ТРАНСПОРТНЫЕ СИСТЕМЫ
2.9.1 – Транспортные и транспортно-технологические системы страны, ее регионов и городов, организация производства на транспорте;
2.9.4. – Управление процессами перевозок;
2.9.6 – Аэронавигация и эксплуатация авиационной техники;
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Modelling of non-scheduled air transportation time series based on ARIMA

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Abstract: Forecasting non-scheduled air transportation demand is essential for effective resource allocation, operational planning, and decision-making. In this paper, the use of the ARIMA (Auto Regressive Integrated Moving Average) model for forecasting non-scheduled air transportation is explored. The ARIMA model is a widely employed time series forecasting technique which combines autoregressive (AR), differencing (I), and moving average (MA) components. It has been successfully applied to various fields and can be adapted to capture the patterns and trends in non-scheduled air transportation data. To forecast non-scheduled air transportation demand, historical data, including relevant variables are firstly collected. The data are processed by identifying and addressing any missing values, outliers, or trends that could affect the model's performance. Next, the ARIMA model is applied to the pre-processed data, utilising techniques such as model identification, parameter estimation, and model diagnostics. The ARIMA model captures the relationships between past observations and uses them to predict future demand for non-scheduled air transportation. The forecasting results from the ARIMA model provide insights into expected demand levels, peak periods, and potential fluctuations in non-scheduled air transportation. These forecasts enable decision-makers to optimise resource allocation, schedule aircraft availability, and enhance operational efficiency. However, it is important to note that the accuracy of ARIMA forecasts depends on various factors, including the quality and representativeness of the data, the appropriate selection of model parameters, and the stability of underlying patterns in the time series data. Regular model evaluation and refinement are crucial in maintaining forecasting accuracy.

Key words: non-scheduled air transportation, time series analysis, ARIMA, statistical analysis, optimal model, forecasting, autoregressive model.

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Моделирование временных рядов нерегулярных воздушных перевозок на основе ARIMA

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Аннотация: Прогнозирование спроса на нерегулярные авиаперевозки имеет важное значение для эффективного распределения ресурсов, оперативного планирования и принятия решений. В этой статье мы исследуем использование модели ARIMA (авторегрессивное интегрированное скользящее среднее) для прогнозирования нерегулярных авиаперевозок. Модель ARIMA – это широко используемый метод прогнозирования временных рядов, который сочетает в себе компоненты авторегрессии (AR), разности (I) и скользящего среднего (MA). Он успешно применяется в различных областях и может быть адаптирован для выявления закономерностей и тенденций в данных о нерегулярных авиаперевозках. Для прогнозирования спроса на нерегулярные авиаперевозки сначала собираются исторические данные, включая соответствующие переменные. Данные предварительно обрабатываются, выявляются и устраняются любые пропущенные значения, выбросы или тенденции, которые могут повлиять на производительность модели. Затем к предварительно обработанным данным применяется модель ARIMA, при этом используются такие методы, как идентификация модели, оценка параметров и диагностика модели. Модель ARIMA фиксирует взаимосвязи между прошлыми наблюдениями и использует их для прогнозирования будущего спроса на нерегулярные авиаперевозки. Результаты прогнозирования модели ARIMA дают представление об ожидаемых уровнях спроса, пиковых периодах и потенциальных колебаниях нерегулярных авиаперевозок. Эти прогнозы позволяют лицам, принимающим решения, оптимизировать распределение ресурсов, планировать доступность самолетов и повышать эксплуатационную эффективность. Однако важно отметить, что точность прогнозов ARIMA зависит от различных факторов, включая качество и репрезентативность данных, соответствующий выбор параметров модели и стабильность основных закономерностей в данных временных рядов. Регулярная оценка и уточнение модели имеют решающее значение для поддержания точности прогнозирования.

Ключевые слова: нерегулярные авиаперевозки, анализ временных рядов, ARIMA, статистический анализ, оптимальная модель, прогнозирование, авторегрессионная модель.

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Introduction

Non-scheduled air transportation, also known as charter or on-demand flights, is characterised by a flexible and responsive operational model. Unlike scheduled flights, which adhere to fixed timetables, non-scheduled flights are tailored to meet specific demands, making them highly variable and subject to dynamic changes. Time series methods play a crucial role in the non-scheduled air transportation field, where operations are often dynamic and subject to various external factors. These methods involve analysing and forecasting data points collected over time to make qualified decisions on future trends and patterns. Currently, passenger flow prediction methods are based on historical data, including time-series methods. Time series methods, such as ARIMA, SARIMA (Seasonal ARIMA), or even more advanced models, can be applied to historical data on passenger counts, booking trends, and other relevant metrics. Forecasting demand is essential for optimising flight schedules, resource allocation, and ensuring adequate capacity to meet customer needs. Several methods have been used for scheduled and non-scheduled air passenger forecasting, including second-degree polynomial [1–5], the autoregressive integrated moving average (ARIMA) model, and the seasonal autoregressive integrated moving average (SARIMA) model [6–9]. The prediction of civil aviation passenger transportation based on the ARIMA model has been investigated by researchers [10]. Forecasting air passengers using a mixture of local expert models and related methods in this field has been implemented in this industry [11]. According to the theory of time-series analysis, the ARIMA model is considered optimal for the prediction and analysis of stationary time series, and the passenger flow data is generally a nonstationary series that needs to be smoothed by difference. The differential autoregressive moving average model (ARIMA) and other related works are being used to predict passenger flow in the several papers. [12–14].

Basing on the facts mentioned above, it can be stated that the ARIMA is the best choice model for calculations in non-scheduled passenger air transportation because:

- The ARIMA model better approximates random processes [15, 16];
- The ARIMA model gives better results in inertial systems (in these systems, each situation depends on the previous situation) [17, 18].

