, they used speed of the bus as an input for BP neural network and speed at next moment as an output. After training huge data the network predicted the speed. The algorithm had less overall prediction error. However when congestion is heavier, the prediction error grows accordingly.

Yu et al. (2013) developed a model for Beijing City in China and used real world historic GPS data to develop the model based on cluster analysis and polynomial fitting. They assumed that for an accurate prediction, road condition, bus velocity, traffic flow, density of crowd and traffic lights should be considered. The model used GPS data monitored every 15-20 seconds. The data was classified by using average distance method and two nearest classes were merged together until there was only one class. The method generated a historic traffic pattern based on bus line, period time and day type. They assumed that traffic flow was similar for a week and thus velocity of the bus was consistent in the same week. The model employed a hierarchical cluster analysis using Euclidean distance to maximize the effects of similar patterns. The model was considered as a simple prediction model without need of extensive computation.

He et al. (2019) considered multiple journeys of a passenger as well as waiting time of the passenger at transfer points to predict the travel time. They predicted riding and waiting time of a journey based on different datasets including historical data and combined the results. They used Long Short-Term Memory (LSTM) for travel time prediction of each segment and historical average method for waiting time. Their model showed better results than the baselines with 55.2% improvement on Mean Absolute Error (MAE).

Although there are numerous studies on travel time prediction, Istanbul still needs a reliable prediction system because some of the previous works focus on special events but Istanbul needs a solution that works anytime. Some works use Neural Networks or Support Vector Machines, although they perform well, Istanbul demands a faster algorithm that responds in a very short time period. Kalman Filter algorithm was used earlier in Istanbul but the method did not meet the expectation. The solution needs to have specific parameters for the city to simplify complexity, keeping in mind flexible transport habits and constant movement of 5 million passengers between districts per day. In this study, a Multiple Linear Regression model was developed to predict travel time for each bus stop interval by taking into account specific factors.

The subsequent chapter gives information about Preparation process with Parameter Selection, Line Selection, Field Observation and Data operations (Collection, Cleaning and Processing). In the next chapter, Travel Time Prediction model is described in detail and a simulation model used for Validation is explained. Then, Results and Conclusion parts are given.

2. PREPERATION

There are approximately 7000 public transportation buses in the city. Each bus has a Line Code and a unique Door Number. Line Codes consist of numbers/numbers and letters e.g. 90, 16C, 18K. Every journey taken by a bus has a unique Journey Number along with a Stream Code showing the direction as every line has 2 directions.

2.1. Parameter Selection

There are various factors effecting the travel flow. First, school periods and summer holidays affect public transportation on a large scale in context of traffic density. In the model, day of year parameter was used to include this factor. Second, traffic pattern on weekdays and weekends diversifies and regular events take place at miscellaneous points of the city on some days of week. Therefore, day of week parameter was used in the model. Third, traffic flow changes at different times of a day and congestion is quite heavy during peak hours. Thus minute of day parameter was selected to show peak hours. Finally, weather conditions also influence traffic flow.
Accordingly, data for rainy days of the year 2019 extracted and included in the model.

2.2. Line Selection

Istanbul is a metropolis with thousands of years of history, accordingly it has an infrastructure that differs for each part of the city. Bus lines in these parts can be categorized into 5 different types; touristic lines, urban lines, suburban lines, relatively short lines and combination of all types. Initially the line 90 was selected for this model because it is a combination of almost all line types. It starts at a small but crowded region. In this region, the roads are relatively narrow due to the historical structure. There is a local bazaar on some days and it causes pedestrian traffic. The line continues in a very crowded street with shopping centers and historical places receiving many shoppers from other parts of the city every day. It ends in tourism centers Karaköy and Eminönü where usually high congestion is observed.

