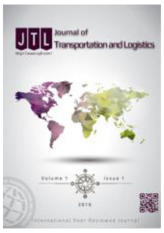

Available online at www.iujtl.com

JTL

Journal of Transportation and Logistics
7 (2) 2022

DOI: 10.26650/JTL.2022.953913

RESEARCH ARTICLE

Predicting the Time of Bus Arrival for Public Transportation by Time Series Models

Süleyman Mete[1], Erkan Çelik[2], Muhammet Gül[3]

ABSTRACT

Bus arrival time prediction is a key factor in passenger satisfaction and bus usage. Bus arrival time information reduces both passenger anxiety and their waiting time at the bus stop. Therefore, giving passengers accurate bus arrival time information is very important in public transportation. Various time series prediction methods are used for bus arrival time in this paper. Moreover, five different performance measurements are considered to assess the accuracy of the prediction models. A case study is presented using real data from Istanbul, Turkey for the proposed models. The models predict bus arrival time on a route for its different segments. The results of the proposed models are compared according to performance measures. The model with the best accuracy result among the eight prediction models can support service operators and the authorities in obtaining better passenger satisfaction.

Keywords: Bus Arrival Time, Prediction, Public Transportation, Time Series Models, Istanbul

Submitted: 17.06.2021 • **Revision Requested:** 13.08.2021 • **Last Revision Received:** 27.10.2022 • **Accepted:** 28.10.2022

1 Süleyman Mete (Doç. Dr.), Gaziantep University, Department of Industrial Engineering, Gaziantep, Turkiye. E-mail: smete@gantep.edu.tr ORCID: 0000-0001-7631-5584

2 **Corresponding author:** Erkan Çelik (Doç.Dr.), Istanbul University, Faculty of Transportation and Logistics, Istanbul, Turkiye. E-mail: erkancelik@istanbul.edu.tr ORCID: 0000-0003-4465-0913

3 Muhammet Gül (Doç. Dr) , Istanbul University, Faculty of Transportation and Logistics, Istanbul, Turkiye. E-mail: muhammetgul@istanbul.edu.tr ORCID: 0000-0002-5319-4289

Citation: Mete, S., Ç.E., & G.M. (2022). Predicting the time of bus arrival for public transportation by time series models. *Journal of Transportation and Logistics, 7*(2), 541-555. https://doi.org/10.26650/JTL.2022.953913

Introduction

Transportation is a significant issue for city planners. Transportation also has a direct impact on all aspects of the community, including education, economy, health, and entertainment activities, and these cannot be maintained without an effective city transportation infrastructure. Therefore, with the growing population, the significance of public transportation is increasing day by day. Most people prefer to utilize public transportation instead of private cars due to air and noise pollution, excessive and unreliable travel times, stress, traffic problems, etc. (Celik et al. 2013; Serin and Mete. 2019). Public transportation is a common passenger transportation service that people can use. It includes different transportation modes, such as buses, trams, train, metro, trolleybuses, etc. (Serin et al. 2021).

Public transportation service quality should be developed in order to persuade more people to switch from private vehicles to public transportation (Aydin et al. 2015). Moreover, while more and more apps are used for bus schedules thanks to the development of smart phones, the information provided on these apps is always limited and not up to date. Long waits at bus stops can discourage passengers from using public transportation. Therefore, vehicle arrival time prediction is very important for the development of the public transportation system. From the passengers' point of view, timely bus arrival time information not only reduces waiting times, but also enables them to organize their travel plans reasonably and choose the most suitable route for travel. In public transportation management, bus arrival time information will greatly enrich the service, help make bus departure interval and operating time more timely, especially in emergency situations, establish more efficient operations, and increase the attractiveness of public transportation (M. Yang et al., 2016). All this reveals the importance of providing passengers with accurate information about the arrival time of the vehicles.

The aim of this paper is to apply effective and dynamic time series models based on the simple average, Holt's linear trend and Holt-Winters, autoregressive integrated moving average (ARIMA), simple exponential smoothing, moving average, SARIMAX, and naive approach methods to predict accurate bus arrival times for the public transportation system. Moreover, this paper examines the improved methodology for real application utilization. This paper intends to make a contribution to stakeholders by considering the provision of eight different time prediction methods in order to improve upon the provision of bus arrival time predictions from only one source (current and historical automatic vehicle location (AVL) data of Istanbul). The contribution of this paper can be summarized as follows: *(i)* the ARIMA method has been applied for the first time to predict bus arrival time; *(ii)* the time series methods have been examined on AVL data of Istanbul; *(iii)* five performance measures have been used to evaluate the time series models (these are the mean squared error (MSE), the mean absolute percentage error (MAPE), the residual sum of squares (RSS), the mean absolute error (MAE), and the root mean square error (RMSE)); *(iv)* the prediction methods used in the study can be applied to any public transportation mode; and *(v)* these predictions can be shared with passengers using smart bus stops or mobile applications.

The rest of the paper structured as follows. Related studies are analyzed in the next section. Materials and method for predicting bus arrival time are shown in section 3. An example case (Istanbul) is examined in section 4, and the results are discussed in section 5. A brief conclusion is provided in the last section.

Related studies

Related studies are reviewed in two groups in this section. First, papers on bus travel time prediction models are reviewed. Then, literature-related applications of time series-based techniques are analyzed. Many researchers and practitioners have started to become interested in bus arrival time prediction. There are various methods developed in the literature for the prediction of bus arrival times, including artificial neural networks (ANN), Kalman filters, non-parametric regression (NPR) models, and support vector machines (SVM) (Yu et al. 2011).

ANN models are mostly used as an approach to arrival time prediction in the literature (Xu and Ying 2017). Chien et al. (2002) proposed two ANNs for link- and stop-based data dynamic bus arrival time prediction, and proposed ANNs are combined with an adaptive algorithm. A dynamic algorithm which integrated the Kalman filter-based algorithm and an ANN was developed by Chen et al. to predict bus arrival times (2004). The dynamic algorithm that was developed is more effective compared with ANN-based models for prediction of bus arrival times, according to test results. Bayesian inference theory with neural networks was proposed by van Hinsbergen et al. (2009) to predict travel times. The results of the proposed approach showed that it had much higher accuracy. Yap et al. (2018) proposed a three-step search procedure for the prediction of public transportation ridership.

