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;
2.9.8 – Интеллектуальные транспортные системы

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Hybrid forecasting model of non-scheduled passenger air transportation

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Abstract: In the article, an ARIMA-Fuzzy-based hybrid model is proposed for forecasting time series of non-scheduled passenger air transportation. As it is known, the ARIMA model is applied to identify linear trends and regularities within time series data as well as for forecasting. The study of scientific research literature shows that the ARIMA model has its own limitations in managing non-linearity and random changes during forecasting. Since the process of non-scheduled air transportation depends on random changes as a stochastic process, the mentioned model does not cover the whole process. For this reason, the ARIMA model does not provide effective enough results outcome strong enough to model non-linear and random changes in the data in the process of non-scheduled air transportation. In this regard, the ARIMA model was applied together with the fuzzy model. The hybrid model, based on ARIMA's autoregression model, is applied together with the random deviation fuzzy model to further increase the accuracy of the forecast. The results obtained as a result of the application of the hybrid model show that the model in this form provides more reliable and efficient forecasts compared to independent models.

Key words: non-scheduled air transportation/transport/services, hybrid model, statistical analysis, fuzzy model, time series analysis, optimal model, forecasting, autoregressive model.

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Гибридная модель прогнозирования нерегулярных пассажирских авиаперевозок

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Аннотация: В статье предлагается гибридная модель на основе ARIMA-Fuzzy для прогнозирования временных рядов нерегулярных пассажирских авиаперевозок. Как известно, модель ARIMA применяется для выявления линейных тенденций и закономерностей в данных временных рядов, а также для прогнозирования. Изучение научной литературы показывает, что модель ARIMA имеет свои ограничения в управлении нелинейностью и случайными изменениями во время прогнозирования. Поскольку процесс нерегулярных авиаперевозок как стохастический процесс зависит от случайных изменений, указанная модель не позволяет описывать весь процесс. По этой причине модель ARIMA не дает достаточно эффективных результатов для моделирования нелинейных и случайных изменений данных в процессе нерегулярных авиаперевозок. В связи с этим для повышения точности прогноза в исследовании применяется гибридная модель, основанная на модели авторегрессии ARIMA вместе с нечеткой моделью случайных отклонений. Апробация разработанной гибридной модели осуществлена на примере прогнозирования пассажиропотоков нерегулярных рейсов в Азербайджане. Полученные результаты показывают, что модель в таком виде обеспечивает более надежные и эффективные прогнозы по сравнению с применением независимых моделей.

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

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Introduction

Forecasting of non-scheduled passenger air transportation is important for optimal management of operations in this area. There are more internal and external factors that affect the process of non-scheduled air transportation than regular air transportation. A part of these factors is formed depending on factors such as the economic situation of the country and the potential of holding internationally important events, and the other part is completely dependent on random factors. For this reason, the selection of the forecasting model and the consideration of the factors that can actively influence the process are crucial.[1] Although the process of non-scheduled passenger air transportation depends more on random factors, these factors change within a certain limited area, that is, there is a basic part that does not change in the process. This fact allows us to forecast it. It should be noted that this field is poorly studied. One of the important issues is the application of forecast models by analyzing the characteristic features of the non-scheduled air transportation process [1].

The researchers developed a combined forecasting method based on the IOWHA operator concept and ARIMA regression models for forecasting passenger traffic in air transport. The IOWHA (Integrated Operator Workload and Health Assessment) concept, when applied to air transportation forecasting, helps improve prediction accuracy by factoring in the workload and health of operators (pilots, air traffic controllers). On the other hand, ARIMA (Autoregressive Integrated Moving Average) is based on time series data; it accounts for trends and seasonal variations. It is a statistical approach. Univariate and multivariate regression analysis models, as well as ARIMA models for time series analysis, were used for passenger traffic forecasting. It was discovered that the models in their combined form provide more effective forecasting results [2]. In other works, in order to increase forecast accuracy, ARIMA and artificial neural network (ANN) models were studied. A machine learning model that can learn more complex relationships from data, suitable for non-linear patterns. In the study, calculations were made based on the airline's monthly passenger statistics. A short-term forecast was made to determine the future demand, and the errors of the results of both models were compared. It was found that the ANN model provides better results than ARIMA [3].

In the next study, a comparison of the distribution of passengers of two airlines was made using geometric Brownian motion (GBM) and ARIMA models. GBM models are ensemble models that improve weak models iteratively, enhancing the prediction accuracy. Since the GBM approach does not fully cover the process, comparisons were made using the traditional ARIMA model for time series forecasting [4].

Demand for passenger air transportation exhibits non-linearity and non-stationarity, respectively. To overcome these situations, a hybrid VMD-ARMA/KELM-KELM approach was analysed by the researchers for short-term forecasting. Here, VMD (Variational Mode Decomposition) is

[1] Doc 8991: Manual on air traffic forecasting. 3rd ed. // ICAO, 2006. 98 p.

used to decompose the time series data of passenger demand into intrinsic modes, helping capture the underlying patterns in the data. ARMA (Auto Regressive Moving Average) is applied to model the linear dependencies between the decomposed signals, improving prediction accuracy, and KELM (Kernel Extreme Learning Machine), a machine learning model, is used to predict passenger demand based on the features extracted from the previous steps. It improves the model's ability to capture non-linear relationships in the data. This approach was applied to predict the non-stationarity of the series and reduce the complexity. Basing on the results of the study, this approach provides effective strong forecasting outcome [5].