Problem statement

In this paper, the time series of non-scheduled passenger air transportation was modeled based on the ARIMA model, and the forecasting results for the relevant period were obtained. Since the process of irregular air transportation is random, it is considered more necessary to forecast with autoregressive models than trend models in order to obtain more optimal forecasting results.

Methods and Methodology

The differential autoregressive moving average model (ARIMA) is an important method for studying time series. In ARIMA (*p*, *d*, *q*), *p* is the number of autoregressive items, q is the moving average item number, and *d* is the number of differences made to make it a stationary sequence. The ARIMA (*p*, *d*, *q*) model is an extension of the ARMA (*p*, *q*) model.

To make calculations, we write the ARIMA model in the following form:

$$Y_t = y_t + z_t, \tag{1}$$

where, y_t is trend and z_t is deviation.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p}, \tag{2}$$

$$z_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}. \tag{3}$$

The vector $\varphi\ (c, \phi_1, \phi_2, \ldots, \phi_p)$ is a $(p+1)$ dimensional vector.

The vector ε_t is a vector of random deviations determined after the trend model is determined. In the first approach, the elements of this vector are defined as the difference between the actual data and the trend model. In this approach, since the vector ε_t is expressed by a linear model, it is calculated by a formula similar to formula (5). The formulae are not given in the article so as not to repeat them.

The method of least squares is applied to find the unknown coefficients. For this, the following issue should be resolved:

$$\sum_{t=1}^{N} [(\bar{Y}_t - Y_t)]^2 \dot{\rightarrow} min. \tag{4}$$

Here, $\bar{Y}_t$ is the actual data, Y_t is the calculation results using the (1) formula, and N is the number of data included in the research (by months), c is the constant, $\phi_1, \phi_2, \ldots, \phi_p$, $\theta_1, \theta_2, \theta_q$ is the coefficient, ε_t is the white noise sequence, p is the autoregressive order, and q is the moving average order.

The solution to problem (4) is reduced to the following matrix equation:

$$A\varphi = B. \tag{5}$$

A is a $(p+1)$ – dimensional square symmetric matrix, the elements of which are as follows: p is a number with plural signs, and when a_{11} is added, the measure is $(p+1)\cdot(p+1)$.

$$A = \begin{pmatrix} n & \sum_{t=1}^{N} \bar{Y}_{t-1} & \sum_{t=1}^{N} \bar{Y}_{t-2} \ldots \sum_{t=1}^{N} \bar{Y}_{t-p} \\ \sum_{t=1}^{N} \bar{Y}_{t-1} & \sum_{t=1}^{N} Y_{t-1}{}^2 & \sum_{t=1}^{N} \bar{Y}_{t-2}\,\bar{Y}_{t-1} \ldots \ldots \sum_{t=1}^{N} \bar{Y}_{t-p}\,\bar{Y}_{t-1} \\ \sum_{t=1}^{N} \bar{Y}_{t-p} & \sum_{t=1}^{N} \bar{Y}_{t-1}\,\bar{Y}_{t-p} & \sum_{t=1}^{N} \bar{Y}_{t-2}\,\bar{Y}_{t-p} \ldots \ldots \sum_{t=1}^{N} \bar{Y}^2{}_{t-p} \end{pmatrix}; \tag{6}$$

$$B = \begin{pmatrix} \sum_{t=1}^{N} \bar{Y}_t \\ \sum_{t=1}^{N} \bar{Y}_t\,\bar{Y}_{t-1} \\ \sum_{t=1}^{N} \bar{Y}_t\ \bar{Y}_{t-p} \end{pmatrix}. \tag{7}$$

Considering expressions (6) and (7) in formula (5), unknown coefficients are found.

Experimental results

First of all, statistical data for non-scheduled passenger air transportation were collected to build the calculation model. These data are presented in Figure 1. As it can be seen from Figure 1, the data covers the period from January 1, 2020, to June 30, 2024, a total of 54 months. Calculations were made using the statistical data of the mentioned periods, and forecasting values for the months of July–December 2024 were obtained based on the ARIMA model. The statistical data used in the construction of the model are based on the statistical indicators provided by Heydar Aliyev International Airport.

Figure 2 shows the autocorrelation function for statistical data on non-scheduled passenger air transportation. It can be seen from here that calculations will be made according to formula (2), taking into account ($p = 3$) in the ARIMA model.

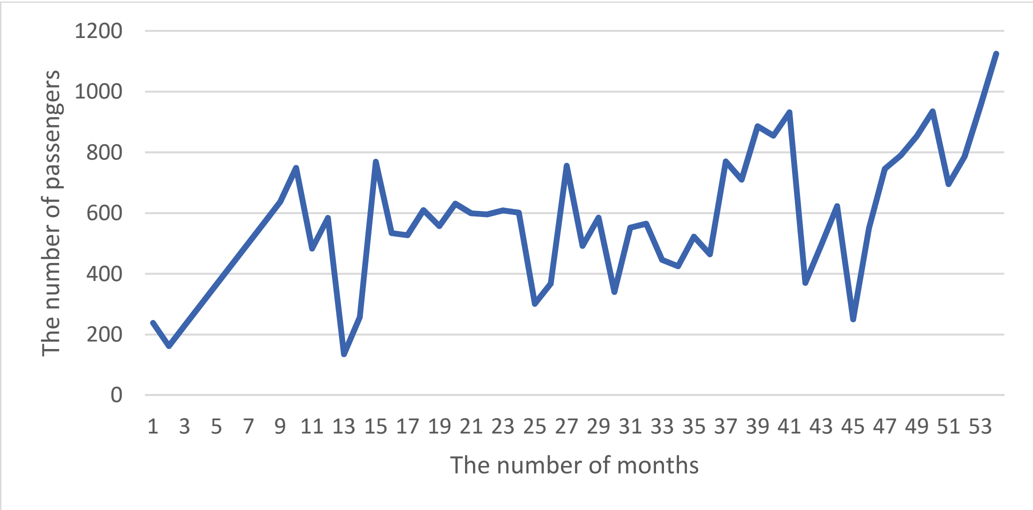

Fig. 1. Monthly dynamics of non-scheduled passenger air transportation from Heydar Aliyev International Airport (Baku/Azerbaijan)