The Kalman filter technique, which is a model-based estimation technology, is implemented for bus arrival time prediction in the literature. Chien and Kuchipudi (2003) used the Kalman filter algorithm in modelling real-time and historic data for bus travel time prediction. The Kalman filter based model was applied to dynamic bus arrival/departure time prediction by Shalaby and Farhan (2004).

NPR models are also used for bus arrival time prediction. Park et al. (2007) developed and evaluated an NPR model to apply a time prediction model using real data. Chang et al. (2010) proposed a model based on nearest neighbor NPR for prediction of travel times among origin and destination bus stops. Their results demonstrated that the developed model is an efficient method for predicting bus travel time with respect to computing time and prediction accuracy. A Long Short-Term Memory (LSTM) model was used to predict accurate bus arrival time for public transportation system by Serin, et al. (2020).

SVM models, a special learning algorithm developed based on learning theory, have been implemented for the prediction of bus travel time. Yang et al. (2016) proposed SVM with a genetic algorithm to forecast bus arrival time. Bin et al. (2006) researched the feasibility and applicability of SVM for the prediction of bus travel time. Experimental results demonstrated that the proposed SVM integrated with a genetic algorithm approach is better than traditional ANN and SVM models due to its higher accuracy and the model's feasibility for estimation of bus arrival time. A combined model of Support Vector Regression and Kalman filter (K-SVR) for bus arrival time prediction was proposed by Zhang, et al. (2021).

Unlike ANN, SVM, and Kalman filter-based models, times series-based models are available in the literature that are well-fitted to this research topic according to their prediction of bus arrival time. Time series forecasting models can be categorized as univariate or multivariate. Various time series models have been used for forecasting. The ARIMA model is the most widely applied time series method, and is applied to various areas such as the furniture industry by Yucesan et al. (2018), healthcare by Kadri et al. (2014), Wei et al. (2016) and Xu et al. (2016), finance by Zhang et al. (2016), energy by Yuan et al. (2016) and Cadenas et al. (2016), and the food industry by Tripathi et al. (2014). There are three parameters in ARIMA models: (p, d, q). While AR terms are denoted with p, the number of non-seasonal differences needed for stationarity is denoted with d and the number of lagged forecast errors in the prediction equation is denoted with q (Xu et al. 2016). Various ARIMA models, such as multivariate vector-ARIMA (Mai et al. 2015), Box-Jenkins ARIMA (Zibners et al. 2006; Champion et al. 2007), ARMA (Aboagye-Sarfo et al. 2015), SARIMA (Butler et al. 2016; Rosychuk et al. 2016), and MSARIMA (Aroua and Abdul-Nour, 2015), have been used by researchers. A simple exponential smoothing method is based on the weighted moving average formula (Champion et al. 2007). This method was successfully applied to many areas, such as in studies by Tratar et al. (2016), Yang et al. (2015), and Tripathi et al. (2014). In addition, the naive approach, simple average, moving average, Holt's linear trend, and Holt's winter trend method are also time series models for forecasting.

The literature is rich enough in terms of time series methods for applying different application areas. However, the current study is differentiated from application areas in that it predicts the time of bus arrival for public transportation. In this paper, time series models based on moving average, naive approach, simple exponential smoothing, simple average, ARIMA, Holt-Winters method, Holt's linear trend, and SARIMAX are applied for bus arrival time prediction of the 500T bus route in Istanbul.

Material and Method

3.1 The prediction framework

The basic components of public transportation are routes, bus stops, and vehicles. These components are represented in Figure 1. Routes are denoted as R_n where n describes the unique number of the route. Vehicles are denoted as $V_{r,n}$ where r refers to route number and n refers to the number of vehicles on the route r. Stations are denoted as S_n where n is the order number of the station from start station to end station of the route.

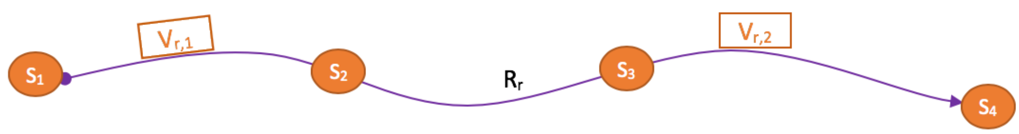

Figure 1. The representation of the basic public transportation components (routes, stations, and vehicles)

The line between two sequential stations is defined as a segment. For example, the line from S_1 to S_2 in Figure 1 is a segment. One or more routes can pass through a segment, and one or more vehicles can travel on a route. This situation is depicted in Figure 2 where S_d is the start (departure) station of the segment and S_a is the end (arrival) station of the segment. The routes that pass through the segment are R_1, $R_{2,}$ and R_3. The vehicles $V_{1,1}$ and $V_{1,2}$ work on route R_1; $V_{2,1}$, $V_{2,2,}$ and $V_{2,3}$ work on route R_2; $V_{3,1}$ and $V_{3,2}$ work on route R_3.

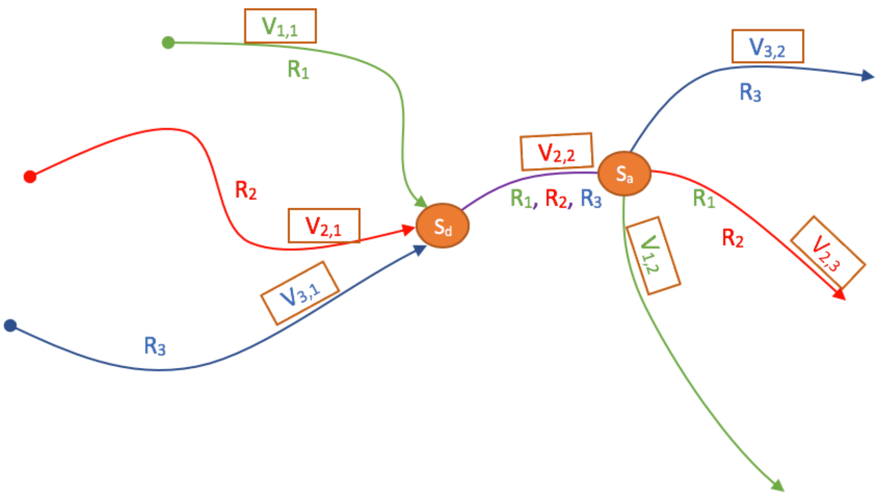

Figure 2. Representative snapshot of part of the public transportation system

Each vehicle sends a signal when arriving at a station. The actual travel time on the segment from S_d to S_a is computed by subtracting the signal time at S_a from the signal times at S_d. This generates sequential time intervals (Δt). These time intervals constructed the travel time between two sequential stations is forecasted using these signals as time series.

