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Forecasting Model of Non-Scheduled Passenger Air Transportation in Fuzzy Approach

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Abstract. In this paper, we delve into the conceptual underpinnings of fuzzy logic and its applicability to forecasting within the context of non-scheduled passenger air transportation. We review relevant literature, highlighting the limitations of traditional forecasting techniques and the rationale for adopting a fuzzy approach. Additionally, we outline the methodology employed in developing the proposed fuzzy forecasting model, emphasizing its adaptability to evolving operational conditions and its potential to enhance decision-making processes within the aviation industry. In the conducted research, a new method of building a forecasting model using a fuzzy approach was proposed for the time series of non-scheduled passenger air transportation with intra-series multiplicative changes. The method is based on the use of membership functions in the calculation of forecast values based on statistical indicators of intra-row changes. In regular air transportation, the intra-series changes of statistical indicators of time series are stable. On charter flights, these changes are unstable. This is due to the strong random effects of external factors (a sudden increase in demand for flights, economic changes, etc.) on the formation of charter flights. For this reason, the application of models based on trend changes does not give good enough results when building forecast models in charter air transportation. Therefore, to solve the problem, we propose to build the forecasting model of non-scheduled passenger air transportation using a fuzzy approach. The researched method was checked based on the actual data of the time series of charter flights. The obtained results were compared with classical forecasting models (ARIMA, Fine, Medium, and Coarse SVM), and it was noted that the results were obtained within acceptable limits.

Keywords: non-scheduled air transportation, forecasting, fuzzy logic, time series analysis, optimal model, classic forecasting models, statistical analysis, SVM method, kernel function

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Introduction

Forecasting demand for non-scheduled passenger air transportation presents unique challenges that stem from its inherent unpredictability and the highly customized nature of its services. Unlike scheduled air services that operate on fixed routes and timetables, non-scheduled air transportation, such as charter flights and private jets, must adapt to variable demand, fluctuating market conditions, and individual customer preferences. In this context, traditional forecasting methods, which rely on historical data and assume relatively stable demand patterns, often fall short. This is where fuzzy forecasting models come into play, offering a more adaptable and nuanced approach to predicting future demand in an environment rife with uncertainties.

The distinction between applying fuzzy forecasting models to non-scheduled versus scheduled air transportation highlights their adaptability and efficiency in handling uncertainty and variability, characteristics more prevalent in non-scheduled operations. To understand why fuzzy forecasting models are particularly optimal for non-scheduled air transportation, let's break down the fundamental differences between non-scheduled (charter, private flights, etc.) and scheduled air transportation, and then dive into the attributes of fuzzy forecasting models.

• Flexibility of Operations: Non-scheduled air transportation offers a high degree of flexibility in terms of destinations, timings, and routes. This is in contrast to scheduled air transportation, which operates based on a fixed timetable.

• Demand Variability: Demand for non-scheduled flights can vary significantly and unpredictably, influenced by numerous factors such as events, seasons, and individual client needs. Scheduled flights have more predictable demand patterns, making traditional forecasting models more applicable.

• Customization and Service: Non-scheduled services are often tailored to specific client requirements, affecting factors such as routing, stops, and onboard services. Scheduled services are standardized for efficiency and scale.

Fuzzy forecasting models excel in environments where data is uncertain, patterns are complex, and traditional statistical models struggle to capture the nuances of human behaviour and unpredictable events. These models use fuzzy logic to handle imprecision and partial truth, making them exceptionally suited for forecasting in situations with high variability and less historical data.

• Handling Demand Uncertainty: The inherent flexibility in demand for non-scheduled air transportation, driven by a myriad of unpredictable factors, makes fuzzy forecasting models ideal. These models can incorporate linguistic variables (like "high demand" or "low demand") that are not easily quantifiable, providing more accurate and adaptable predictions.

• Customization Needs: Fuzzy models can effectively account for the wide variety of customization in non-scheduled flights, which would be challenging for more rigid, traditional forecasting models. By considering the fuzziness in customer preferences and requirements, operators can better predict demand and preferences.