Another study investigated the separate application of ARIMA and BSTS models in forecasting demand for passenger and cargo air transportation. The BSTS (Bayesian Structural Time Series) model applies a Bayesian approach to time series forecasting, incorporating uncertainty into the model. It was determined that compared to the ARIMA model, the BSTS model also gave a strong outcome [6].

The modelling and forecasting of air cargo traffic was investigated by the researchers using the combined SARIMA-X/EGARCH model. The SARIMA-X/EGARCH model is used for forecasting cargo transportation in aviation. It combines two powerful methodologies. Here, SARIMA-X (Seasonal Auto Regressive Integrated Moving Average with Exogenous Variables) extends the SARIMA model by incorporating seasonal effects and external factors (exogenous variables) that influence cargo demand. It captures both trend and seasonality in the time series data of cargo transportation. EGARCH (Exponential Generalised Autoregressive Conditional Heteroskedasticity) is used to model the volatility or variability in the data, especially in cases where the variance is not constant over time. It helps capture sudden changes or shocks in the cargo transportation process that might not be predicted by traditional models. Socio-economic factors affecting the demand have been identified. As a result of the research, a forecast of air cargo traffic until 2030 was obtained [7].

Another study on air cargo traffic forecasting used ConvLSTM2D and an artificial neural network architecture approach. Here, ConvLSTM2D (Convolutional LSTM) is a deep learning model that learns spatial and temporal dependencies in time series data. As a result of the research, it was determined that GDP (Gross Domestic Product) and PCG (GDP per Capita) have a significant impact on the demand for domestic and international cargo air transportation. In addition, results for the next 5 years were obtained as a short-term forecast [8].

In the next study, the application of the gravity model for forecasting the demand for cargo air transportation was investigated. Through this model, the influence of external factors affecting the field of cargo air transport was also investigated [9].

ARIMA + GARCH + the bootstrap method was proposed by the researchers to forecast air passenger traffic. Here, GARCH (Generalised Autoregressive Conditional Heteroskedasticity) is used to model and predict the volatility (or variability) of time series data. On the other hand, the bootstrap method is a resampling technique used to estimate the uncertainty of forecasts. It generates multiple simulated datasets by randomly sampling from the original data, allowing researchers to assess the variability and robustness of their forecasted values. Statistical tests were used to evaluate the performance of the method. This method shows effective results [10].

An analysis of air traffic congestion during the COVID-19 pandemic, as well as research into forecasting recovery flight schedules for the future, has been conducted by researchers. Intervention analysis and SARIMAX methods (SARIMAX is an extension of the ARIMA model that includes seasonal effects and external factors (exogenous variables)) were applied for this [11].

An integrated mathematical model of Singular Value Decomposition (SVD), Genetic Algorithms (GA), and the Adaptive Neural Fuzzy Inference System (ANFIS) were applied in order to solve issues related to reducing transportation costs and CO_2 emissions in multimodal transportation (cargo). The model is based on the historical data of this area. Based on the results of the study, the model provided effective and optimal results for multimodal transportation [12]. Research works in this field were continued using the fuzzy-analytic hierarchy process [13].

As a continuation of the research work, the development of an ARIMAX model (ARIMAX is similar to SARIMAX, but it does not necessarily account for seasonality) [14], short-term forecasting of passenger flow at the airport [15], the SARIMA damp trend grey forecasting model in the airline industry [16], forecasting of passenger flow in air transportation based on nonlinear vector auto-regression neural network [17], forecasting of the overload factor in transport systems based on nonlinear vector auto-regression neural network [18], a forecasting model based on ARIMA and artificial neural networks for end-of-life vehicles [19], and air transport passenger flow forecasting based on SARIMA-Backpropagation Neural Network were investigated [20].

As it can be seen from the scientific literature analysed above, the researched forecast models were applied in the forecasting of regular passenger and cargo air transportation. Non-scheduled air transportation has not been the subject of this type of research. Trend models perform better in forecasting scheduled air transportation than non-scheduled air transportation. Additionally, irregular air transportation is more stochastic in nature, so it was decided that an ARIMA-Fuzzy approach would better represent the process. The obtained forecast results prove this once again. Currently, among the methods we investigated (linear [21], non-linear regression, autoregression models, stochastic models, SVM method [1], etc.), ARIMA and fuzzy models have been chosen. Through this hybrid method, we have minimised the errors which occurred using other methods. It is possible to test other hybrid methods in future studies. We would like to point out that the research on the forecasting of non-scheduled air transportation has not been investigated by local and foreign researchers. Since this is a specific field, various methods have been analysed and applied basing on the characteristics of the mentioned field. The results obtained in this article and the previous studies can be observed in the list of references. Analysing the characteristic features of the field of non-scheduled air transportation, the application of various forecasting methods to this field is examined. This also paves the way for obtaining new scientific results in the less researched field of air transportation.