3.2 Naive Approach

This approach considers the **estimated** data point to be equal to the last observed data point (Alaoui et al. 2017). The formulation of the approach is given in Eq. (1)

$$\hat{y}_{t+1} = y_t \tag{1}$$

3.3 Simple Average

A simple average is the simplest forecasting technique. This technique estimates the estimated value equal to the average of all previously observed values. Hence, the formulation is given in Eq. (2)

$$\hat{y}_{t+1} = \frac{1}{t}\sum_{i=1}^{t} y_i \tag{2}$$

3.4 Moving Average

The use of value(s) for the first period will greatly affect estimates for the next period. Hence, only the values of the last few rounds are regarded as a development over the simple average. The moving average technique uses a time period window to calculate the average. The predicted value(s) in a time series is forecasted based on the average of the previous values by a fixed end number "p" in a simple moving average model. Thus, the moving average is calculated using Eq. (3) as follows (Shumway and Stoffer, 2000):

$$\hat{y}_{t+1} = \frac{1}{p}\sum_{i=t-p}^{t} y_i \qquad \text{for all } i > p \tag{3}$$

On the other hand, the weighted moving average method is a progression of moving average method. This method is a moving average with a different weight. The values of a weighted moving average technique take different weights in past observations. The formulation of this technique is given in Eq. (4), as follows:

$$\hat{y}_{t+1} = \frac{1}{p}\sum_{i=t-p}^{t} w_i * y_i \tag{4}$$

3.5 Simple Exponential Smoothing

This method is a suitable forecasting technique with no trend or seasonal pattern data (Gass and Harris, 2000; Cadenas et al. 2010).

Assuming that f_t is the forecasted data and y_t is the actual data, the errors are obtained as follows:

$$e_t = y_t - f_t \tag{5}$$

The method considers the forecasted value for the previous period and regulates it using the forecasted error. Therefore, the forecasted value for the following period is:

$$f_{t+1} = f_t + a(y_t - f_t) \tag{6}$$

where a is *a* constant between 0 and 1.

3.6 Holt's Linear Trend

This technique allows forecasting of data with a trend. This method involves both trend and the average value in the series. Three equations are used to determine Holt's Linear Trend (Chatfield and Yar, 1988). Eq. (7) is given for the combination of two smoothing equations (Eq. (8) for level and Eq. (9) for the trend) to obtain the expected forecast ŷ.

$$\hat{y}_{t+h} = \ell_t + hb_t \tag{7}$$

$$\ell_t = y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{8}$$

$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{9}$$

3.7 Holt-Winters Method

The Holt-Winters method considers both trend and seasonality to forecast future values. It implements exponential smoothing of the seasonal parts with level and trend. Due to the seasonality factor, this method is the best option within the rest of the models (Chatfield and Yar, 1988). This method includes the forecast Eq. (10), level Eq. (11), trend Eq. (12) and seasonal component Eq. (13) with three smoothing parameters α, β, and γ.

$$\hat{y}_{t+h} = \ell_t + hb_t + b_{t+h-s} \quad (10)$$

$$\ell_t = \alpha(y_t - b_{t-s}) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \quad (11)$$

$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \quad (12)$$

$$S_t = \gamma(y_t - \ell_t) + (1-\gamma)S_{t-s} \quad (13)$$

where s denotes the length of the seasonal cycle, for $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$, and $0 \leq \gamma \leq 1$.

Eq.11 demonstrates a weighted average among the non-seasonal forecast for time t and the seasonally adjusted observation. Holt's linear method and trend equation are identical. A weighted average among the current seasonal index and the same season's previous year seasonal index is indicated by the seasonal equation.

3.8. ARIMA

The AR(p) and MA(q) models applied to forecasting are represented as in Eqs (14)-(15), respectively (Kadri et al. 2014)

$$Y_t = \sum_{i=1}^{p} a_i \, Y_{t-i} + \varepsilon_t \quad (14)$$

$$Y_t = \varepsilon_t + \sum_{j=1}^{q} b_j \, \varepsilon_{t-j} \quad (15)$$

where a_i are non-seasonal AR parameters, ε_t is zero mean Gaussian noise and b_j are non-seasonal MA parameters.

The ARMA (p, q) model consists of p and q as autoregressive terms and moving average terms, respectively. It is written as in Eq. (16):

$$Y_t = c + a_1 Y_{t-1} + \cdots + a_p Y_{t-p} + \varepsilon_t + b_1 \varepsilon_{t-1} + \cdots + b_q \varepsilon_{t-q} \quad (16)$$

In case of non-stationarity of the data, a differencing notation is required for reducing the non-stationarity, as the ARIMA model (Yuan et al. 2016).

3.9. SARIMAX

Based on ARIMA, SARIMA includes seasonality notations. SARIMAX is formed by adding an external input to a SARIMA model. It uses an exogenous variable in the time series modeling process (Papaioannou et al. 2016; Chen and Tjandra, 2014).

Case study

In this part, the time series models have been evaluated for bus arrival time prediction at bus stops using real data from Istanbul, Turkey. Istanbul is a crowded city with a population of more than 15 million, and the majority of Istanbul residents travel by road transportation (Yanık et al. 2017). Additionally, more than 1/4 of Istanbul residents use bus, metrobus, or private buses. Approximately 13 million people per day use public transportation in Istanbul (IETT, 2018). Istanbul's advanced public transportation system consists of real time location tracking, transit vehicle tracking, informing passengers at bus stops about vehicle location, and fare collection through an electronic system. Since the electronic panels show the bus timelines at the stations, tracking the expected arrival time of buses to the stop is possible. Passengers utilize this information to plan their route. Istanbul has developed, and has a complicated network with more than 1,000 bus routes. As a case study, one of the most crowded and longest lines (500T: Tuzla Şifa Mah.-Cevizlibağ) was selected to evaluate the prediction models (Figure 3). The selected line crosses the bridge connecting Europe and Asia every day and has many bus routes and stops that are in high demand (Figure 4). Its length is approximately 73.6 km. The real time details of the L. Kirdar Has. Acil bus stop, which has 20 different lines, are presented in Table 1 as an example.

