TRANSPORT PROBLEMS 2022 Volume 17 Issue 1
PROBLEMY TRANSPORTU DOI: 10.20858/tp.2022.17.1.05

Keywords: rail transport; passenger flow; time series models

Anna BORUCKA[1], Patrycja GUZANEK[2]*

PREDICTING THE SEASONALITY OF PASSENGERS IN RAILWAY TRANSPORT BASED ON TIME SERIES FOR PROPER RAILWAY DEVELOPMENT

Summary. Planning the frequency of rail services is closely related to forecasting the number of passengers and is part of the comprehensive analysis of railway systems. Most of the research presented in the literature focuses only on selected areas of this system (e.g. urban agglomerations, urban underground transport, transfer nodes), without presenting a comprehensive evaluation that would provide full knowledge and diagnostics of this mode of transport (i.e. railway transport). Therefore, this article presents methods for modelling passenger flow in rail traffic at a national level (using the example of Poland). Time series models were used to forecast the number of passengers in rail transport. The error, trend, and seasonality (ETS) exponential smoothing model and the model belonging to the ARMA class were used. An adequate model was selected, allowing future values to be forecast. The autoregressive integrated moving average (ARIMA) model follows the tested series better than the ETS model and is characterised by the lowest values of forecast errors in relation to the test set. The forecast based on the ARIMA model is characterised by a better detection of the trends and seasonality of the series. The results of the present study are considered to form the basis for solving potential rail traffic problems, which depend on the volume of passenger traffic, at the central level. The methods presented can also be implemented in other systems with similar characteristics, which affects the usability of the presented solutions.

1. INTRODUCTION

Forecasting the number of passengers is an important part of planning the frequency of rail transport, and issues related to the organization and evaluation of railway systems are very often analysed and researched. For example, the literature provides various solutions to selected aspects of the problem of constructing a rational timetable for trains in railway networks [26, 10, 29]. Aspects related to passenger satisfaction are also widely analysed, including travel time [9, 22], quality of travel expressed the level of satisfaction with the service, cleanliness of carriages [7], functioning of the ticketing system, method of providing information, and travel comfort [23]. An interesting article on the analysis and evaluation of the quality of passenger rail transport logistics was proposed by Dedik et al. [6]. The authors describe the relationship between logistics and transport, logistic needs of transport and logistics functions in rail transport. They also provide quality assessment, including a description of the indicators used and propose a new evaluation methodology.

[1] Military University of Technology; gen. Sylwestra Kaliskiego 2, 00-908 Warsaw, Poland; email: anna.borucka@wat.edu.pl; orcid.org/0000-0002-7892-9640
[2] Military University of Technology; gen. Sylwestra Kaliskiego 2, 00-908 Warsaw, Poland; email: patrycja.guzanek@student.wat.edu.pl; orcid.org/0000-0001-6650-7187
* Corresponding author. E-mail: patrycja.guzanek@student.wat.edu.pl

The safety of travel is particularly emphasised [7, 15, 17, 23]. In [28], an analysis of the safety of passenger traffic at the station was proposed based on risk theory. By combining fuzzy theory with the comprehensive assessment method, a holistic model based on passenger flow density and evacuation time was developed to identify and analyse the overall security level of a transit station.

Interesting works related to rail transport also include studies on the method of optimal (in terms of energy-saving) train driving, ways to meet specific safety requirements [27], and the adaptive design of the proportional-integral-derivative controller, which significantly improves the accuracy of a train's speed control and solves the problem of speed fluctuations when moving through variable terrain [12].

The common element of most analyses that influences travel planning [26, 10], travel time [9, 22], quality of transport [7, 23, 6], and safety is the number of passengers. Therefore, the assessment and prediction of this factor are particularly important as the foundation of other studies.

The passenger flow rate may depend on many factors and is subject to systematic and random changes. Therefore, it is important to conduct research to identify a mathematical model that effectively describes the analysed time series and guarantees that predictions are as close as possible to real observations [3, 14]. For example, in [8], the passenger flow was forecast during a disruption of the operation of one of the selected metro lines in the Chinese province of Guangdong in order to estimate the potential for danger. In [21], the reconstruction of the current communication system in Java, Indonesia, was analysed by estimating the number of passengers using existing means of transport (e.g. road, rail, and air) who would be willing to switch to high-speed rail. For this purpose, the multinomial logit model was used.

In [20], a dynamic regression model was used to forecast peak spreading in urban rail transit demand, while, in [25], a short-term forecast model was developed for rail transport as one of the most important issues in the urban intelligent transport system. For this purpose, a new model called the spatio-temporal long short-term network (which is based on the long short-term network) was used.

The literature shows that most of the analyses focus on large urban agglomerations. The popularity of rail transport (especially underground systems [11, 30]) is systematically increasing, especially due to the deteriorating conditions of road transport (congestion, stoppages in traffic jams, increased exhaust emissions, and smog [4]). Overall evaluations of national rail networks are comparatively rare. They have been done, for example, in relation to South Korea [16], Sweden [1], and Slovakia [5]. Moreover, most of the publications concern the application of single mathematical methods to solve a specific transport problem. Few works propose and compare several variants to choose the optimal solution [2].