Every model has its own advantages and relevant application areas. Depending on the application field, researchers tend to use more statistical methods in some cases, while deep learning and optimisation methods are employed in others. As it is shown in the analysis of the research literature, various models have been applied by researchers in forecasting regular passenger and freight air transportation. It is particularly noteworthy that, for the first time, we have applied some of these models in a hybrid form for forecasting the time series of non-scheduled passenger air transportation. By investigating the characteristics of non-scheduled passenger air transportation, applying forecasting models, and obtaining effective results, this leads to the emergence of relevant scientific results in this field.

Problem statement

The statistical indicators of the time series of non-scheduled passenger air transportation depend on many internal and external factors and, at the same time, are formed depending on the political and economic situation of the country to which the airline belongs. The economic changes taking place in the country, as in other areas, are also reflected in the non-scheduled air transport field. As a result, non-scheduled passenger air transportation for each country is country-specific, which makes it difficult to apply classical forecasting methods. The different nature of the changes makes it difficult to apply the same classic forecast model to all countries. Considering the mentioned facts, a hybrid ARIMA-fuzzy approach is applied to overcome this problem. Intra-series changes in non-scheduled passenger air transportation were taken as an additive dependence of trend changes and random changes. Another problem encountered during research in this field is the lack of information. This can be mainly explained by the stagnation in the field of civil aviation due to the global pandemic situation in recent years. On the other hand, the lack of influence of long-term internal and external factors in the time series of non-scheduled passenger air transportation makes it difficult to think about how the process changes. Despite all these problems, every airline that performs non-scheduled passenger air transportation has an aircraft fleet and infrastructure that do not change for a certain period of time, which it carries out transportation. This feature allows us to apply an ARIMA model for trend changes based on actual time series data.

A fuzzy approach is applied to the difference of forecast results of the ARIMA model with actual data of non-scheduled passenger air transportation. As a result, a hybrid ARIMA-Fuzzy forecasting model is proposed. The proposed hybrid model allows for minimizing the errors obtained from the application of the ARIMA model, as a result, to build a more accurate forecast model. This hybrid method was applied for the first time to forecast non-scheduled passenger air transportation, and effective results were obtained.

The research is dedicated to forecasting the time series of non-scheduled passenger air transportation in the Republic of Azerbaijan. As it is known, since the beginning of 2020, the world has been influenced by a global pandemic. This situation, as in other sectors of the economy, has caused significant disruptions in the civil aviation industry. After the pandemic, the pace of economic change has been different. Additionally, with the start of the large-scale Patriotic War in Azerbaijan during this period, a significant part of the territories of the country was liberated. This, in turn, contributed to the further diversification of the national economy. It should also be noted that large infrastructure projects, including the construction of new airports, were carried out in these liberated areas. Furthermore, the holding of several international socio-economic events in the country has led to an increase in the volume of non-scheduled passenger air transportation. Considering all these factors, the statistical data on non-scheduled passenger air transportation in the Republic of Azerbaijan can be divided into two periods: data until 2019 and data from 2020 onwards.

At the beginning of the study, it was decided to build a hybrid model using data from the new phase of the country's economic development (i.e., data from 2020 onwards). This approach, based on the new pace of the country's economy, will lead to more effective and optimal forecasting results for non-scheduled passenger air transportation.

Taking into account the factors mentioned above, the monthly number of passengers in 2020–2023 (a total of 48 months) is included in the model for forecasting the time series of non-scheduled passenger air transportation. Calculations of the hybrid model will be made based on the statistics provided for 2020–2022. The data of 12 months of the last year (i.e., 2023) are chosen to test the accuracy of the forecast model. The data of the other 3 years are included in the calculations.

Solution method

Based on the above-mentioned facts in order to analyze the characteristics of non-scheduled passenger air transportation,the following model is proposed to solve the problem

$$Y_t = y_t + x_t. \tag{1}$$

Here, t indicates the current year, y_t is determined by the ARIMA model.

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

x_t characterizes random changes and is modeled based on a fuzzy approach.

We apply the method of least squares to find the unknown coefficients. For this, the following issue should be resolved:

$$\sum_{t=1}^{N} \left[\left(\bar{Y}_t - y_t \right) \right]^2 \dot{\to} min. \tag{3}$$

Here, $\bar{Y}_t$ is the actual data, Y_t is the final forecast results, and N is the number of data included in the research (by months), c is the constant, $\phi_1, \phi_2, ..., \phi_p$, p is the autoregressive order.