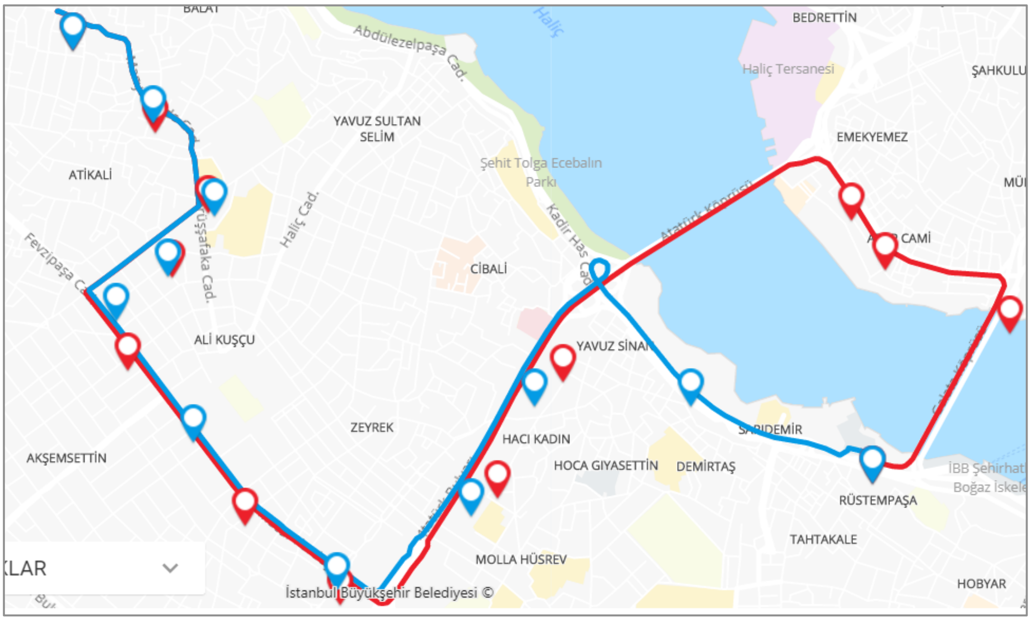

Figure 1. Map of Line 90.

Later, 6 more lines were added to the work to ensure that the model had precision for any type of lines; 14, 16C, 18K, 17, 11ÜS and 252. These lines have different characteristics. The line 252 operates between Asia and Europe, starts in Pendik district with a population of 711894, passing through the Bosphorus Bridge it ends in Şişli. The line 17 uses the coastal route, starts in Pendik district, and reaches to Kadıköy by passing through Bağdat Street, which is a very busy street with many popular shops. 18K and 11ÜS are the lines of Sultanbeyli district where the settlement density is high. These lines end in Kadıköy and Üsküdar districts where settlement is even more intense.

Table 1. Number of Bus Stops, Length and Total Travel Time for selected lines.

	Bus Stops	Length (km)	Total Travel Time (min)
11ÜS	55 - 58	35	83
14	71 - 73	26.5	66.5
16C	72 - 71	35	108
17	68 – 67	28	67
18K	31 – 31	32	76.5
252	57 – 57	34.6	83
90	13 – 11	5.4	12

Table 1 shows number of bus stops on a line for each direction, length of the lines in km and real total travel time in minutes. For most of the lines, real travel time is more than an hour. Although some lines are really long with 35 km length and 70+ bus stops, there are longer lines in the city.

2.3. Field Observations

Before starting development of the model, we decided to make a fieldwork and experience several journeys of the line 90. As stated earlier weather conditions, school time and peak hours are the most common components that slows the traffic flow significantly. The fieldwork was done to observe the effects of these components.
In addition, a survey was conducted with the drivers on their travel experience. Some general questions asked to the drivers are:

- What days is congestion highest?
- What time is congestion highest during a day?
- How does rain/snow effect a journey?

All drivers agreed that congestion is highest on weekends and Wednesdays because of the local bazaar; in the mornings and evenings, during peak hours and when there is a traffic accident. They also stated that rain effects traffic positively because less pedestrian traffic causes less congestion. This surprising result was confirmed by the prediction model also. Travel time calculated from one stop to another is less when it is rainy on this line.
In addition, they expressed that there was a time limit to be complied for each direction. The drivers can adjust the total travel time of a journey to complete within the given time limit. Therefore the velocity of the bus does not depend on the traffic flow but the time limit. Therefore they do not speed up to reach the bus stop as soon as possible. This causes fluctuation in the travel time for the same interval.

2.4. Data Collection

Travel data is obtained from Global Positioning System (GPS) via 3 types of In-Vehicle Computers located in the buses. Whenever a bus reaches to a bus stop, the computer sends time information to the center and the data is stored into a database. Every journey from one bus stop to another recorded in 2019 for 6 lines was extracted from the database to build the model. 2020 data was used for validation. The weather archive was downloaded from weather forecast web site for Istanbul (URL1).

2.5. Data Cleaning

When the data was analyzed for the model, some missing records and negative values were detected due to disconnections on the GPS. This data was filtered out. Z-score was applied to remove any outliers and 95% of data is used to build the model. Under normal circumstances, a travel time for an interval takes about max 15 minutes on the selected lines, therefore any outlier not in the range of 0-2000 sec for a single interval, removed from the test data.