The conclusions drawn from the literature review motivated the present study, the aim of which is to model the passenger flow in rail traffic at the national level (in Poland). The research hypothesis is that it is possible to reliably forecast the traffic of passengers travelling by rail based on historical data. Selected mathematical models dedicated to time series with the characteristics presented by the collected observations were proposed, the selection criteria were determined, and the selected models were evaluated. In addition to identifying the model, another goal of this study is to forecast the number of passengers in subsequent periods. The proposed method indicates the procedure algorithm, mathematical models that can be used, their evaluation, and the choice of the best one. This method can constitute the basis for solving problems in rail traffic, depending on the volume of passenger traffic. It can also be implemented to evaluate this phenomenon in systems other than rail systems.

The present article consists of the introduction, evaluation and characteristics of the collected research sample, a presentation of the mathematical methods used, and the construction of mathematical models used for empirical data on the number of passengers on the Polish railway lines. Then, the proposed models were evaluated, and the best one was selected. Finally, a summary of the results obtained, final conclusions, and the concept of further research were presented.

2. FORECASTING THE NUMBER OF RAIL TRANSPORT PASSENGERS

2.1. Characteristics of the research sample

Observations regarding the number of passengers in rail transport from 2014-2019 were investigated [24]. The data presented in Fig. 1 was archived on a monthly basis.

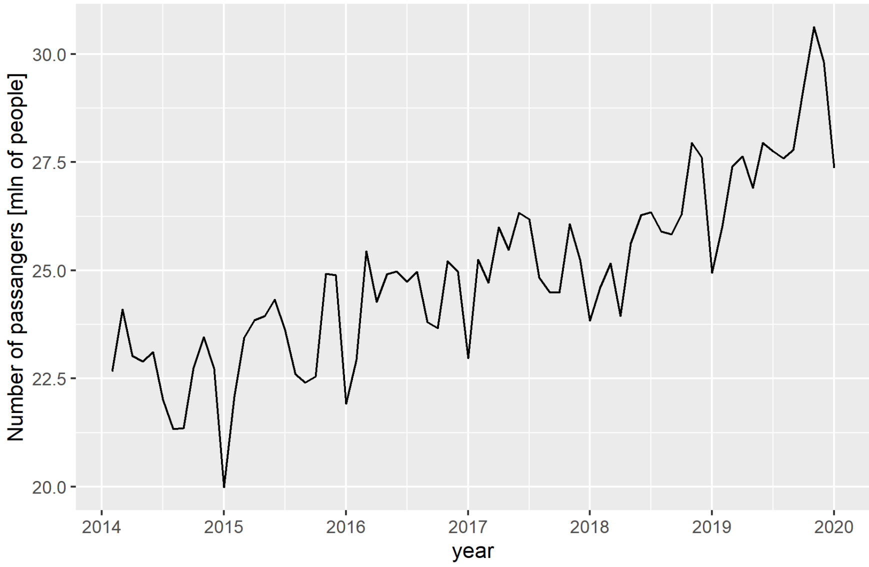

Fig. 1. The number of passengers using rail transport from 2014-2019

Fig. 1 shows a clear long-term trend. Moreover, the data is subject to seasonal changes, which is confirmed by Fig. 2.

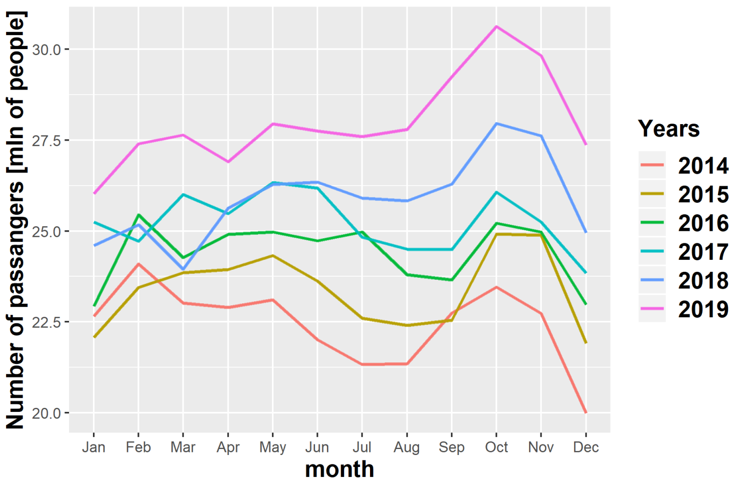

Fig. 2. Graph of the seasonality of rail passengers from 2014-2019

The period from January to February includes the winter holidays in Poland. During this period, there is an increased demand for transport services, especially long-distance services. The increase seen in Fig. 2 results from the interest of passengers in using the railways to go on vacation during the winter break. Another increase in the number of passengers is visible at the beginning of May, which is related to the May long weekend. As in the case of the winter holidays, passengers eagerly choose rail as a means of transport, as it allows them to reach their destinations, even those that are several hundred kilometres away.