The solution to problem (3) is reduced to the following matrix equation:

$$A\varphi = B, \tag{4}$$

A is a $(p + 1)$ – dimensional square symmetric matrix, the vector $\varphi = \left(c, \phi_1, \phi_2, ..., \phi_p\right)$ is a $(p + 1)$ dimensional vector.

$$A=\begin{pmatrix} N & \sum_{t=1}^{N}\overline{Y}_{t-1} & \sum_{t=1}^{N}\overline{Y}_{t-2}....\sum_{t=1}^{N}\overline{Y}_{t-p} \\ \sum_{t=1}^{N}\overline{Y}_{t-1} & \sum_{t=1}^{N}\overline{Y}_{t-1}^{\,2} & \sum_{t=1}^{N}\overline{Y}_{t-2}\overline{Y}_{t-1}......\sum_{t=1}^{N}\overline{Y}_{t-p}\overline{Y}_{t-1} \\ \sum_{t=1}^{N}\overline{Y}_{t-p} & \sum_{t=1}^{N}\overline{Y}_{t-1}\overline{Y}_{t-p} & \sum_{t=1}^{N}\overline{Y}_{t-2}\overline{Y}_{t-p}.......\sum_{t=1}^{N}\overline{Y}_{t-p}^{2} \end{pmatrix}, \quad (5)$$

$$B=\begin{pmatrix} \sum_{t=1}^{N}\overline{Y}_{t} \\ \sum_{t=1}^{N}\overline{Y}_{t}\ \overline{Y}_{t-1} \\ \sum_{t=1}^{N}\overline{Y}_{t}\ \overline{Y}_{t-p} \end{pmatrix}. \quad (6)$$

Considering expressions (5) and (6) in formula (4), unknown coefficients are found:

$$\overline{\varphi}=A^{-1}\cdot B. \quad (7)$$

Taking into account the coefficients calculated according to the formula (7) in (2), the calculations for the months of the forecast year are made. We define the difference of the results obtained with the actual data as x_t. As a result, 12 calculated (x_t). (x_t) characterizes the random deviations between the actual data and the model, and the modelling is as follows in the fuzzy approach.

Let us enter the following notation to build the hybrid model:

In each of the random time series (x_t), we get new vectors by passing one unit from the origin. Thus, more characteristic features of (x_t) changes gained are ensured. Note that by repeating these operations 11 times, all possible displacements can be taken into account.

Here, n is the number of displacement operations involved in the research;

In our case, we take $n = 3$ for simplicity.

x_{tj} is an element of the sequence obtained in the above-mentioned manner $\left(i=\overline{1,n}, j=\overline{1,12}\right)$.

As a characteristic of intra-series changes, the increase (or decrease) factor is calculated as follows:

$$M_{kj}=x_{kj}-x_{k-1,j}\left(k=\overline{2,n}; j=\overline{1,12}\right). \quad (8)$$

In the time series calculated by the formula (1), the thresholds are positive (the case of increases in non-scheduled passenger air transportation) $\left(\mathrm{M}^{+}{}_{\mathrm{kj}}\right)$ and negative (the case of decreases) $\left(\mathrm{M}^{-}{}_{\mathrm{kj}}\right)$. and their numbers are, respectively. It is denoted as (n+) and (n−). It is assumed that M_{kj} is 0. In this case, the value 0 is considered in $\left(\mathrm{M}^{+}{}_{\mathrm{kj}}\right)$ or $\left(\mathrm{M}^{-}{}_{\mathrm{kj}}\right)$ depending on the values before and after the occurrence of this case.

The maximum, minimum, and average quantities of increase (decrease) values for the corresponding months of the years involved in the study $(\mathrm{MAX}^{\pm}(\mathrm{j}),\ \mathrm{MIN}^{\pm}(\mathrm{j})$ və $\mathrm{O}^{\pm}_{average}(\mathrm{j}))$ are calculated. The absence of a positive or negative trend in any year should be taken into account in the calculation of the mentioned indicators.

Using these calculated values, a membership function for intra-series changes in non-scheduled passenger air transportation based on the terms "low increase" ("low decrease"), "average increase" ("average decrease"), and "high increase" ("high decrease") can be constructed.

As mentioned above, numerous factors affecting the time series of non-scheduled air transportation prove that intra-series changes are of a fuzzy nature. Let us use the statistical method of constructing membership functions to evaluate the terms. With this method, it is possible to construct the membership function by taking positive signs as an increase and negative signs as a decrease. In this case, the above-mentioned terms are respectively defined as follows:

$$\mu^{+}(x,j)=\left\{\begin{matrix} x: M\cdot N^{+}(j)/\,little\ growth, O^{+}_{average}(j)/\,average\ growth, \\ MAX^{+}(j)/\,too\ much\ growth \end{matrix}\right\}, \quad (9)$$

$$\mu^{-}(x,j)=\left\{\begin{matrix} x: M\cdot N^{-}(j)/\,little\ decrease, O^{-}_{average}(j)/\,averagedecrease, \\ M\cdot N^{-}(j)/\,too\ much\ reduction \end{matrix}\right\}.$$

Let us determine the characteristics of intra-series changes using the above formulae. In this purpose, let us use the weighting coefficient for 12 quantities selected, the mean square deviation, and intra-series fractal changes for each value of n in which the increase or decrease characteristics of intra-series changes were involved in the study.