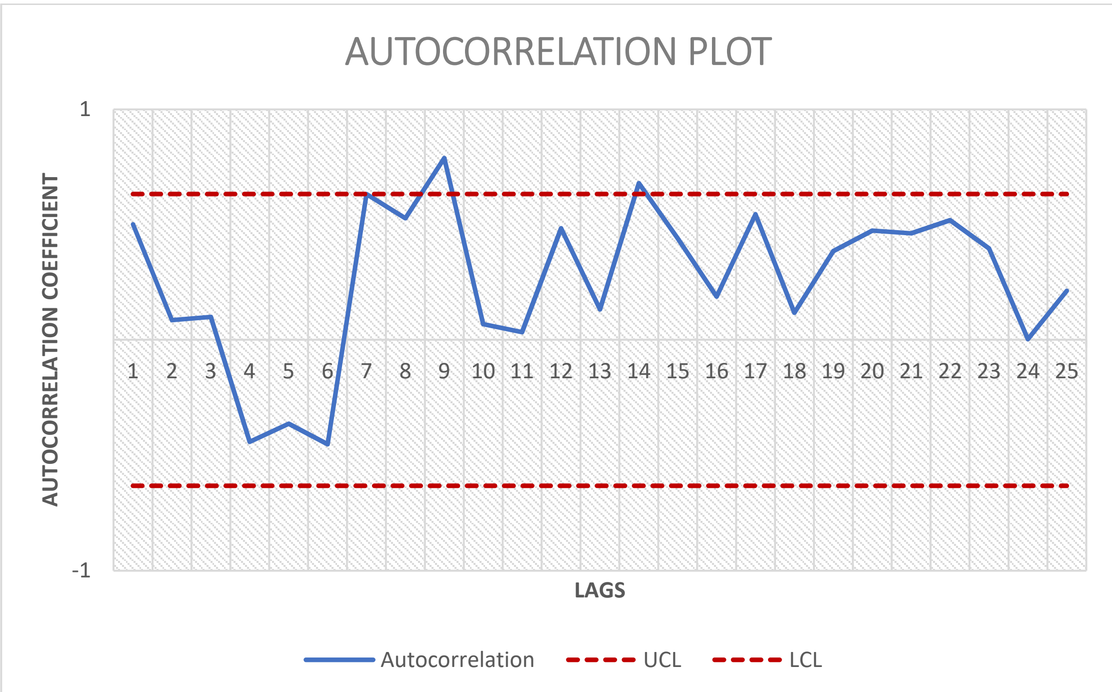

Fig. 2. Autocorrelation function according to Figure 1

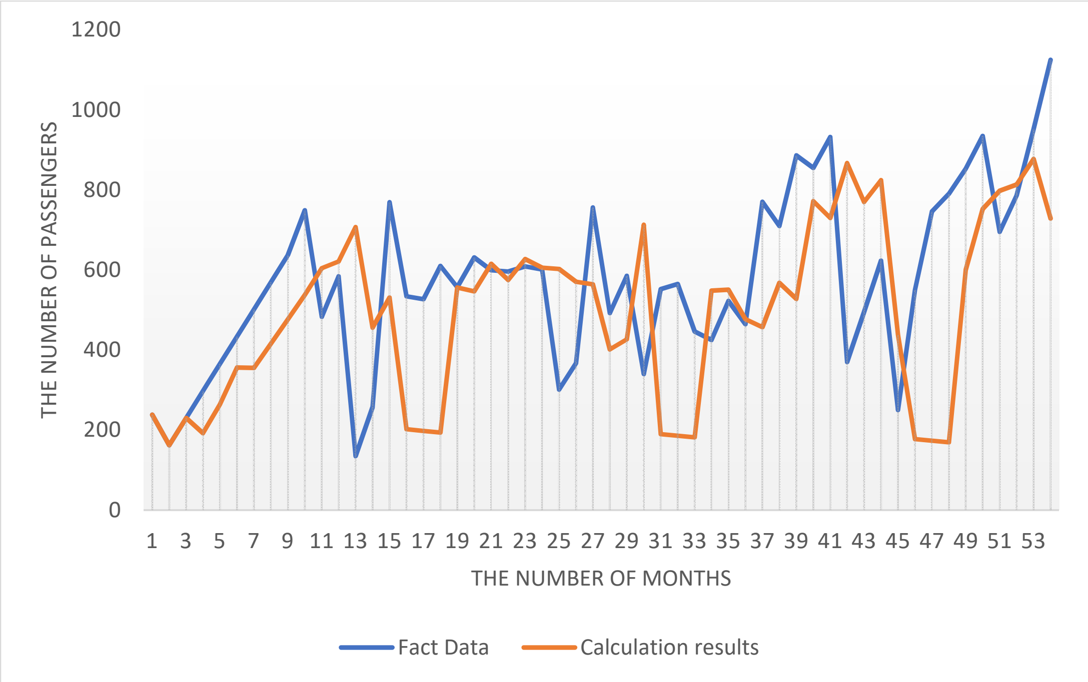

Fig. 3. Calculation results based on the formula (2)

Here, **UCL** is the upper confident level and **LCL** is the lower confident level.

After the autocorrelation function is established, the ARIMA model is reported based on the preliminary results obtained. By substituting these values in formula (2), (ϕ_1, ϕ_2, ϕ_3) and the values of c are obtained (reports were made in the MATLAB 2023a software package). Preliminary calculation results are shown in Figure 3. As it can be seen from Figure 3, if we compare the results obtained during the calculations based on the formula (2) with the actual indicators, we will see that there are serious differences in some points from the observations made. This indicates that those actual results are anomalous in the general results. In general, anomalous deviations in the general trend are observed in non-scheduled passenger air transportation.