Between May and August, there is a decline in interest in using railways. This is due to the fact that during the holiday period, passengers who use it to get to their place of study or work cease to use it. Passengers do not use monthly or periodic tickets during this time. Many people use rail transport to go on vacation during the summer holidays, but these uses of rail transport represent individual trips (as opposed to cyclical trips), determined by the vacation date. In addition, during the holiday season, individual means of car transport or air transport are also popular and are chosen especially often in the case of foreign travel.

The increase starting in September and continuing in October is due to the return of students and the end of the holiday period. At this point, long-term tickets regain popularity.

The decline in November and December is due to the lack of demand for long-distance routes. The weather conditions that characterise the winter period are not favourable for short-distance travel. During the winter, some passengers stop using railways in favour of carpooling.

A systematic increase in the number of passengers is also noticeable in the subsequent analysed years, which confirms the growing development observed in Fig. 1. Moreover, there is a clear seasonal trend. As a result, the series is non-stationary. The separated components of the tested time series are presented in Fig. 3.

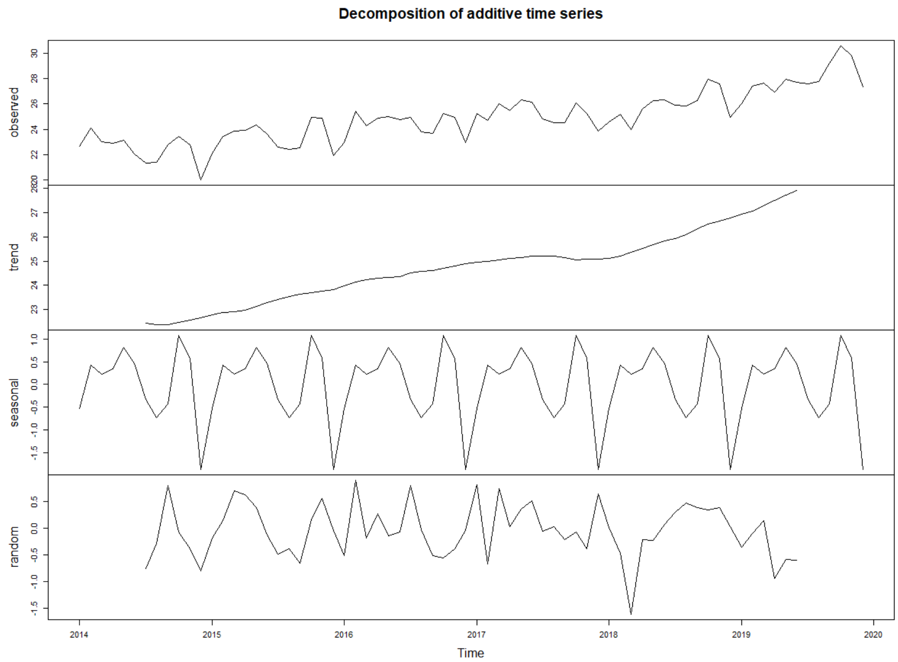

Fig. 3. Decomposition of the tested time series

The error, trend, and seasonality (ETS) and autoregressive integrated moving average (ARIMA) exponential smoothing models were proposed to describe the analysed series. The optimal variant in each group was selected on the basis of the information criterion assessment (AIC - Akaike information criterion). The collected data set was divided into two groups – a teaching set and a test set – to check which of the proposed models is more appropriate for forecasting future values. The training set was used to construct models identifying the series under study and to define the forecast for the next period. These predictions were later compared with the test set. The teaching set includes observations made from January 2014 to December 2018, while the test set covers the entire year of 2019. The adopted division is shown in Fig. 4.

2.2. Forecasts using exponential smoothing

This study uses ETS, a general class of the exponential smoothing state space model. Elements can be combined in an additive, multiplicative, or mixed manner. The trend in exponential smoothing is a combination of two components (i.e. level l and increment b), which are linked together, taking into account the damping parameter $\phi \in [0,1]$ in five possible ways. Marking T_h as the trend forecast for h successive periods, we get the following [13]:

N - No trend (none):

$$T_h = l \tag{1}$$

A - Additive:

$$T_h = l + bh \tag{2}$$

Ad - Additive damped:

$$T_h = l + (\phi + \phi^2 + \cdots + \phi^h)b \tag{3}$$

M - Multiplicative:

$$T_h = lb^h \tag{4}$$

Md - Multiplicative damped:

$$T_h = lb^{(\phi+\phi^2+\cdots+\phi^h)} \tag{5}$$

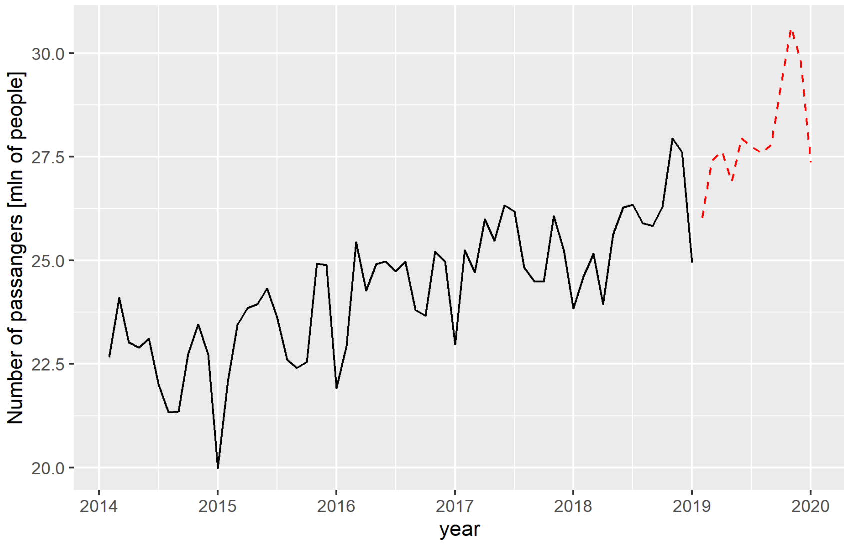

Fig. 4. Division of the collected observations into the teaching and test sets

Taking into account only the seasonal component (no seasonality, additive variant, and multiplicative variant) and the trend, we obtain 15 exponential smoothing models. Taking into account additionally random additive or multiplicative disturbances, we obtain 30 different models [13].

The value optimising the form of the model may be the minimisation of the selected information criterion (AIC, AICC, BIC) or the forecast error (MSE, MAPE). In this article, the AIC was used to compare the models.

Let k be the number of estimated parameters and L be the maximum likelihood function of the model. The AIC value is calculated using the following formula:

$$AIC = -2lnL + 2k \tag{6}$$

The parameters of various ETS models were estimated, and the AIC information criterion and the MAPE error were calculated for each. The results are presented in Tab. 1.

Based on the results, a model was selected with the smallest values of the AIC criterion and the MAPE error. This model was the ETS (ANA) model; however, this model does not take into account the previously diagnosed trend. Therefore, for further analysis, a model with an additive trend was also selected – ETS (AAA) – whose AIC and MAPE values were comparatively low. The ETS (AAA) model is of the following form:

$$x_t = l_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t, \tag{7}$$

$$l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t, \tag{8}$$

$$b_t = b_{t-1} + \beta\varepsilon_t, \tag{9}$$

$$s_t = s_{t-m} + \gamma\varepsilon_t, \tag{10}$$

where $\{\varepsilon_t\}_{t\geq 1}$ is a series of residuals.

If $b_0 = 0$ and $\beta = 0$, we get the ETS model (A,N,A), defined by the equation:

$$x_t = l_{t-1} + s_{t-m} + \varepsilon_t, \tag{11}$$

$$l_t = l_{t-1} + \alpha\varepsilon_t, \tag{12}$$

$$s_t = s_{t-m} + \gamma\varepsilon_t \tag{13}$$

where $\{\varepsilon_t\}_{t\geq 1}$ is a series of residuals.

The estimated parameters of both models are presented in Tab. 3.

The matching of smoothing models to the test observations is presented in Fig. 5. The model takes into account the trend and, thus, better reflects the character of the series.

Table 1

The AIC criterion and MAPE error for selected exponential smoothing models

model	AIC	MAPE
ANN	262.409	3.802
MAdM	222.165	2.067
MMdM	221.542	2.095
AAA	215.970	2.074
MAA	216.562	2.074
MMN	263.159	3.625
MAN	264.034	3.697
MNA	213.601	2.007
MNN	263.373	3.802
ANA	212.770	2.007
AAN	263.218	3.697
MNM	233.950	2.460

Table 3

Estimated values of parameters of the ETS (AAA) and ETS (ANA) models

model	Smoothing parameters		
ETS(A,N,A)	$\alpha = 0.6434$		$\gamma = 0{,}0001$
ETS(A,A,A)	$\alpha = 0.4572$	$\beta = 0{,}0001$	$\gamma = 0{,}0001$

2.3. Forecast using the ARIMA model

In the next stage of the study, a model belonging to the ARIMA (*p, r, q*) class, which is a group of stationary time series models, was used. Depending on the temporal correlation structure, we distinguished the following [4]:

Model AR (p) - autoregressive model, which we call the $\{x_t\}_{t\in N}$ series satisfying the equation below:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \dots + \alpha_p x_{t-p} + \varepsilon_t, \tag{14}$$

where $\{\epsilon_t\}_{t\in N}$ is a sequence of independent random variables with a normal distribution $N(0, \sigma^2)$.

Such a series takes into account the existence of a temporal correlation of previous implementations of the dependent variable x_t. The value of the dependent variable at time *t* is a linear combination of its time-delayed values and the white noise disturbance.

Model *MA (q)* - moving average, which we call the $\{x_t\}_{t\in N}$ series, which satisfies the following equation:

$$x_t = \varepsilon_t - \beta_1\varepsilon_{t-1} - \beta_2\varepsilon_{t-2} - \dots - \beta_q\varepsilon_{t-q} \tag{15}$$

where $\{\epsilon_t\}_{t\in N}$ is a sequence of independent random variables with a normal distribution $N(0, \sigma^2)$.