$$\delta_j^{\pm} = \frac{\sum_{i=1}^{n^{\pm}} M_{ij}^{\pm}}{\sum_{i=1}^{n} \left| M_{ij} \right|}, j = \overline{1,12}; \tag{10}$$

$$\sigma_j^{\pm} = \sqrt{\frac{\sum_{i=1}^{n^{\pm}} \left(M_{ij}^{\pm} - O_{ij}^{\pm} \right)^2}{n^{\pm}}}, j = \overline{1,12}; \tag{11}$$

$$\nu_j^{\pm} = \frac{\sigma_j^{\pm}}{O_{average}^{\pm}}, j = \overline{1,12}. \tag{12}$$

Based on the above calculations, the result for the forecast year (2023) is calculated. Based on the base year, let us calculate the indicators for the forecast year as follows:

Since the membership function characterizes the changes for 12 quantities selected of calculations are carried out for all n number of changes:

$$Q^{\pm}(x, j) = \mu^{\pm}(x, j) \cdot \delta^{\pm}(j). \tag{13}$$

Let us use the numerical value of the fractal dimension of the series as a random characteristic of the variations within the series.

$$P^{\pm}(j) = \sigma^{\pm}(j) \cdot \nu^{\pm}(j). \tag{14}$$

We can accept the numerical value of changes in all selected elements of the sequence xt for the forecast year based on formula (8):

$$\begin{aligned} R(x, j) = &\left(Q^{+}(x, j) + P^{+}(j) \right) + \\ &+ \left(Q^{-}(x, j) + P^{-}(j) \right), j = \overline{1,12}. \end{aligned} \tag{15}$$

Taking Rx, j as the values of random deviations calculated using the fuzzy approach, a hybrid model is constructed according to formula (1).

Experimental results

First of all, statistical data for non-scheduled passenger air transportation were collected in order to build the calculation 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 is clear from here that calculations will be made according to formula (2), taking into account (p = 3) in the ARIMA model.

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). Calculation results are shown in Figure 3. It can be seen from the comparison of the calculation results based on formula (2) with the actual indicators, 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.

Based on the data in Figure 4, a series consisting of random variations for the (n = 3) condition is constructed. The values of the model in a fuzzy approach based on formulae (8)–(15) for the elements of that series are calculated. The obtained results are considered in formula (1). The final results are shown in Table 1.

According to Figure 6, it can be noted that the average relative error of the forecast results obtained with the independent ARIMA model is 14.2%, and this value is equal to 7.1% in the forecast results of the hybrid ARIMA-Fuzzy model. As it can be seen from the calculation results, the hybrid ARIMA-Fuzzy forecast model has more than 2 times stronger outcome than the independent ARIMA model.

Conclusions

As a result, it should be noted that in the article, for the first time, a fuzzy model was applied together with the Regression (ARIMA) model for the forecasting of non-scheduled passenger air transportation. The errors obtained based on the