Table 1. Real time bus stop details

Line Details	Predicted waiting time (min.)	Line Details	Predicted waiting time (min.)	Line Details	Predicted waiting time (min.)	Line Details	Predicted waiting time (min.)
251	1	KM23	10	KM25	20	500L	34
500L	1	17K	11	500T	21	KM11	34
130Ş	2	16KH	14	KM11	22	251	37
E-10	2	130A	14	500L	24	500T	38
500T	4	KM21	15	130Ş	25	130A	39
500L	5	KM12	15	E-10	25	130Ş	40
16S	7	21K	15	KM29	30	KM23	40
130Ş	8	251	16	130Ş	30	16Z	41
134YK	9	17S	16	134YK	32	16KH	41
KM11	10	134YK	16	500T	32	E-10	42
21U	10	500T	17	16S	33	500T	42

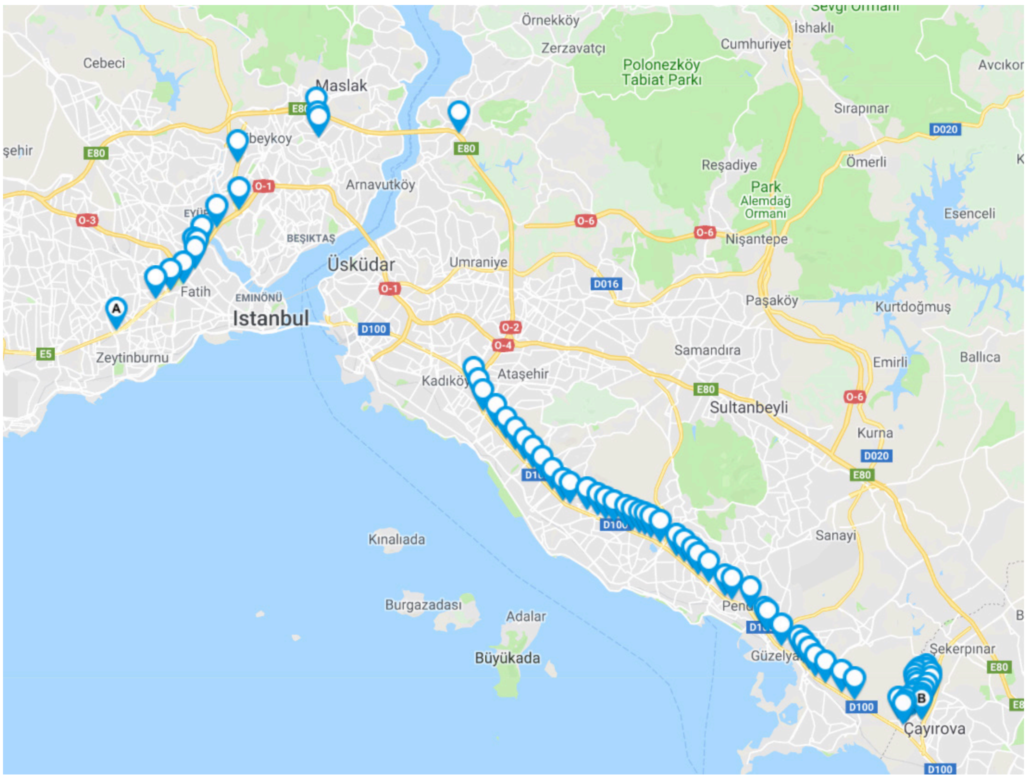

Figure 3: Zeytinburnu Çirpici-Şifa Route

4.1. Performance Measures

MAE, MAPE, MSE, RMSE, and RSS are considered to evaluate the prediction results of the methods.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \tag{17}$$

$$MAPE = \left(\frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t}\right) * 100 \tag{18}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2 \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \tag{20}$$

$$RSS = \sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right|^2 \tag{21}$$

Discussions and Results

The proposed framework is solved under eight different time series methods for predicting bus arrival time on a route in the city of Istanbul. In Istanbul, the predicting arrival time information is provided by an electronic bus stop board system. To improve upon the provision of bus arrival time predictions from one source, this study aims to contribute to stakeholders by considering eight different time predictions. The output data of the study includes the following information: (1) route id, (2) segment number, (3) departure station id, (4) arrival station id, (5) sample size (cleared signal size), (6) signal size, (7) method used, and (8) performance measures (MSE, RMSE, MAE, MAPE, RSS, elapsed time).