Such a series takes into account the existence of the temporal correlation of the random component. Its strength and nature are determined by the q parameter (i.e. the order of the moving average model and the individual coefficients of the model (β_q)).

It is possible to create combined (mixed) models [19]. For example, by combining the AR and MA models, we can obtain the ARMA time series of the form given bloom:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_p x_{t-p} + \varepsilon_t \beta_0 + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \\ -\beta_2 \varepsilon_{t-2} - \ldots - \beta_q \varepsilon_{t-q} \tag{16}$$

ARMA class models concern stationary series [18]. If this assumption is not met, transformations (e.g. differentiation) need to be applied to obtain it. In this way, the ARIMA model and the seasonal ARIMA (SARMIMA), which takes seasonality into account, are obtained. In these models, the operation of differentiation with delay *d* was used.

In the analysed set of observations, we dealt with a trend and seasonality. This is also indicated by the analysis of the graphs of the autocorrelation function, where the function values slowly decay, and of the partial autocorrelation, where significant values for the delay equal to 12 are shown (Fig. 6). This means that the tested series is not stationary.

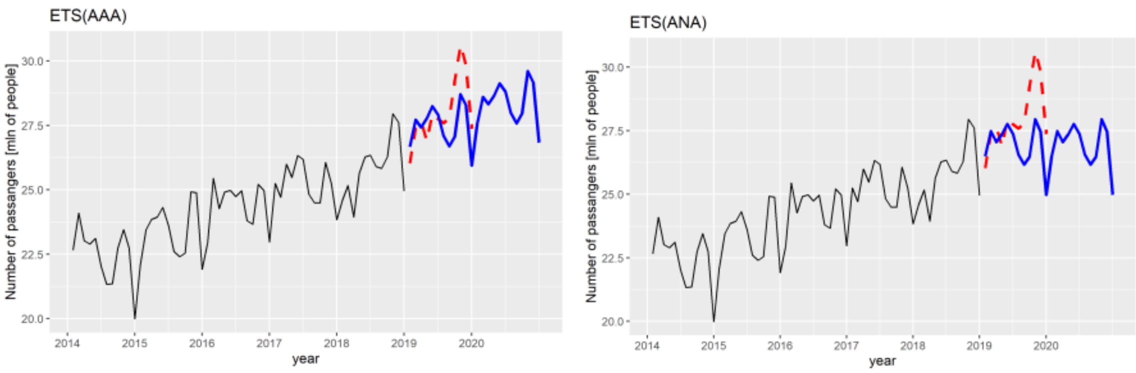

Fig. 5. Graph of the tested time series and forecasts according to the ETS (AAA) and ETS (ANA) models

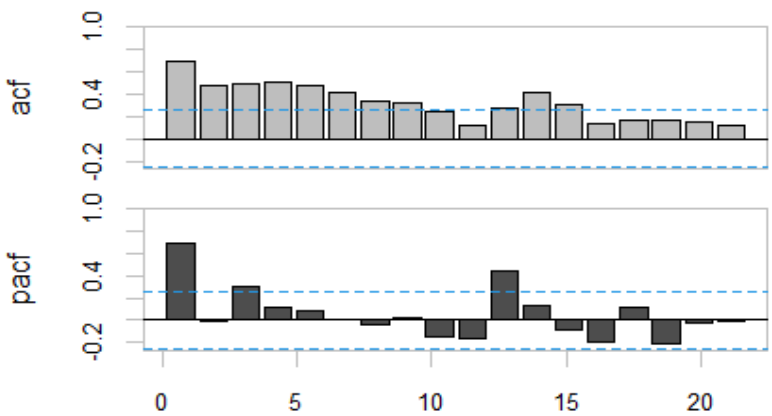

Fig. 6. Graphs of the autocorrelation and partial autocorrelation functions

The lack of stationarity was confirmed by the augmented Dickey-Fuller (ADF) test. The results obtained for the subsequent delays are presented in Tab. 4.

Table 4

ADF test results

type	no drift no trend		with drift no trend		with drift and trend	
lag	ADF	p.value	ADF	p.value	ADF	p.value
0	0 0.049	0.655	- 3.23	0.024	-5.51	0.010
1	0.020	0.646	-2.79	0.070	-6.31	0.010
2	0.554	0.799	-1.58	0.490	-4.32	0.010
3	0.735	0.851	-1.11	0.654	-3.99	0.016

As the results of the ADF test show (Tab. 4), stationarity was achieved for the series with drift and trend. Therefore, both the drift and trend will be taken into account when constructing the ARIMA model. The parameters estimated for the model without drift were also presented so that comparisons could be made. The selected results, for which all estimated parameters were statistically significant, are presented in Tab. 5.