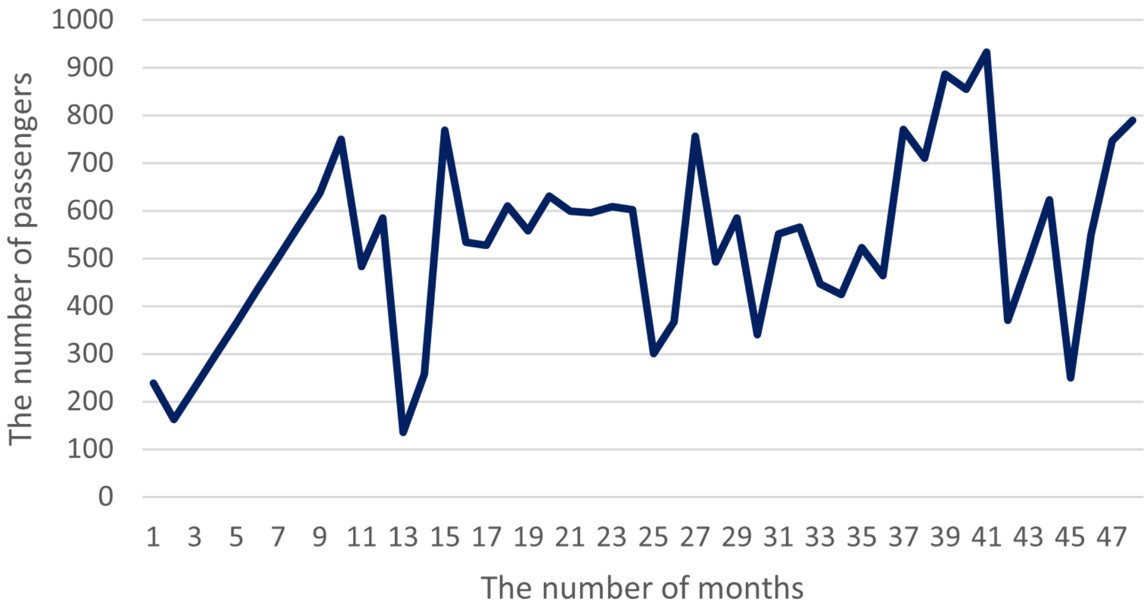

Fig. 1. Monthly dynamics of non-scheduled passenger air transportation

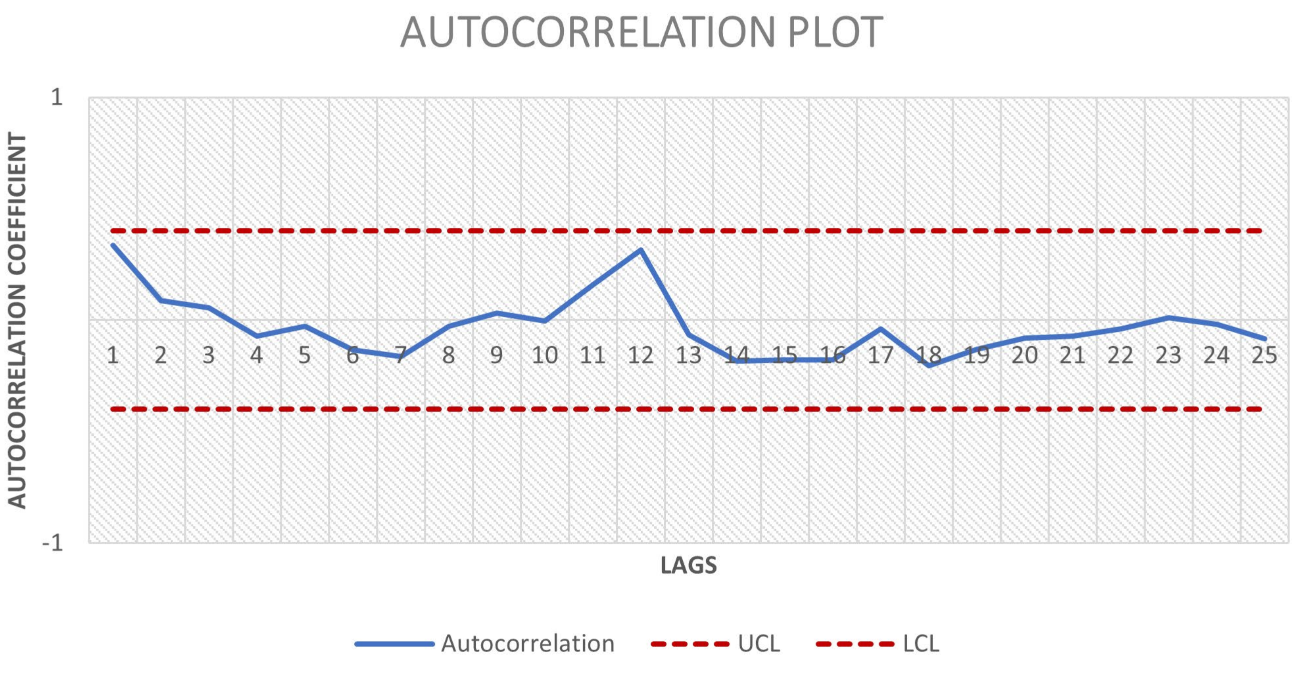

Fig. 2. Autocorrelation function according to Figure 1

ARIMA model were further fixed and strong forecast outcome was obtained based on the hybrid ARIMA-Fuzzy model. The conducted research is considered crucial for both airlines and airports. The hybrid model will provide effective results in the increasing of economic efficiency, operational planning, resource allocation, etc. for non-scheduled passenger air transportation.