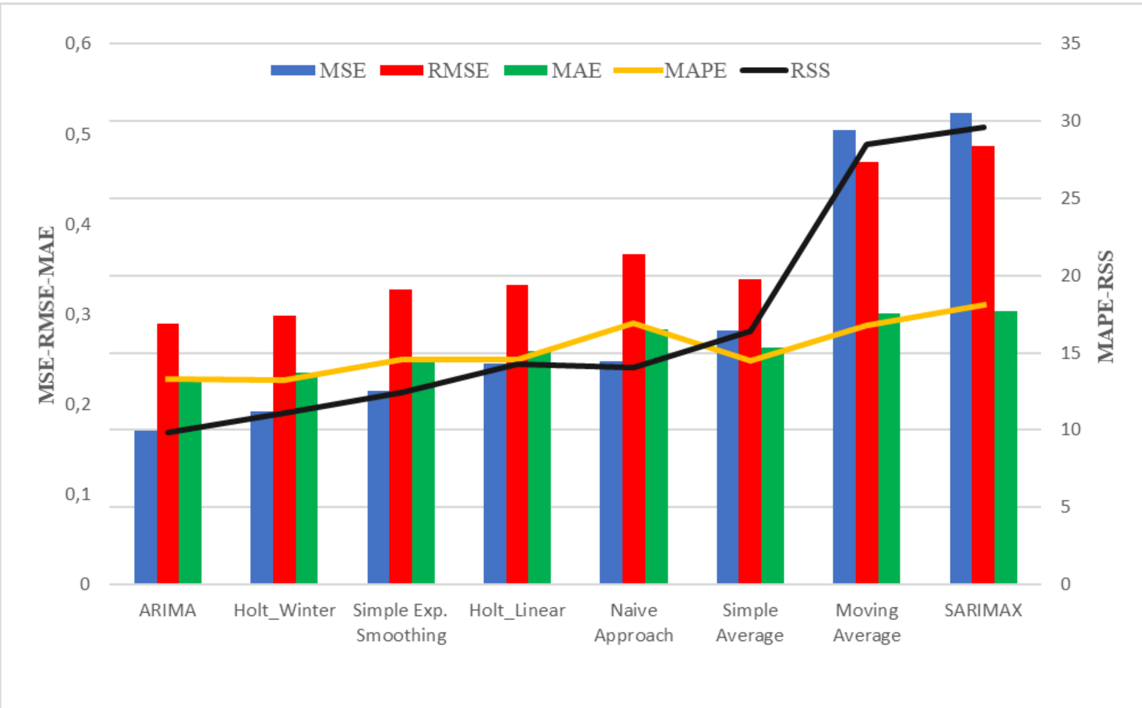

Figure 4. The comparison of the performance of eight time series models

We chose 1 route that includes 76 bus stations, as shown in Figure 3. Eight different time series methods were used to estimate arrival time. The average values of the MSE, RMSE, MAE, MAPE, and RSS of each segment of the observed route are summarized in Table 2. It can be easily seen that ARIMA (2,0,1) exhibits some advantages over others in most of the performance measures. MSE, RMSE, MAE, and RSS values in the ARIMA (2,0,1) model are the lowest of all models (0.171, 0.289, 0.230 and 9.864). The Holt-Winters model has the highest prediction accuracy according to the MAPE, with a value of 13.229. When the elapsed time is considered, it seems that the Holt-Winters model has provided the solution in the longest time (778.192 seconds).

The average value of the MAE, MAPE, MSE, RMSE, and RSS with all segments for the 500T bus route are illustrated in Figure 4. In Figure 4, the eight time series models are presented on a horizontal axis. It is observed that the ARIMA (2,0,1) model has the best prediction performance with respect to MSE, RMSE, and RSS. The MAPE value is between 13.285% and 18.111% for all models. Although the performance of the ARIMA (2,0,1) model is better than the others, if the elapsed time is considered, simple exponential smoothing can be used as another option for the prediction of bus arrival time because of the fast solution time (see Table 2).

Moreover, we demonstrated the results of each segment according to the ARIMA (2,0,1) model and SARIMAX model, which are the best and worst performance, respectively. Figure 5 shows the results of five performance measures of the ARIMA (2,0,1) model for the observed route.

Table 2. Average values of performance measures with respect to eight time series methods in bus arrival time prediction for the observed route

Methods	Performance measures					
	MSE	RMSE	MAE	MAPE	RSS	Elapsed Time (in second)
ARIMA (2,0,1)	0.171	0.289	0.230	13.285	9.864	122.747
Holt-Winters	0.192	0.298	0.235	13.229	11.112	778.192
Simple Exponential Smoothing	0.215	0.327	0.249	14.555	12.427	0.306
Holt's Linear Trend	0.245	0.333	0.259	14.571	14.242	4.526
naïve approach	0.248	0.366	0.283	16.892	14.037	0.014
Simple average	0.282	0.339	0.263	14.48	16.393	0.053
Moving average	0.504	0.469	0.301	16.769	28.495	0.395
SARIMAX (1,0,1)(1, 0, 1, 5)	0.523	0.487	0.303	18.111	29.61	170.236

Figures 6 and 7 demonstrate prediction of bus arrival times using the ARIMA model against the observed values with respect to the segment fitted best and worst in terms of MAPE values.

According to results of the ARIMA model in Figure 6, the results are very close to the observed data. This means that the accuracy of the models is sufficient. Therefore, using this method provides better and more accurate information to the passenger.

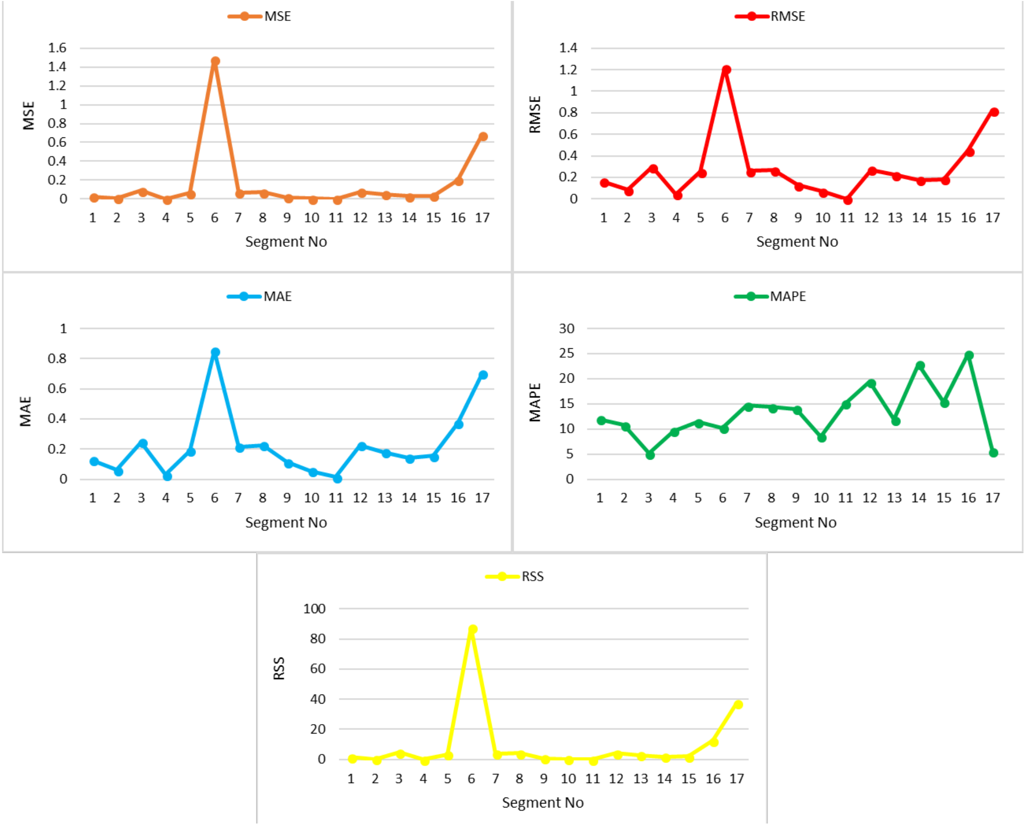

Figure 5. MSE, RMSE, MAE, MAPE, and RSS of bus arrival times predicted from each segment (ARIMA model)