Table 5

Results of the parameter estimations of selected ARIMA class models

	Coefficients:		Std. Error	z value	Pr(>|z|)	AIC	BIC
ARIMA(1,0,0)(1,1,0)[12] with drift	ar1	0.491	0.132	3.699	0.0002161 ***	115.44	122.93
	sar1	-0.648	0.113	-5.707	1.147e-08 ***		
	drift	0.071	0.010	6.600	4.092e-11 ***		
ARIMA(0,0,0)(1,1,1)[12]	sar1	0.998	0.014	70.397	< 2.2e-16 ***	154.47	160.08
	sma1	-0.953	0.189	-5.021	5.127e-07 ***		
ARIMA(0,0,0)(0,1,1)[12] with drift	sma1	-0.567	0.210	-2.697	0.006977 **	124.35	129.97
	drift	0.072	0.006	11.728	< 2.2e-16 ***		

The best matching was obtained for the ARIMA (1.0.0) (1.1.0) [12] model with drift, for which the AIC and BIC values are the lowest. The matching of this model to the tested series is presented in Fig. 7.

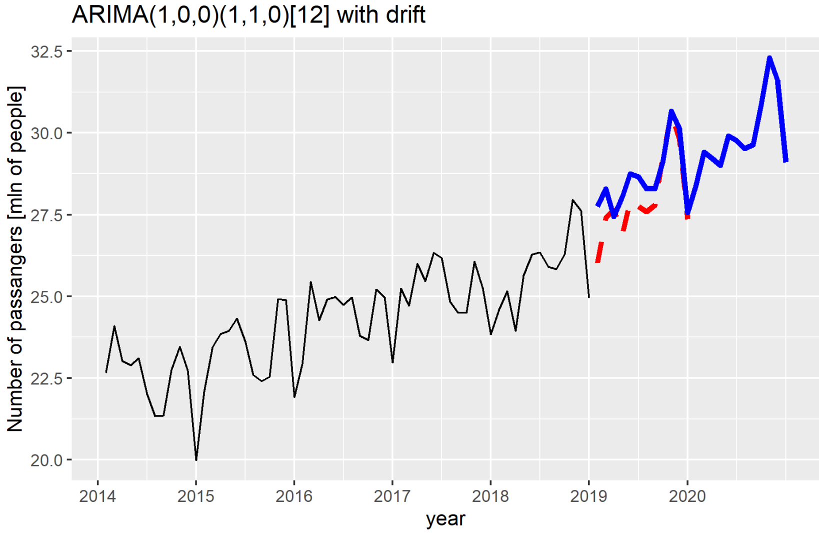

Fig. 7. Graph of the tested time series and forecasts according to the ARIMA model (1.0.0) (1.1.0) [12] with drift

3. RESULTS AND DISCUSSION

The ARIMA model follows the studied series much better than the ETS model (Fig. 8). It is also characterised by the lowest forecast errors (Tab. 6) in relation to the test set.

Table 6

ETS (AAA) and ARIMA model forecast errors (1,0,0) (1,1,0) [12] with drift in relation to the test data

model	ME	RMSE	MAE	MPE	MAPE	MASE
ETS(AAA)	0,543	1,140	0,928	1,824	3,253	0,870
ARIMA	0,015	0,664	0,501	-0,006	1,989	0,392

Predictions based on the ARIMA model detect both the trend and the seasonality of the series better than other models. The rest of the model is quite good (Fig. 9), and the Ljung-Box test (X-squared = 23.631, p-value = 0.482) indicates no serial correlation. The results are confirmed by the Box-Pierce test (X-squared = 18.38, p-value = 0.784). Moreover, the distribution of the residues is consistent with the normal distribution at the significance level of $\alpha = 0.01$. This was confirmed by the results of the Lilliefors test (D = 0.120, p-value = 0.011) and the Shapiro-Wilk test (W = 0.978, p-value = 0.249).

4. CONCLUSIONS

In response to the few comprehensive studies in the literature, the passenger flow in the rail traffic at the national level was mathematically analysed. The results show that it is possible to forecast reliably based on available historical data. The study uses selected mathematical models designed for time series with appropriate characteristics of the information collected.

The number of railway passengers was forecast based on data from Poland from 2014-2019. An unequivocal conclusion was drawn about the constantly growing number of passengers using rail transport. It was noticed that the seasonality of using the railways is directly related to the occurrence of seasonal breaks in compulsory schooling and depends on their length. The number of passengers increases during the winter holidays and on long weekends, while it decreases during the summer holidays (specifically considering long-term tickets). The analysis of seasonality suggests that the main recipients of transport services may be students who move between their hometowns and academic centres.

The ETS and ARIMA models were used to describe the analysed series. The ARIMA model follows the tested series better than the ETS model and exhibits fewer forecast errors for the test set. However, as the study was conducted using time series, it did not take into account factors such as transport policy, population size, or economic conditions. The above-mentioned factors undoubtedly impact the number of passengers using rail transport. Nevertheless, the research hypothesis was confirmed. By using two models and comparing the results of their application, railway passenger traffic was forecast reliably.

This article can serve as a basis for further studies covering a wider time horizon and taking into account more variables (e.g. user profile). Knowledge of passenger requirements would allow for personalisation of the offer to the largest group of recipients possible. A similar analysis may also be carried out for other modes of transport, which would not only allow passenger traffic to be forecast but would also make comparisons between the branches possible.