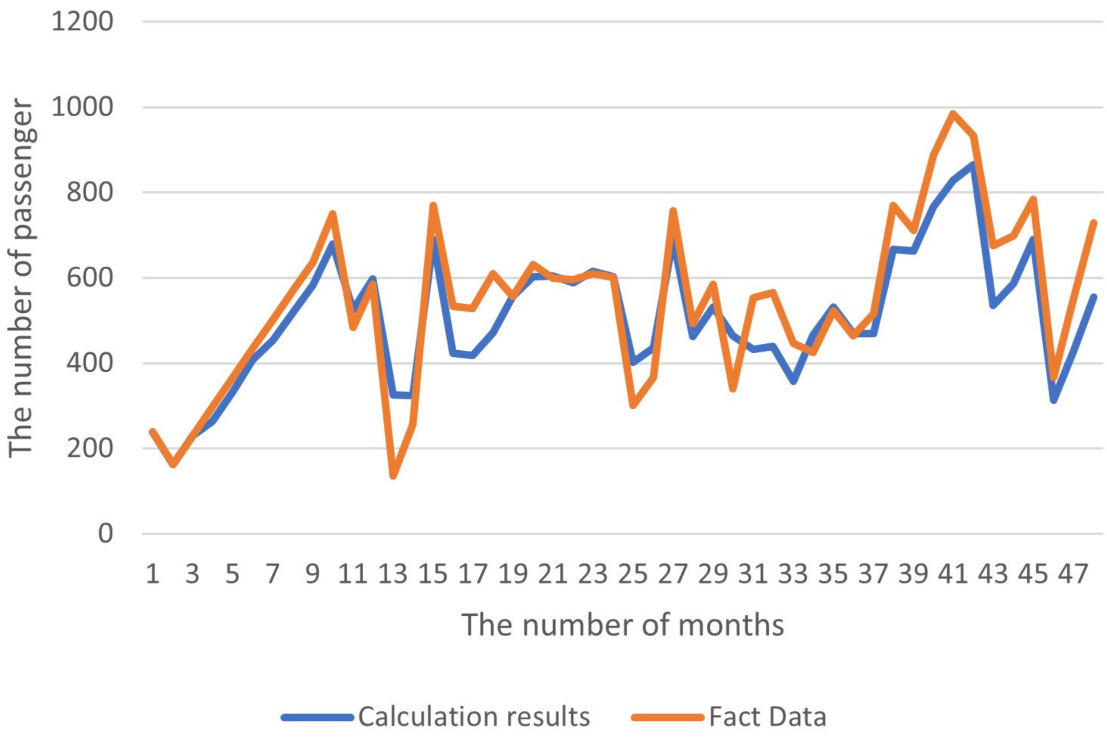

Fig. 3. Calculation results based on the formula (2)