In the next step, in the ARIMA model, the difference between the initial calculation results and the real data is calculated (fig. 4), and the autocorrelation function (fig. 5) is constructed for this difference, and reports are continued. It is clear from Figure 5 that the next calculations will be made according to formula (3), taking into account (q = 3) in the ARIMA model. After solving the system equation obtained by writing the corresponding values in the formula (3), the values of $(\theta_1, \theta_2, \theta_3)$ and are obtained (reports were made in the MATLAB 2023a software package). Calculation results are obtained by substituting these values into formula (3) (fig. 6).

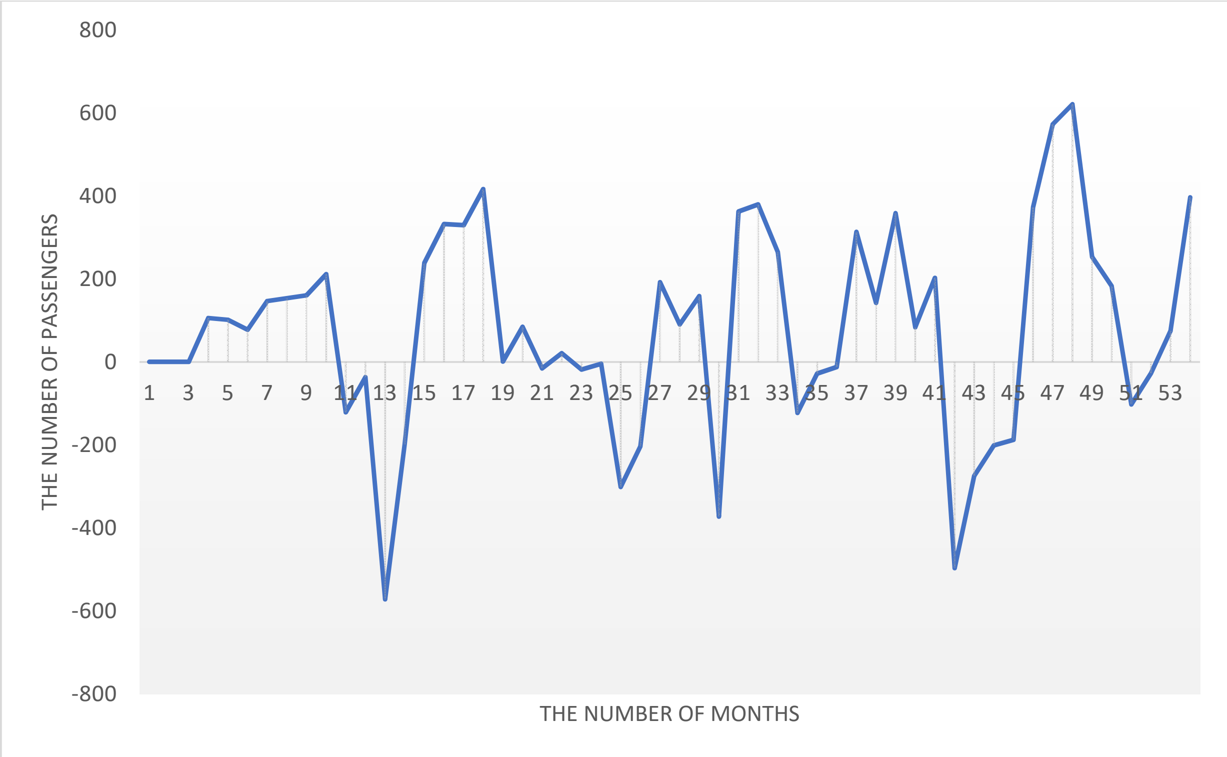

Fig. 4. The differences between the fact data and the calculation results are based on the formula (2)