2.6. Data Processing

Journeys were grouped for each Journey Number and by looping through the intervals, travel time was calculated for each bus stop. By using Arrival Time in the raw data, Measured Travel Time (MTT) from bus stop t_i to t_j was calculated as follow;

$$MTT = t_j - t_i \tag{1}$$

$$j = i + 1 \tag{2}$$

From weather file, dates for rainy days were converted to minutes to use in the model. Day of year, day of week, minute of day parameters were calculated by using Travel Date Time and added to the data file as integer values.

3. TRAVEL TIME PREDICTION MODEL

In this paper a Multiple Linear Regression algorithm is used to make a prediction model. Linear Regression algorithm is used to predict a dependent variable based on an independent variable. It sets a relationship between the two variables and tries to find a value that is closest to the real data. When number of independent variables more than one, then the algorithm is called Multiple Linear Regression.

According to Linear Regression models there is a linear relationship between the input variables X={X□, X□,….X□} and an output variable Y;

$$Y = T_0 + T_1X_1 + T_2X_2 + .. + T□X□ \tag{3}$$

Where T□…T□ are the coefficients to be calculated. Total travel time T was calculated as sum of predicted travel time (P) for each bus stop interval:

$$T = \sum_{i=1}^{n-1} P(X,Y)_i \tag{4}$$

$$P(X,Y) = Y_0 + Y_1X_1 + Y_2X_2 + .. + Y_4X_4 \tag{5}$$

Table 2. Symbol table for Equation (5).

	Explanation
P	Predicted Travel Time
Y□	Coefficient
Y□	Rain Coefficient
X□	Rainy/Not Rainy Data
Y□	Day of Year Coefficient
X□	Day Of Year Data
Y□	Day Of Week Coefficient
X□	Day Of Week Data
Y□	Minute Of Day Coefficient
X□	Minute Of Day Data

Table 3. An example of coefficients table.

Bus Stop Interval	Coefficients
114781_214671_D	[10.10097562, 0.08541317, 4.26538981, 0.37404211, 84.44304225]
114782_117242_G	[-2.85168458e+01, 6.07373827e-02, 1.79116817e+00, 2.99144607e-01,-1.13585302e+02]
117241_114781_D	[20.92963144, 0.03740569, -2.16415727, 0.15873143, 23.57377834]
117242_303361_G	[49.75525906, -0.23432515, -15.93854232, 0.30572268, -15.20367102]
117261_302361_D	[1.40037836e+01, 1.77404500e-01, -1.97240535e+01, 2.09095511e-01, 1.95342741e+02]
117271_117261_D	[6.82475335e+01, -5.64102913e-02, -1.87162121e+00, 1.29336826e-01,3.60045707e+01]
117281_117271_G	[29.54838069, 0.05922496, -4.43299639, 0.14020044,-12.87168654]
132431_117281_G	[4.5483451 , 0.27656409, -10.57550108, 0.16317783, 118.42572471]
114781_214671_D	[10.10097562, 0.08541317, 4.26538981, 0.37404211, 84.44304225]
114782_117242_G	[-2.85168458e+01, 6.07373827e-02, 1.79116817e+00, 2.99144607e-01,-1.13585302e+02]

Coefficients were calculated for each bus stop interval as seen on Table 3. First column shows the interval with direction where second column shows coefficients for rain, day of year, day of week and minute of day parameters. The values were used in prediction equation to calculate the travel times. The model was trained with 2019 data.

4. VALIDATION

4.1. Simulation

To validate the model, a simulation model was developed by using different types of lines in addition to the line 90. 2020 data was used for the validation. However because of the Covid-19 curfews there are some irregularities on the transportation data after March. Some days, there were no public transportation. Therefore only January and February data was used for the line 11US, 17, 14, 252, 16C and 18K.

A random bus stop was selected as a destination point, assuming that a passenger is waiting at the stop for a bus. Then another bus stop was chosen randomly as the location of the expected bus. In case the bus is not exactly at the stop but in between two stops, a time difference was obtained from the exact location to the nearest stop. From where the bus was located, travel time for each interval was calculated by using the Equation (5) above, until the bus arrives to the destination point.