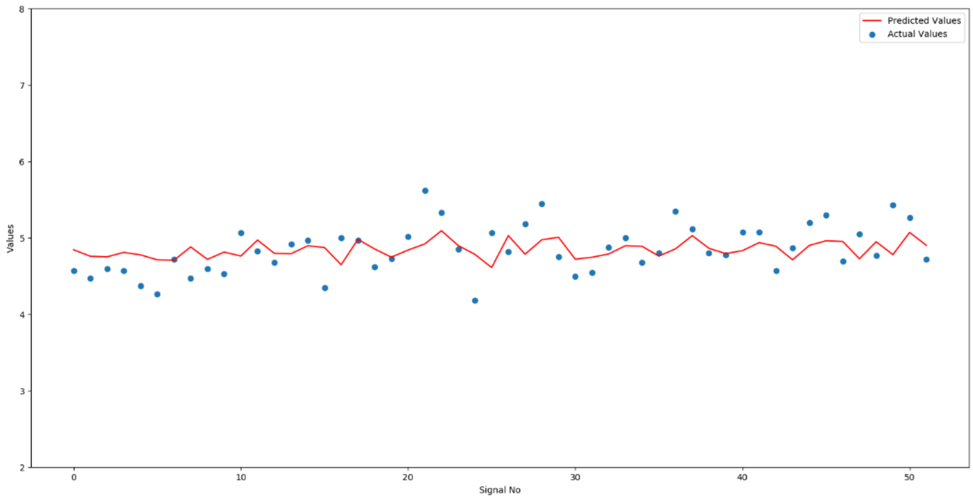

Figure 6. Predictability of the ARIMA model (with best MAPE value)

Figure 8 demonstrates the results of the SARIMAX(1,0,1)(1, 0, 1, 5) model for the observed route with different segment. According to average results of the five-performance measures, the SARIMAX model is the worst method compared to the other time series models.

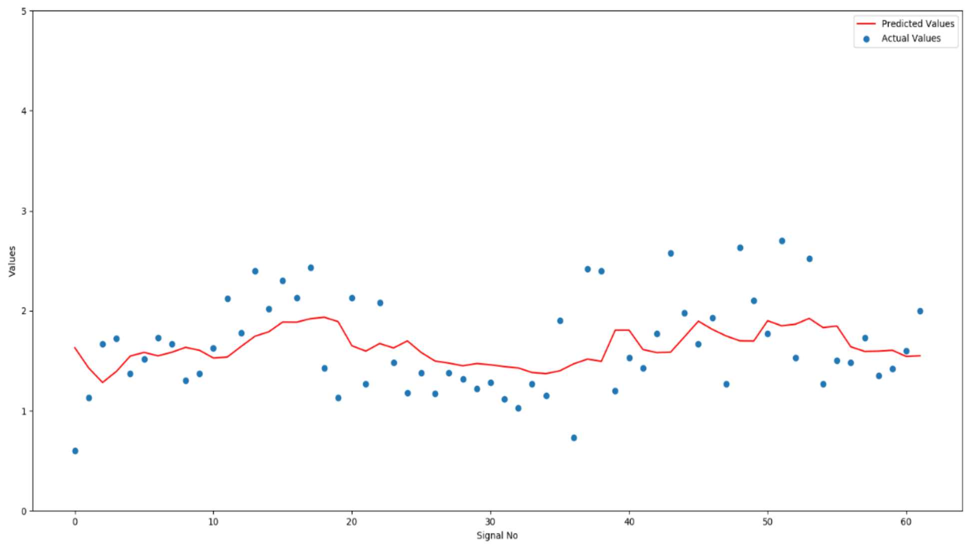

Figure 7. Predictability of the ARIMA model (with worst MAPE value)