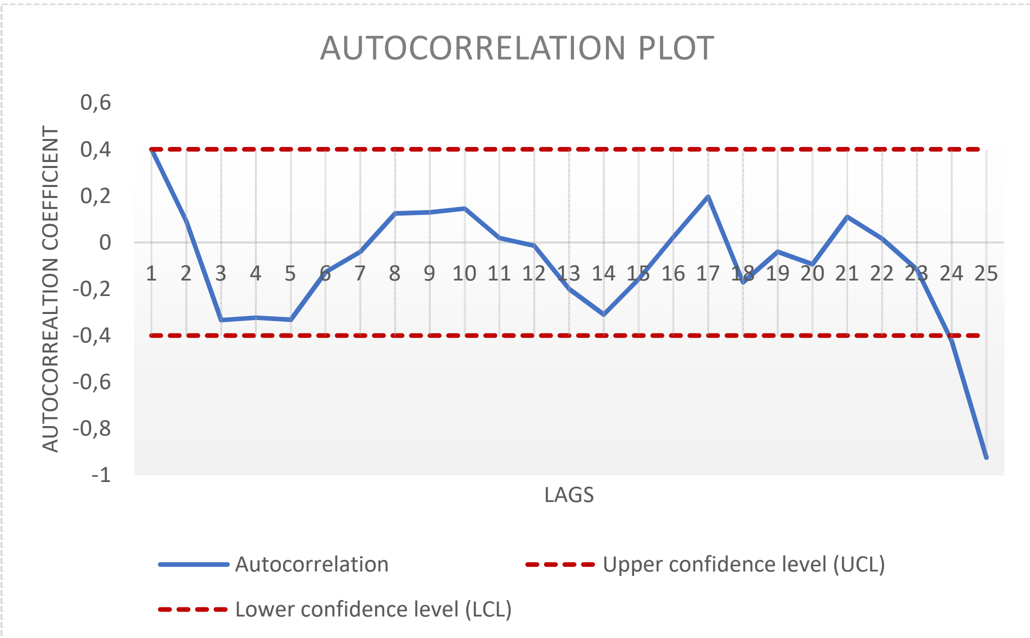

Fig. 5. The autocorrelation function according to Figure 4 results

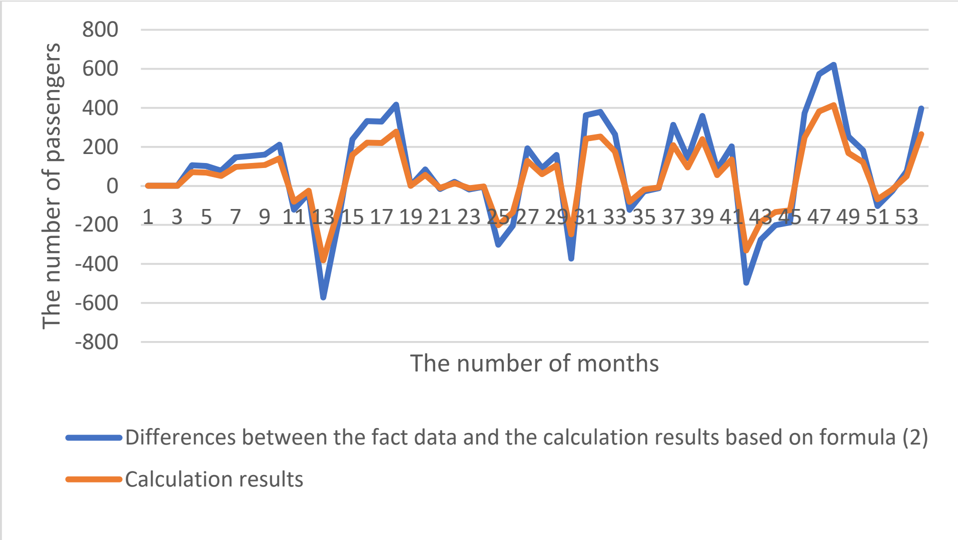

Fig. 6. Calculation results based on the formula (3)

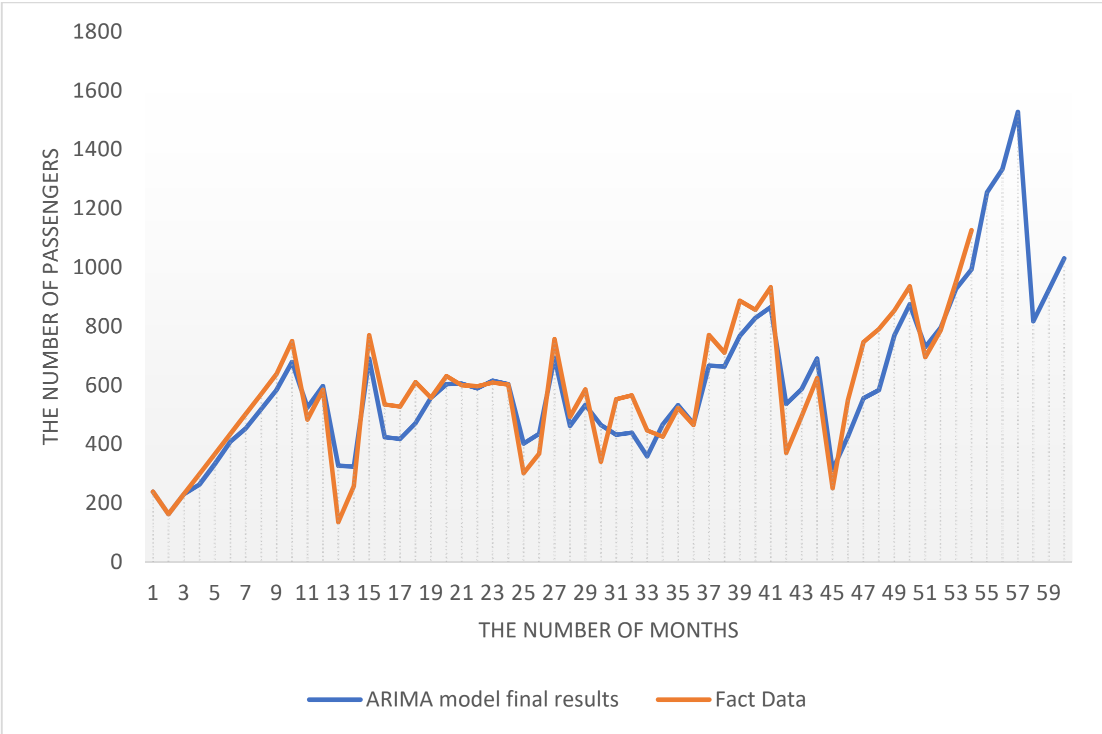

Fig. 7. Calculation results in the ARIMA model based on the formula (1)

To determine the final calculation results in the ARIMA model (Φ_1, ϕ_2, ϕ_3), $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$, $(\theta_1, \theta_2, \theta_3)$ the values of c and variables are substituted in the formula (1), respectively, and the final calculation results are obtained. The mentioned calculation results are shown in Figure 7. It is clear from Figure 7 that the calculation results are quite optimal and close to the real data. Based on the ARIMA model, forecast indicators for July–December 2024 were calculated using the calculations made for 2020–2024. These results are shown in Figure 7 at points 54–59. According to the forecasting results obtained on the basis of the ARIMA model, the increase in passenger transportation by charter flights during the next 6 months of 2024 is expected to be approximately 1.5 times higher than in previous periods. This indicator corresponds to the pace of economic activity currently developing in the republic.