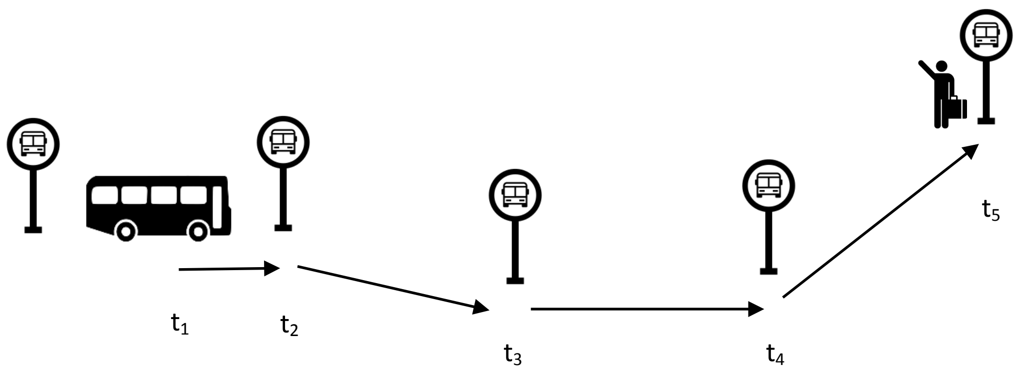

Figure 2. Simulation model for travel time prediction.

Travel time t_i for each bus stop was added to each other and a total travel time T was calculated as follows where n is number of bus stops and n-1 is number of intervals.

$$T = \sum_{i=1}^{n-1} ti \tag{6}$$

4.2. Results

The simulation generated more than 10.000 journeys for each line. There is a cumulative error rate in the model that increases when the bus moves from one interval to another. Root Mean Square Error (RMSE) was calculated to show the cumulative error rate for the simulation journeys for the 6 lines; 11ÜS, 14, 16C, 17, 18K, 252.

Table 4. RMSE for 6 bus lines; 11ÜS, 14, 16C, 17, 18K and 252.

	NUMBER OF GENERATED JOURNEYS	RMSE
11ÜS	13109	0.059
14	11159	0.021
16C	13455	0.020
17	14772	0.016
18K	11002	0.088
252	13561	0.153
11ÜS	13109	0.059
14	11159	0.021

The model shows best performance on the line 17 with RMSE of 0.016. The line 252 has highest RMSE with 0.153. Although the regression model was developed based on a single line at the beginning, it performs well on all tested lines.

Different types of models were used to compare the results. First, average of 2019 real data with 502.384 records for each interval of the line 16C was calculated. Then a random journey was selected from the real data. Simulation result for the same journey was obtained and these three travel times were compared as below.

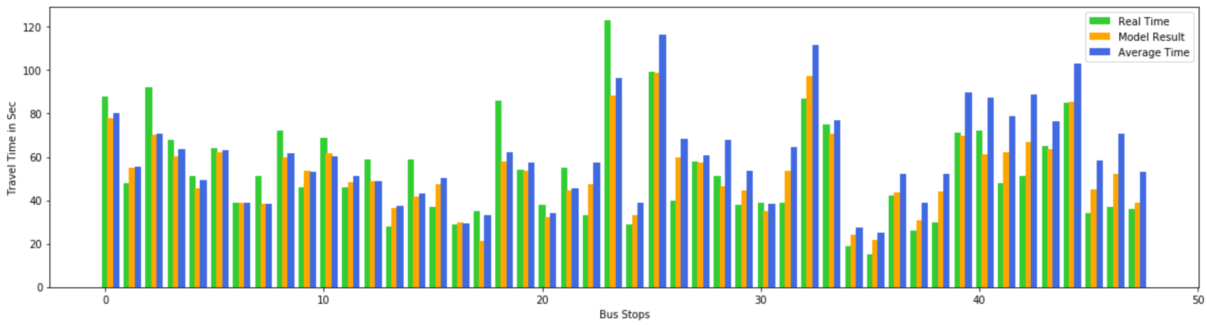

Figure 3. Comparison of results for 16C; Real Travel Time, Average Travel Time and Predicted Travel Time (Model Result).

The prediction model showed 8.85 Mean Absolute Error (MAE) for the selected journey while average model showed 13.45 MAE.

Same approach tested for 15 random days under different weather conditions, with different number of intervals and for both peak and non peak hours. For example, journey 8, 9, 10 and 15 in Fugure 4 were generated on rainy days while others were generated when there was no precipitation. The prediction model performed better with smaller error rate, under tested conditions for most of the journeys.