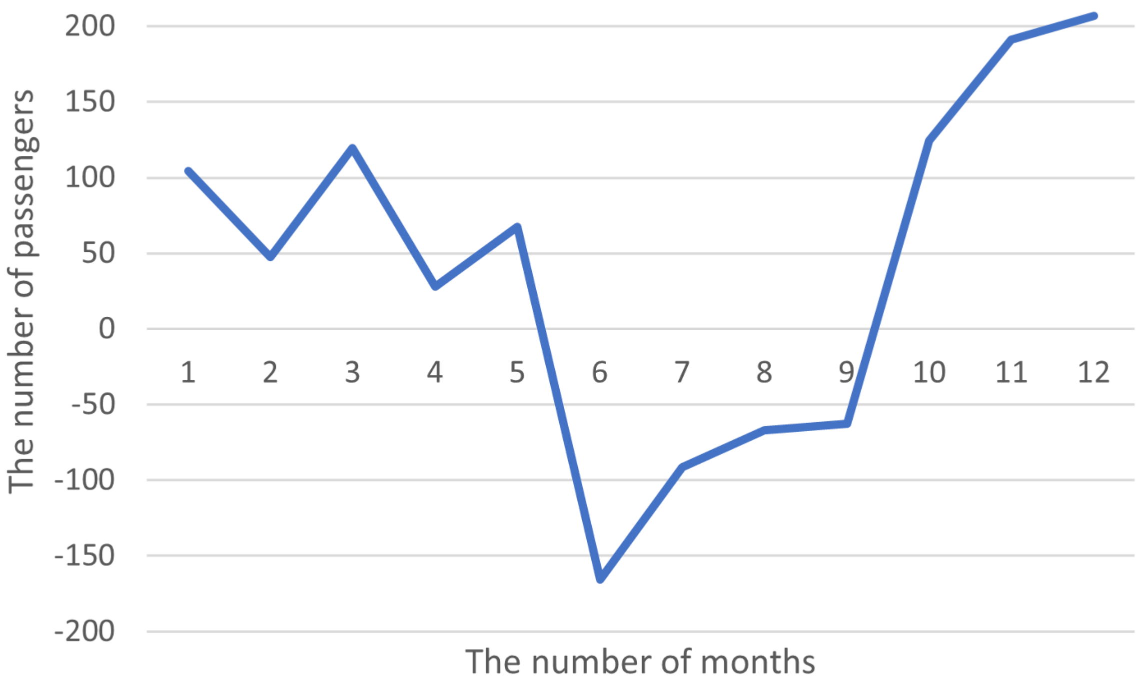

Fig. 4. The differences between the fact data and the calculation results

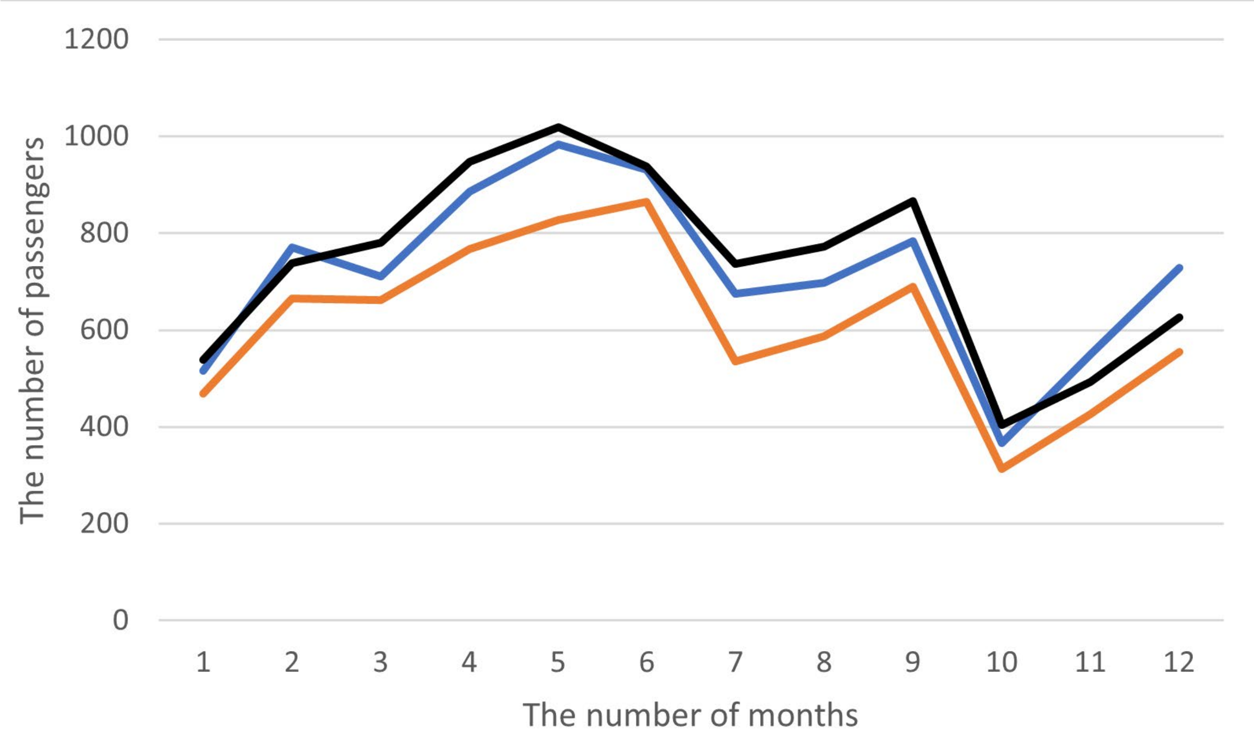

Fig. 5. Comparative forecasting results of ARIMA and hybrid ARİMA-Fuzzy models

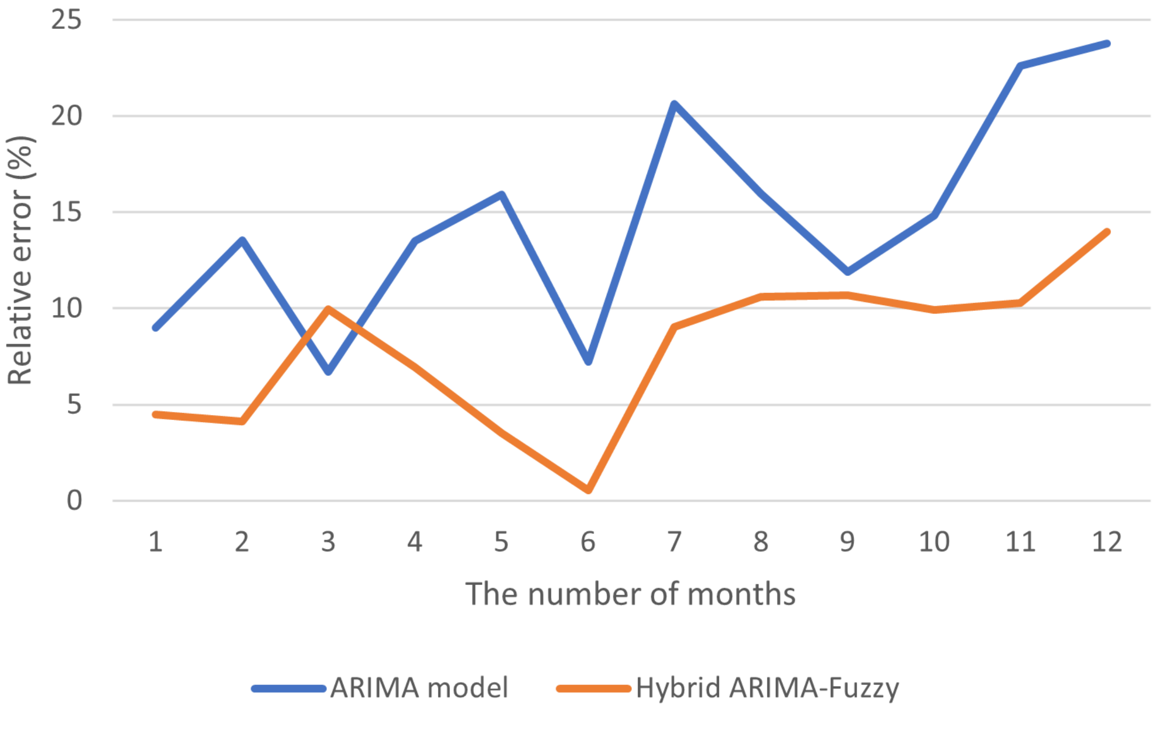

Fig. 6. Relative error of forecasting results of ARIMA and hybrid ARİMA-Fuzzy models based on actual indicators

Table 1

Forecasting results of non-scheduled passenger air transportation (2023) according to the hybrid (ARIMA-Fuzzy) model

Months	Rj	Hybrid ARIMA-Fuzzy model results for 2023	Fact data-2023
January	69.43171	538.0239	515
February	72.63433	738.2524	770
March	118.168	780.7149	710
April	181.1136	947.6439	886
May	191.5479	1018.746	984
June	72.37245	936.9405	932
July	200.2406	735.9233	675
August	185.4639	772.1275	698
September	176.7653	866.8007	783
October	90.84436	403.4238	367
November	67.66142	493.4551	550
December	71.0323	626.1355	728

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