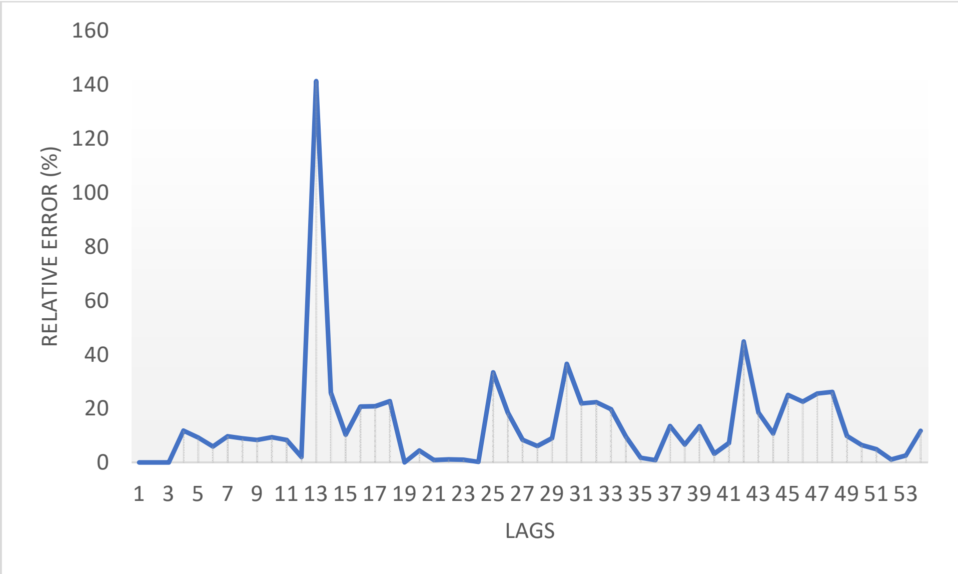

Fig. 8. Relative error of the calculation results obtained in the ARIMA model (%)

Finally, after calculating the relative error of the calculation results obtained in the ARIMA model, it was determined that the average relative error is 14.2%. This result shows that the ARIMA model is an effective base model for calculations in non-scheduled passenger air transportation.

As it can be seen from Figure 8, there is a certain regularity in the change of relative errors. Only one of these steps (step 13) has an anomalously high value of the relative error, that is, there is a deviation. This also corresponds to the characteristics of non-scheduled air transport. Figure 1 shows the dynamics of non-scheduled passenger air transport. From here it is clearly seen that the number of passengers at the 12th step is 584, and at the 13th step it is equal to 135. This also showed itself in the calculation of relative errors. The demand for this type of air transportation can suddenly increase or decrease (suddenly increasing demand during various socio-economic events or decreasing demand during a global pandemic). In such cases, different smoothing methods are usually used. That is, if there are anomalous deviations at several steps among the collected statistical data, or if there is no data for that period at all, then the values of those steps are restored by applying smoothing methods. Then, the smoothed values are entered into the model. In this way, it is possible to achieve more effective results from the model. In our study, this situation is observed in only one out of 53 steps, which does not negatively affect the final result. That is, the average relative error is within the norm. The main reason for not reducing that step with the smoothing method is to preserve the process natural flow. That is why there were no serious errors in the final result. As it was mentioned above, if the number of such cases is large, it will be necessary to apply smoothing methods.

The research relevance

Non-scheduled passenger air transportation is formed on the basis of order, unlike regular air transportation. There are many external factors that influence this process. For example, the socio-economic situation of the country, the welfare level of the population, demographic indicators, environmental issues, etc. Many of these factors usually remain constant; that is, they do not change. It is clear from this that a part of non-scheduled passenger air transportation is formed depending on the socio-economic situation of the country, and the other part is completely dependent on random factors. Taking into account the mentioned facts, a basic model for forecasting these processes in further studies is applied and it will play a basic role in predicting processes in this form in future studies. Considering the traditional regression models, it will be seen that in these models, it is necessary to evaluate the influence of each factor. The process of non-scheduled air transportation is formed under the influence of one or more factors. That is, it is impossible to take into account all external factors within the process. Considering this, we implemented the process, taking into account the time and not the factors separately. The main goal is to determine the base segment for each airport based on long-term observations, and by applying machine learning methods to this segment, create completely new and first-of-its-kind methods for this process. Taking this into account, the methodology proposed here is relevant for these processes and offers a methodical approach for modelling processes in this form in the future. The main scientific innovations of the research can be noted as follows:

1. The scientific innovation in the article is a methodology that can play a basic role in the modelling of completely stochastic processes such as non-scheduled passenger air transportation. Based on this methodology, we have chosen ARIMA as a base method. That is, this method includes both the regression equation and the re-consideration of the errors obtained from it at the same time.

2. The application of the ARIMA method to the forecasting of non-scheduled passenger air transportation is the first and is a novelty. Since the non-scheduled passenger air transportation process is a completely stochastic process, the application of these methods to the mentioned field is a novelty.

3. Modelling is not carried out using only one method, as the mentioned process of air transportation depends on many random factors. Another scientific novelty of the research is that the obtained results serve as a basis for the application of machine learning methods in future research. That is, the part determined by these methods will serve as a trend model in the future. This will be a base part that can be separated from the general (main) model and given fully analytically (i.e., calculable). The remaining differences will be taught at each step, and machine learning methods will be created. That is, this method serves as a basis for future research. Since the application of these types of models in forecasting non-scheduled passenger air transportation is new, it is crucial to have basic results for more efficient forecasting. With the results obtained in this study, we developed a fundamental concept for the development of further forecasting models for the process of non-scheduled passenger air transportation. Other researchers can use the results obtained using this approach as a basis in future studies when building forecasting models for processes with regularities such as non-scheduled passenger transportation.

Research results and discussion

The influence of seasonal factors was not considered in the research. The main reason is that non-scheduled flights are not seasonal because they are made to order. The data in the study covers the period from 2020 to 2024. As it is known, due to the global pandemic conditions, the data on non-scheduled passenger air transportation for these periods is still not accurate and complete. Due to the pandemic, the data was restored by applying existing smoothing methods for months whose data is not completely accurate. Since seasonal factors are not taken into account, the ARIMA model was applied in the research. The results of the study also show that the seasonal factor does not play a very crucial role in the modelling of non-scheduled passenger air transportation. A number of researchers have taken this factor into account when forecasting regular passenger air traffic. These data are given in the literature review section. When applying this model to non-scheduled passenger air transportation for the first time, the effect of seasonal factors was not taken into account. It was found that, unlike regular air transportation, the effect of this factor does not create such serious differences in non-scheduled passenger air transportation. It is considered optimal to achieve this result for another scientific innovation of the research.