Figure 4: MAE of Prediction Model and Average Model for 15 journeys on different days including sunny and rainy weather, short and long journeys, peak and non-peak hours.

5. CONCLUSION

Travel time prediction is essential as a part of Passenger Information Systems. This work demonstrates a Multiple Linear Regression method to maintain a solution for Istanbul with extraordinary traffic pattern. 4 highly effective factors were selected among others as parameters for the model; day of year, day of week, minute of day and weather forecast.

Field observations were arranged to experience effects of these factors on different days and times. After the model was developed by using the selected factors, a simulation model was built to verify the model.
The proposed model outperforms the average travel time for each bus stop interval on different lines. The model can be a good solution for Istanbul traffic.

Although there are some parameters specific to the line 90, the model was tested on various lines. In the future, the parameters can be adjusted for each lines. Bus type, drivers' speed habit and intersections were eliminated to prevent algorithm complexity. These parameters might be used in the future work.

REFERENCES

Achar, A., Bharathi, D., Kumar, B. A., & Vanajakshi, L. (2020) Bus Arrival Time Prediction: A Spatial Kalman Filter Approach. IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 3, pp. 1298-1307, doi: 10.1109/TITS.2019.2909314.

Choudhary, R., Khamparia, A., & Gahier, A. K. (2016) Real time prediction of bus arrival time: A review. 2016 2nd International Conference on Next GenerationComputing Technologies (NGCT), Dehradun, pp. 25-29, doi: 10.1109/NGCT.2016.7877384.

Garcia, F. C. C., & Retamar, A. E. (2016) Towards building a bus travel time prediction model for Metro Manila. 2016 IEEE Region 10 Conference (TENCON), Singapore, pp. 3805-3808, doi: 10.1109/TENCON.2016.7848775.

Hapsari, I., Surjandari, I., & Komarudin. (2018) Visiting Time Prediction Using Machine Learning Regression Algorithm. 2018 6th International Conference on Information and Communication Technology (ICoICT), Bandung, pp. 495-500, doi: 10.1109/ICoICT.2018.8528810.

He, P., Jiang, G., Lam, S., & Tang, D. (2019) Travel-Time Prediction of Bus Journey With Multiple Bus Trips. IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 11, pp. 4192-4205, doi: 10.1109/TITS.2018.2883342.

Kwak, S., & Geroliminis, N. (2020) Travel Time Prediction for Congested Freeways With a Dynamic Linear Model. IEEE Transactions on Intelligent Transportation Systems, doi: 10.1109/TITS.2020.3006910.

Lin, D., Tsao, W., Yu, C., Liu, H., & Chang, Y. (2019) The Travel Time Prediction by Machine Learning Methods with Traffic Data in Chiayi City, Taiwan. 2019 4th International Conference on Electromechanical Control Technology and Transportation (ICECTT), Guilin, China, pp. 257-260, doi: 10.1109/ICECTT.2019.00065.

Pan, J., Dai, X., Xu, X., & Li, Y. (2012) A Self-learning algorithm for predicting bus arrival time based on historical data model. 2012 IEEE 2nd International Conference on Cloud Computing and Intelligence Systems, Hangzhou, pp. 1112-1116, doi: 10.1109/CCIS.2012.6664555.

Rice, J., & van Zwet, E. (2001) A simple and effective method for predicting travel times on freeways. ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No.01TH8585), Oakland, CA, pp. 227-232, doi: 10.1109/ITSC.2001.948660.

Tan, C., Park, S., Liu, H., Xu, Q., & Lau, P. (2008) Prediction of Transit Vehicle Arrival Time for Signal Priority Control: Algorithm and Performance. IEEE Transactions on Intelligent Transportation Systems, vol. 9, no. 4, pp. 688-696, doi: 10.1109/TITS.2008.2006799.

URL1 : Weather for 243 countries of the world, http://rp5.ru

Yang, J. S. (2005) Travel time prediction using the GPS test vehicle and Kalman filtering techniques. Proceedings of the 2005, American Control Conference, 2005, Portland, OR, USA, pp. 2128-2133 vol. 3, doi: 10.1109/ACC.2005.1470285.

Yu, H., Xiao, R., Du, Y., & He, Z. (2013) A Bus-Arrival Time Prediction Model Based on Historical Traffic Patterns. 2013 International Conference on Computer Sciences and Applications, Wuhan, pp. 345-349, doi: 10.1109/CSA.2013.87.