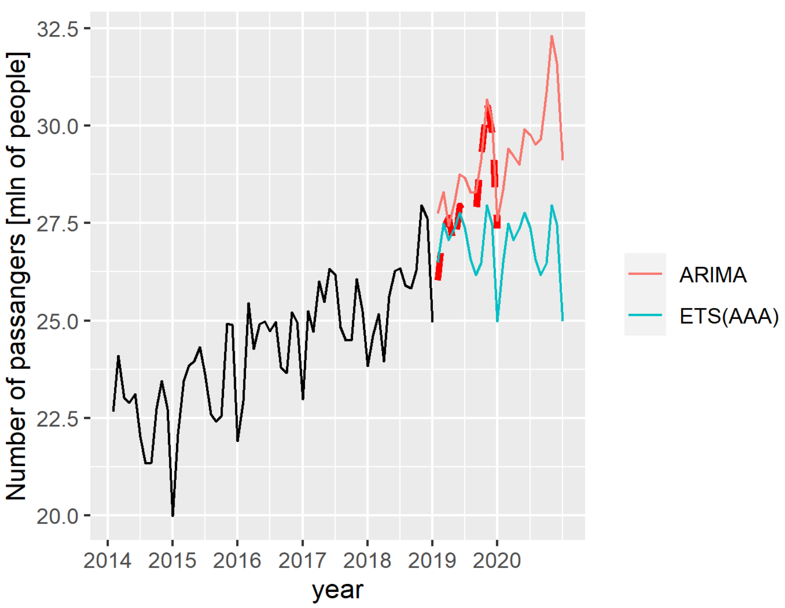

Fig. 8. Comparison of the forecast according to the ARIMA and ETS models

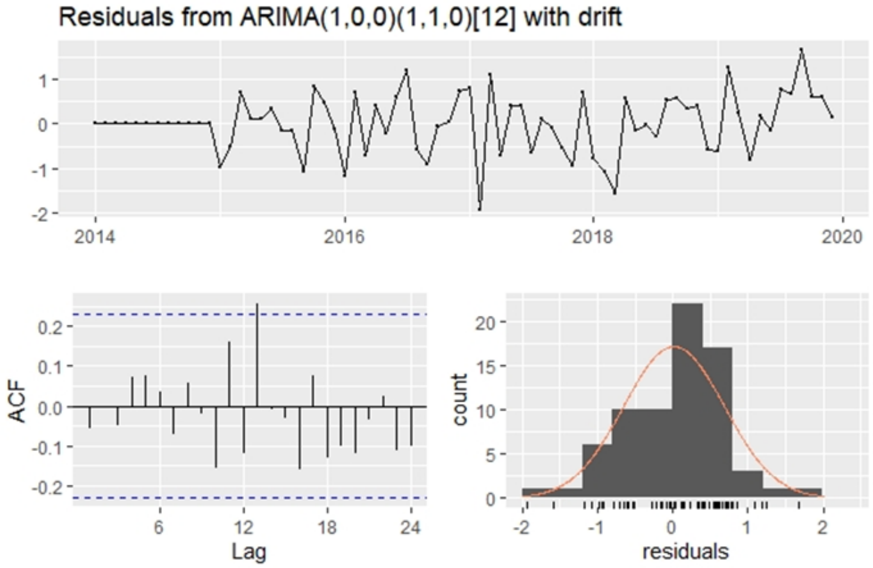

Fig. 9. Analysis of the residuals distribution of the ARIMA model (1.0.0) (1.1.0) [12]

References

1. Andersson, M. & Brundell-Freij, K. & Eliasson, J. Validation of aggregate reference forecasts for passenger transport. *Transportation Research Part A: Policy and Practice.* 2017. Vol. 96. P. 101-118.
2. Banerjee, N. & Morton, A. & Akartunali, K. Passenger demand forecasting in scheduled transportation. *European Journal of Operational Research.* 2020. Vol. 286. No. 3. P. 797-810.
3. Borucka, A. Logistic regression in modeling and assessment of transport services. *Open Engineering.* 2020. Vol. 10(1). P. 26-34.
4. Borucka, A. & Wiśniowski, P. & Mazurkiewicz, D. & Świderski, A. Laboratory measurements of vehicle exhaust emissions in conditions reproducing real traffic. *Measurement.* 2021. Vol. 174. No. 108998.
5. Box, G.E.P & Cox, D.R. An analysis of transformations. *Journal of the Royal Statistical Society: Series B (Methodological).* 1964. Vol. 26(2). P. 211-243.
6. Brumercikova, E. & Sperka, A. Problems of access to services at railway stations in freight transport in the Slovak Republic. *Sustainability.* 2020. Vol. 12(19). No. 8018.
7. Dedík, M. & Gašparík, J. & Záhumenská, Z. Quality assessment in the logistics of rail passenger transport. In: *MATEC Web of Conferences*. EDP Sciences. 2017. No. 00009. P. 1-7.
8. Eboli, L. & Mazzulla, G. Relationships between rail passengers' satisfaction and service quality: a framework for identifying key service factors. *Public Transport.* 2015. Vol. 7(2). P. 185-201.
9. Gao, H. & et al. Forecast of passenger flow under the interruption of urban rail transit operation. In: *International Conference on Electrical and Information Technologies for Rail Transportation*. Springer, Singapore. 2019. P. 283-291.
10. Hai, Y. & Lam, W.H.K. Optimal road tolls under conditions of queueing and congestion. *Transportation Research, Part A: Policy and Practice.* 1996. Vol. 30 (5). P. 319-332.
11. Hassannayebi, E. & et al. Train schedule optimization in a high-speed railway system using a hybrid simulation and meta-model approach. *Computers & Industrial Engineering.* 2019. Vol. 138. No. 106110.
12. Heidary, R. & Esmaeili, M. & Gharouni Nik, M. Effects of train operational parameters on ground-borne vibrations induced by twin metro tunnels. *International Journal of Rail Transportation.* 2021. Vol. 9(2). P. 144-156.
13. Hou, T. & Guo, Yang-Yang & Niu, Hong-Xia. Research on speed control of high-speed train based on multi-point model. *Archives of transport.* 2019. Vol. 50. No. 2. P. 35-46.