Conclusions

In conclusion, the ARIMA model offers a valuable tool for forecasting non-scheduled air transportation demand. By leveraging historical data and capturing patterns, it provides decision-makers with insights to optimise operations and meet the dynamic needs of non-scheduled air travel. Anomalous deviations were observed at several points in the general trend when calculations were made in the ARIMA model. This is due to the characteristics of non-scheduled air transportation. It is possible to find such cases with this type of transportation. Although we incorporated some of the anomalous deviations that occurred in the actual data in our research into the process without applying smoothing methods, this step did not affect the final results. It is important to note that when reporting for airports with intensive non-scheduled flights, adding actual data to the process after processing with smoothing methods will provide better results. Additionally, since each airport's capabilities (number of aircraft, airport infrastructure, number of flight crew, etc.) are limited, the time sequence of non-scheduled flights (although a random process) varies within a certain limited interval. Regardless of how it changes in this limited interval, a forecast model for a specific airport can be built with machine learning (deep learning) methods due to the inertia of non-scheduled passenger air transportation. The above-mentioned method (ARIMA) will become a basis for making building this model. Further research and refinement of the model can enhance its forecasting capabilities and contribute to improved decision-making in the industry.

References

1. **Tang, X., Deng, G.** (2016). Prediction of civil aviation passenger transportation based on ARIMA model. *Open Journal of Statistics*, vol. 6, no. 5, pp. 824–834. DOI: 10.4236/ojs.2016.65068

2. **Samagaio, A., Wolters, M.** (2010). Comparative analysis of government forecasts for the Lisbon Airport. *Journal of Air Transport Management*, vol. 16, issue 4, pp. 213–217. DOI: 10.1016/j.jairtraman.2009.09.002

3. **Scarpel, R.A.** (2013). Forecasting air passengers at São Paulo international airport using a mixture of local experts model. *Journal of Air Transport Management*, vol. 26, pp. 35–39. DOI: 10.1016/j.jairtraman.2012.10.001

4. **Profillidis, V.A.** (2000). Econometric and fuzzy models for the forecast of demand in the airport of Rhodes. *Journal of Air Transport Management*, vol. 6, issue 2, pp. 95–100. DOI: 10.1016/S0969-6997(99)00026-5

5. **Profillidis, V.A.** (2012). An ex-post assessment of a passenger demand forecast of an airport. *Journal of Air Transport Management*, vol. 25, pp. 47–49. DOI: 10.1016/j.jairtraman.2012.08.002

6. **Zhang, G.P.** (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, vol. 50, pp. 159–175. DOI: 10.1016/S0925-2312(01)00702-0

7. **Andreoni, A., Postorino, M.N.** (2006). A multivariate ARIMA model to forecast air transport demand. *In: European Transport Conference (ETC).* Strasbourg, France, 14 p. Available at: https://trid.trb.org/View/846533 (accessed: 10.11.2023).

8. **Taneja, K., Ahmad, S., Ahmad, K., Attri, S.D.** (2016). Time series analysis of aerosol optical depth over New Delhi using Box-Jenkins ARIMA modeling approach. *Atmospheric Pollution Research*, vol. 7, issue 4, pp. 585–596. DOI: 10.1016/j.apr.2016.02.004

9. **Suhartono, S., Lee, M.H., Prastyo, D.D.** (2015). Two levels ARIMAX and regression models for forecasting time series data with calendar variation effects. *In: AIP Conference Pro-*

ceedings, vol. 1691, issue 1, ID: 050026. DOI: 10.1063/1.4937108 (accessed: 10.11.2023).

10. Ge, M., Junfeng, Zh., Jinfei, W., Huiting, H., Xinghua, Sh., Hongye, W. (2021). ARIMA-FSVR hybrid method for high-speed railway passenger traffic forecasting. *Mathematical Problems in Engineering*, vol. 2021, ID: 9961324, 5 p. DOI: 10.1155/2021/9961324 (accessed: 10.11.2023).

11. Box, G.E.P., Jenkins, G.M., Reinsel, G.C. (2008). Time series analysis: Forecasting and control. New York, John Wiley & Sons Inc., 755 p. DOI: 10.1002/9781118619193

12. Box, G.E.P., Tiao, G.C. (1975). Intervention analysis with applications to economic and environmental problems. *Journal of the American Statistical Association*, vol. 70, no. 349, pp. 70–79.

13. Ren, G., Gao, J. (2019). Comparison of NARNN and ARIMA models for short-term metro passenger flow forecasting. *In: Proceedings of the 19th COTA International Conference of Transportation Professionals*, Nanjing, China. DOI: 10.1061/9780784482292.119 (accessed: 10.11.2023).

14. Tsai, T.-H., Lee, C.-K., Wei, C.-H. (2009). Neural network based temporal feature models for short-term railway passenger demand forecasting. *Expert Systems with Applications*, vol. 36, issue 2, pp. 3728–3736. DOI: 10.1016/j.eswa.2008.02.071

15. Ni, L., Chen, X., Qian, H. (2010). ARIMA model for traffic flow prediction based on wavelet analysis. *In: Proceedings of the 2nd International Conference on Information Science and Engineering IEEE*. China, Hangzhou, pp. 1028–1031. DOI: 10.1109/ICISE.2010.5690910 (accessed: 10.11.2023).

16. Xie, Y., Zhang, P., Chen, Y. (2021). A fuzzy ARIMA correction model for transport volume forecast. *Mathematical Problems in Engineering*, vol. 2021, ID: 6655102, 10 p. DOI: 10.1155/2021/6655102 (accessed: 10.11.2023).