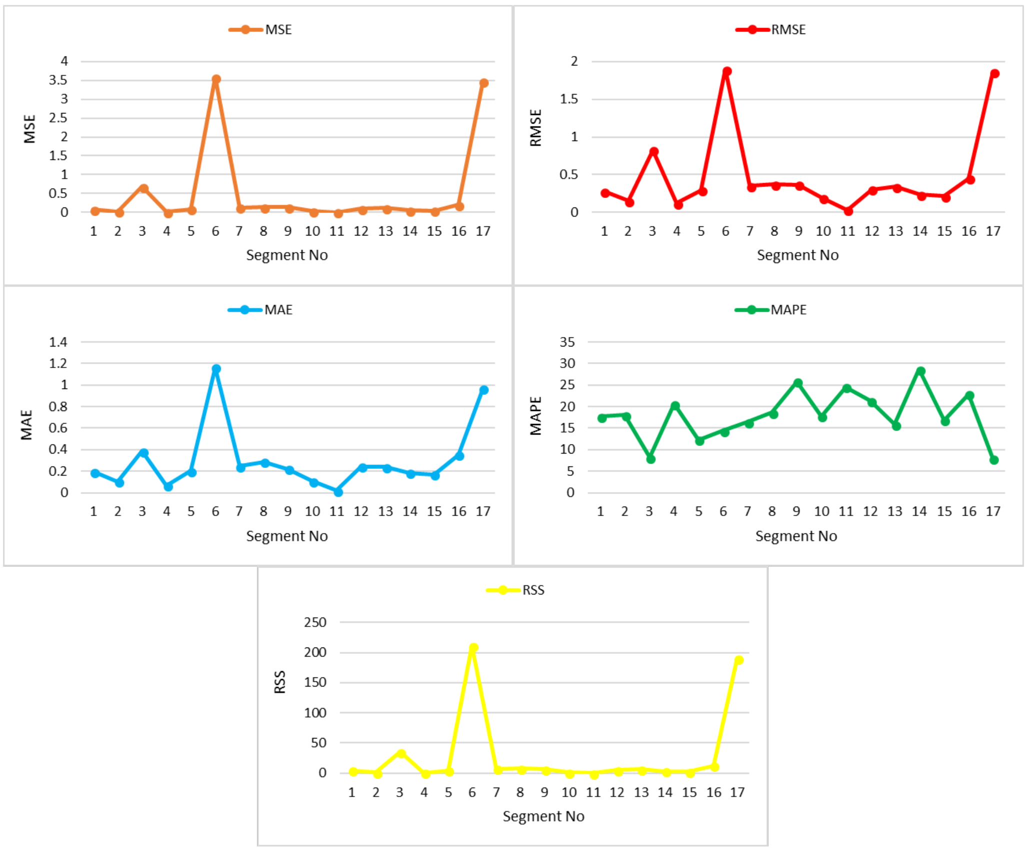

Figure 8. MSE, RMSE, MAE, MAPE, and RSS of bus arrival times predicted from each segment (SARIMAX model)

Conclusion

Giving accurate bus arrival time information to passengers is vital in reducing waiting times and passenger anxiety at the bus stop. This paper examines the success of different time series models under five performance measures for the prediction of bus arrival time at a bus stop on the 500T route in Istanbul. Different time series models from the literature were applied for predicting bus arrival time. These models are naïve approach, moving average, simple average, ARIMA, Holt's linear trend, simple exponential smoothing, Holt-Winters method, and SARIMAX. The MSE, MAPE, RMSE, MAE, and RSS are used to evaluate the performance of the prediction methods. According to the obtained results, ARIMA (2,0,1) shows some advantages over the others in most of the performance measures. In addition, the Holt-Winters model has the highest prediction accuracy with respect to MAPE. On the other hand, if the elapsed time is considered, the Holt-Winters model gives a solution in the longest time. Hence, decision makers can select the best method according to their preferences. The prediction methods used in the study can be applied to any public transportation, but we have evaluated the results using Istanbul public transportation data available on the IETT web site. These predictions are shared with passengers using smart bus stops or a mobile application.

In this paper, eight time series models were applied to only one bus route, which is a limitation of the study. For further study, the applied models could be used for different and multiple public transportation routes. In future studies, a machine learning-based solution approach could be applied to estimate bus arrival time.

Peer Review: Externally peer-reviewed.
Conflict of Interest: Authors declared no conflict of interest.
Financial Disclosure: Authors declared no financial support.
Author Contributions: Conception/Design of Study- S.M., E.Ç., M.G.; Data Acquisition- S.M., E.Ç., M.G.; Data Analysis/ Interpretation- S.M., E.Ç., M.G.; Drafting Manuscript- S.M., E.Ç., M.G.; Critical Revision of Manuscript- S.M., E.Ç., M.G.; Final Approval and Accountability- S.M., E.Ç., M.G.

References

Aboagye-Sarfo, P., Mai, Q., Sanfilippo, F. M., Preen, D. B., Stewart, L. M., & Fatovich, D. M. (2015). A comparison of multivariate and univariate time series approaches to modelling and forecasting emergency department demand in Western Australia. Journal of Biomedical Informatics, 57, 62-73.

Alaoui, S. S., Farhaoui, Y., & Aksasse, B. (2017, April). A comparative study of the four well-known classification algorithms in data mining. In International Conference on Advanced Information Technology, Services and Systems (pp. 362-373). Springer, Cham.

Aroua, A., & Abdul-Nour, G. (2015). Forecast emergency room visits–a major diagnostic categories-based approach. International Journal of Metrology and Quality Engineering, 6(2), 204.

Aydin, N., Celik, E., & Gumus, A. T. (2015). A hierarchical customer satisfaction framework for evaluating rail transit systems of Istanbul. Transportation Research Part A: Policy and Practice, 77, 61-81.

Bin, Y., Zhongzhen, Y., & Baozhen, Y. (2006). Bus arrival time prediction using support vector machines. Journal of Intelligent Transportation Systems, 10(4), 151-158.

Butler, M. B., Gu, H., Kenney, T., & Campbell, S. G. (2016). P017: Does a busy day predict another busy day? A time-series analysis of multi-centre emergency department volumes. CJEM, 18(S1), S83-S84.

Cadenas, E., Jaramillo, O. A., & Rivera, W. (2010). Analysis and forecasting of wind velocity in chetumal, quintana roo, using the single exponential smoothing method. Renewable Energy, 35(5), 925-930.

Cadenas, E., Rivera, W., Campos-Amezcua, R., & Heard, C. (2016). Wind speed prediction using a univariate ARIMA model and a multivariate NARX model. Energies, 9(2), 109.

Celik, E., Bilisik, O. N., Erdogan, M., Gumus, A. T., & Baracli, H. (2013). An integrated novel interval type-2 fuzzy MCDM method to improve customer satisfaction in public transportation for Istanbul. Transportation Research Part E: Logistics and Transportation Review, 58, 28-51.

Champion, R., Kinsman, L. D., Lee, G. A., Masman, K. A., May, E. A., Mills, T. M., &Williams, R. J. (2007). Forecasting emergency department presentations. Australian Health Review, 31(1), 83-90.

Chang, H., Park, D., Lee, S., Lee, H., & Baek, S. (2010). Dynamic multi-interval bus travel time prediction using bus transit data. Transportmetrica A, 6(1), 19-38.

Chatfield, C., & Yar, M. (1988). Holt-Winters forecasting: some practical issues. The Statistician, 129-140.

Chen, Y., & Tjandra, S. (2014). Daily collision prediction with SARIMAX and generalized linear models on the basis of temporal and weather variables. Transportation Research Record: Journal of the Transportation Research Board, (2432), 26-36.

Chen, M., Liu, X., Xia, J., & Chien, S. I. (2004). A dynamic bus-arrival time prediction model based on APC data. Computer-Aided Civil and Infrastructure Engineering, 19(5), 364-376.