14. Hyndman, R. & et al. *Forecasting with exponential smoothing: the state space approach*. Springer Science & Business Media. 2008.
15. Jasiulewicz-Kaczmarek, M. & Żywica, P. & Gola, A. Fuzzy set theory driven maintenance sustainability performance assessment model: A multiple criteria approach. *Journal of Intelligent Manufacturing.* 2021. Vol. 32. P. 1497-1515.
16. Kang, R. & et al. Intelligent forecasting of automatic train protection system failure rate in China High-speed Railway. *Eksploatacja i Niezawodnosc.* 2019. Vol. 21(4). P. 567-576.
17. Kim, K. & Kim, J. The impact of high-speed railways on unequal accessibility based on ticket prices in Korea. *Sustainability.* 2020. Vol. 12(16). No. 6302.
18. Konowrocki, R. & Chojnacki, A. Analysis of rail vehicles' operational reliability in the aspect of safety against derailment based on various methods of determining the assessment criterion. *Eksploatacja i Niezawodnosc.* 2020. Vol. 22(1). P. 73-85.
19. Kosicka, E. & Kozłowski, E. & Mazurkiewicz, D. Intelligent systems of forecasting the failure of machinery park and supporting fulfilment of orders of spare parts. In: *International Conference on Intelligent Systems in Production Engineering and Maintenance*. Springer, Cham. 2017. P. 54-63.
20. Kozłowski, E. & et al. Machining sensor data management for operation-level predictive model. *Expert Systems with Applications.* 2020. Vol. 159. No. 113600.
21. LI, R. & Rushton, Lee & Jones, M. Peak spreading forecast in urban rail transit demand. In: *Proc. Australian Transp. Res. Forum (ATRF)*. 2016. P. 1-15.
22. Lubis, H.A. & Pantas, V.B. & Farda, M. Demand forecast of Jakarta-Surabaya high speed rail based on stated preference method. *International Journal of Technology.* 2019. Vol. 10(2). P. 405-416.
23. Lyons, G. & et al. Comparing rail passengers' travel time use in Great Britain between 2004 and 2010. *Mobilities.* 2013. Vol. 8(4). P. 560-579.
24. Obsie, A. & Woldeamanuel, M. & Woldetensae, B. Service quality of addis ababa light rail transit: passengers' views and perspectives. *Urban Rail Transit.* 2020. Vol. 6(4). P. 231-243.
25. Raport Urzędu Transportu Kolejowego „Statystyka Przewozów Pasażerskich". [In Polish: Report of the Railway Transport Office "Passenger Transport Statistics"].
26. Tang, Q. & Yang, M. & Yang, Y. ST-LSTM: A deep learning approach combined spatio-temporal features for short-term forecast in rail transit. *Journal of Advanced Transportation.* 2019. Article ID 8392592.
27. Xu, R. & Wang, F. & Zhou, F. Train stop schedule plan optimization of high-speed railway based on time-segmented passenger flow demand. In: *ICTE 2019*. Reston, VA: American Society of Civil Engineers. 2020. P. 899-906.
28. Zhelieznov, K.I. & et al. The revised method for calculating of the optimal train control mode. *Archives of Transport*. 2019. Vol. 51. No. 3. P. 21-34.
29. Zheng, Y. & et al. Risk theory-based safety evaluation of passengers in rail transit station. In: *International Conference on Electrical and Information Technologies for Rail Transportation*. Springer, Singapore. 2017. P. 725-734.
30. Zhou, W. & You, X. & Fan, W. A mixed integer linear programming method for simultaneous multi-periodic train timetabling and routing on a high-speed rail network. *Sustainability.* 2020. Vol. 12(3). P. 1131.
31. Zhu, T. & et al. Rail vehicle crashworthiness based on collision energy management: an overview. *International Journal of Rail Transportation.* 2021. Vol. 9(2). P. 101-131.

Received 20.11.2020; accepted in revised form 09.03.2022