17. Khan, M.M.H., Muhammad, N.S., El-Shafie, A. (2020). Wavelet based hybrid ANN-ARIMA models for meteorological Drought forecasting. *Journal of Hydrology*, vol. 590, ID: 125380. DOI: 10.1016/j.jhydrol.2020.125380 (accessed: 10.11.2023).

18. Wu, J., Li, Z., Zhu, L., Li, C. (2017). Hybrid model of ARIMA model and GAWNN for dissolved oxygen content prediction. *Transactions of the Chinese Society for Agricultural Machinery*, vol. 48, pp. 205–210. DOI: 10.6041/j.issn.1000-1298.2017.S0.033

Список литературы

1. **Tang X., Deng G.** Prediction of civil aviation passenger transportation based on ARIMA model // Open Journal of Statistics. 2016. Vol. 6, no. 5. Pp. 824–834. DOI: 10.4236/ojs.2016.65068

2. **Samagaio A., Wolters M.** Comparative analysis of government forecasts for the Lisbon Airport // Journal of Air Transport Management. 2010. Vol. 16, iss. 4. Pp. 213–217. DOI: 10.1016/j.jairtraman.2009.09.002

3. **Scarpel R.A.** Forecasting air passengers at São Paulo international airport using a mixture of local experts model // Journal of Air Transport Management. 2013. Vol. 26. Pp. 35–39. DOI: 10.1016/j.jairtraman.2012.10.001

4. **Profillidis V.A.** Econometric and fuzzy models for the forecast of demand in the airport of Rhodes // Journal of Air Transport Management. 2000. Vol. 6, iss. 2. Pp. 95–100. DOI: 10.1016/S0969-6997(99)00026-5

5. **Profillidis V.A.** An ex-post assessment of a passenger demand forecast of an airport // Journal of Air Transport Management. 2012. Vol. 25. Pp. 47–49. DOI: 10.1016/j.jairtraman.2012.08.002

6. **Zhang G.P.** Time series forecasting using a hybrid ARIMA and neural network model // Neurocomputing. 2003. Vol. 50. Pp. 159–175. DOI: 10.1016/S0925-2312(01)00702-0

7. **Andreoni A., Postorino M.N.** (2006). A multivariate ARIMA model to forecast air transport demand [Электронный ресурс] // European Transport Conference (ETC). France: Strasbourg, 2006. 14 p. URL: https://trid.trb.org/View/846533 (дата обращения: 10.11.2023).

8. **Taneja K.** (2016). Time series analysis of aerosol optical depth over New Delhi using Box-Jenkins ARIMA modeling approach / K. Taneja, S. Ahmad, K. Ahmad, S.D. Attri //

Atmospheric Pollution Research. 2016. Vol. 7, iss. 4. Pp. 585–596. DOI: 10.1016/j.apr.2016.02.004

9. **Suhartono, S., Lee M.H., Prastyo D.D.** Two levels ARIMAX and regression models for forecasting time series data with calendar variation effects [Электронный ресурс] // AIP Conference Proceedings, 2015. Vol. 1691, issue 1, ID: 050026. DOI: 10.1063/1.4937108 (дата обращения: 10.11.2023).

10. **Ge M.** ARIMA-FSVR hybrid method for high-speed railway passenger traffic forecasting / M. Ge, Zh. Junfeng, W. Jinfei, H. Huiting, Sh. Xinghua, W. Hongye [Электронный ресурс] // Mathematical Problems in Engineering. 2021. Vol. 2021. ID: 9961324. 5 p. DOI: 10.1155/2021/9961324 (дата обращения: 10.11.2023).

11. **Box G.E.P., Jenkins G.M., Reinsel G.C.** Time series analysis: Forecasting and control. New York, John Wiley & Sons Inc., 2008. 755 p. DOI: 10.1002/9781118619193

12. **Box G.E.P., Tiao G.C.** Intervention analysis with applications to economic and environmental problems // Journal of the American Statistical Association. 1975. Vol. 70, no. 349. Pp. 70–79.

13. **Ren G., Gao J.** Comparison of NARNN and ARIMA models for short-term metro passenger flow forecasting [Электронный ресурс] // Proceedings of the 19th COTA International Conference of Transportation Professionals. China, Nanjing. DOI: 10.1061/9780784482292.119 (дата обращения: 10.11.2023).

14. **Tsai T.-H., Lee C.-K., Wei C.-H.** Neural network based temporal feature models for short-term railway passenger demand forecasting // Expert Systems with Applications. 2009. Vol. 36, iss. 2. Pp. 3728–3736. DOI: 10.1016/j.eswa.2008.02.071

15. **Ni L., Chen X., Qian H.** ARIMA model for traffic flow prediction based on wavelet analysis [Электронный ресурс] // Proceedings of the 2nd International Conference on Information Science and Engineering IEEE. China, Hangzhou, 2010. Pp. 1028–1031. DOI: 10.1109/ICISE.2010.5690910 (дата обращения: 10.11.2023).

16. **Xie Y., Zhang P., Chen Y.** A fuzzy ARIMA correction model for transport volume forecast [Электронный ресурс] // Mathematical Problems in Engineering. 2021. Vol. 2021. ID: 6655102. 10 p. DOI: 10.1155/2021/6655102 (дата обращения: 10.11.2023).

17. **Khan M.M.H., Muhammad N.S., El-Shafie A.** Wavelet based hybrid ANN-ARIMA models for meteorological Drought forecasting [Электронный ресурс] // Journal of Hydrology. 2020. Vol. 590. ID: 125380. DOI: 10.1016/j.jhydrol.2020.125380 (дата обращения: 10.11.2023).

18. **Wu J.** Hybrid model of ARIMA model and GAWNN for dissolved oxygen content prediction / J. Wu, Z.B. Li, L. Zhu, C. Li // Transactions of the Chinese Society for Agricultural Machinery. 2017. Vol. 48, pp. 205–210. DOI: 10.6041/j.issn.1000-1298.2017.S0.033

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