Chien, S. I. J., & Kuchipudi, C. M. (2003). Dynamic travel time prediction with real-time and historic data. Journal of Transportation Engineering, 129(6), 608-616.

Chien, S. I. J., Ding, Y., & Wei, C. (2002). Dynamic bus arrival time prediction with artificial neural networks. Journal of Transportation Engineering, 128(5), 429-438.

Kadri, F., Harrou, F., Chaabane, S., & Tahon, C. (2014). Time series modelling and forecasting of emergency department overcrowding. Journal of Medical Systems, 38(9), 107-127.

Mai, Q., Aboagye-Sarfo, P., Sanfilippo, F. M., Preen, D. B., & Fatovich, D. M. (2015). Predicting the number of emergency department presentations in Western Australia: A population-based time series analysis. Emergency Medicine Australasia, 27(1), 16-21.

Papaioannou, G. P., Dikaiakos, C., Dramountanis, A., & Papaioannou, P. G. (2016). Analysis and modeling for short-to medium-term load forecasting using a hybrid manifold learning principal component model and comparison with classical statistical models (SARIMAX, Exponential Smoothing) and artificial intelligence models (ANN, SVM): The case of Greek electricity market. Energies, 9(8), 635.

Park, S. H., Jeong, Y. J., & Kim, T. J. (2007). Transit travel time forecasts for location-based queries. Journal of the Eastern Asia Society for Transportation Studies, 7, 1859-1869.

Rosychuk, R. J., Youngson, E., & Rowe, B. H. (2016). Presentations to emergency departments for COPD: A time series analysis. Canadian Respiratory Journal, 2016. http://dx.doi.org/10.1155/2016/1382434

S.I. Gass, C.M. Harris (Eds.), Encyclopedia of operations research and management science (Centennial edition), Kluwer, Dordrecht, The Netherlands (2000).

Serin, F., & Süleyman, M., (2019). Public transportation graph: A graph theoretical model of public transportation network for efficient trip planning. Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi, 25(4), 468-472.

Serin, F., Mete, S., Gul, M., & Celik, E. (2020). Deep Learning for Prediction of Bus Arrival Time in Public Transportation. In Logistics 4.0 (pp. 126-135). CRC Press.

Serin, F., Mete, S., & Ozceylan, E. (2021). Graph Traversal-based Solutions for Trip Planning in Public Transportation Graph. In 2021 International Conference on Information Technology (ICIT) (pp. 190-194). IEEE.

Shalaby, A., & Farhan, A. (2004). Prediction model of bus arrival and departure times using AVL and APC data. Journal of Public Transportation, 7(1), 41-61.

Shumway, R. H., & Stoffer, D. S. (2000). Time series analysis and its applications. Studies In Informatics And Control, 9(4), 75-163.

Tratar, L. F., Mojškerc, B., & Toman, A. (2016). Demand forecasting with four-parameter exponential smoothing. International Journal of Production Economics, 181, 162-173.

Tripathi, R., Nayak, A. K., Raja, R., Shahid, M., Kumar, A., Mohanty, S., ... & Gautam, P. (2014). Forecasting rice productivity and production of Odisha, India, using autoregressive integrated moving average models. Advances in Agriculture, 2014.

Van Hinsbergen, C. I., Van Lint, J. W. C., & Van Zuylen, H. J. (2009). Bayesian committee of neural networks to predict travel times with confidence intervals. Transportation Research Part C: Emerging Technologies, 17(5), 498-509.

Wei, W., Jiang, J., Liang, H., Gao, L., Liang, B., Huang, J., ... & Qin, F. (2016). Application of a combined model with autoregressive integrated moving average (ARIMA) and generalized regression neural network (GRNN) in forecasting hepatitis incidence in Heng county, China. PloS one, 11(6), e0156768.

Xu, H., & Ying, J. (2017). Bus arrival time prediction with real-time and historic data. Cluster Computing, 20(4), 3099-3106.

Xu, Q., Tsui, K. L., Jiang, W., & Guo, H. (2016). A hybrid approach for forecasting patient visits in emergency department. Quality and Reliability Engineering International, 32(8), 2751-2759.

Yang, D., Sharma, V., Ye, Z., Lim, L. I., Zhao, L., & Aryaputera, A. W. (2015). Forecasting of global horizontal irradiance by exponential smoothing, using decompositions. Energy, 81, 111-119.

Yang, M., Chen, C., Wang, L., Yan, X., & Zhou, L. (2016). Bus arrival time prediction using support vector machine with genetic algorithm. Neural Network World, 26(3), 205-217.

Yanık, S., Aktas, E., & Topcu, Y. I. (2017). Traveler satisfaction in rapid rail systems: The case of Istanbul metro. International Journal of Sustainable Transportation, 11(9), 642-658.

Yap, M. D., Nijënstein, S., & van Oort, N. (2018). Improving predictions of public transport usage during disturbances based on smart card data. Transport Policy, 61, 84-95.

Yu, B., Lam, W. H., & Tam, M. L. (2011). Bus arrival time prediction at bus stop with multiple routes. Transportation Research Part C: Emerging Technologies, 19(6), 1157-1170.

Yuan, C., Liu, S., & Fang, Z. (2016). Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1, 1) model. Energy, 100, 384-390.

Yucesan, M., Gul, M., & Celik, E. (2018). Performance comparison between ARIMAX, ANN and ARIMAX-ANN hybridization in sales forecasting for furniture industry. Drvna industrija: Znanstveni časopis za pitanja drvne tehnologije, 69(4), 357-370.

Zhang, G., Zhang, X., & Feng, H. (2016). Forecasting financial time series using a methodology based on autoregressive integrated moving average and Taylor expansion. Expert Systems, 33(5), 501-516.

Zhang, X., Yan, M., Xie, B., Yang, H., & Ma, H. (2021). An automatic real-time bus schedule redesign method based on bus arrival time prediction. Advanced Engineering Informatics, 48, 101295.

Zibners, L. M., Bonsu, B. K., Hayes, J. R., & Cohen, D. M. (2006). Local weather effects on emergency department visits: a time series and regression analysis. Pediatric Emergency Care, 22(2), 104-106.