• Operational Flexibility: The operational flexibility required for non-scheduled air transportation benefits from the adaptive nature of fuzzy forecasting models. These models can quickly adjust to new data and scenarios, essential for managing the dynamic scheduling and routing of non-scheduled flights.

- Cost Efficiency in Uncertain Conditions: In the context of non-scheduled transportation, where each operation might differ significantly from the last, fuzzy forecasting helps in optimizing resource allocation, minimizing unnecessary expenditures on fuel, crew, and maintenance, thereby enhancing cost efficiency under uncertain conditions.

It should be noted that fuzzy prediction methods apply fuzzy numbers to account for uncertain changes in the input data.

Researchers have explored the use of Gaussian Support Vector Machines (SVM) methods in forecasting non-scheduled passenger air transportation processes in Heydar Aliyev International Airport. They determined that according to the results of calculations based on different Gaussian kernel functions, the medium Gaussian SVM model provided effective results. [1]

Fuzzy time series have also been used in demand forecasting by other researchers. In this study, they used the k-means approach, triangular fuzzy demand numbers, and weighted fuzzy logic connections. The experiment has shown that the proposed approach gives more effective results than other models considered in this work. [2]

Studies include fuzzy time series and gray forecasting methods applied to predict tourist arrival demand in the United States. The researchers found that it is not necessarily necessary to apply complex models to obtain optimal forecasting results.

The fuzzy logic and ARIMA model were compared by researchers to predict the passenger demand of the high-speed railway of Beijing-Shanghai in China. According to the results fuzzy logic predicts the passenger demand more accurately than the ARIMA model. [3,5]

Fuzzy time-series forecasting of tourism demand in Indonesia's Bali and Soekarno-Hatta islands has also been studied by researchers. The authors concluded that fuzzy time series are superior and provide optimal results compared to classical methods such as Box-Jenkins, seasonal ARIMA, Holt Winters, and time series regression.

In order to forecast short-term passenger flow demand at Hong Kong airport, researchers applied a combined method of singular spectrum analysis, adaptive network-based fuzzy inference systems, and advanced particle swarm optimization. [6,7]

In another study, researchers used a fuzzy time series model to predict the number of Japanese tourists visiting Taiwan each year. A new Fourier method was used to revise the analysis of the residual terms of the forecasts made by the fuzzy time series model. [8]

In the following studies, fuzzy theory was combined with the SVM method. In this study, a fuzzy rule extraction method from SVMs is presented to forecast tourism demand. [9]

The fuzzy time series (FTS) model has demonstrated an effective solution to the limitation of predicting approximate numerical forecast values of historical data. An improved fuzzy time series (IFTS) forecasting model using data variations has also been proposed by researchers to effectively forecast approximate numerical forecast values of historical data. It has been found that IFTS provides better accurate prediction results than other fuzzy SVRs.

The analyses conducted show that classical linear regression and trend models are often unable to deal effectively with various nonlinearities, complex uncertainties, and the chaotic behavior of observed stochastic processes. [10]

The time series of non-scheduled air transportation is formed by the influence of a number of external factors. When studied as a classical time series, the time series of this type of air transportation is considered to be a complex additive or multiplicative dependence of two limits: deterministic and stochastic. In this case, the first threshold is based on the trend model (approximation of functions, interpolation and extrapolation methods, smoothing, etc.), and the second threshold is based on various mathematical and stochastic methods (dispersion, factor and correlation analysis, autoregression methods, random number modeling methods, etc.). In many cases, the models built are limited to only known measurements and are not sufficiently adequate because the process characteristics outside the measurements are not taken into account during the case studies.

While fuzzy forecasting models can also benefit scheduled air transportation, especially in handling irregularities and seasonal variations, the structured nature of scheduled services – with extensive historical data and more predictable demand patterns – often makes traditional forecasting methods sufficiently effective. The strengths of fuzzy forecasting models are simply more aligned with the challenges presented by non-scheduled air transportation. The application of fuzzy forecasting models is particularly optimal for non-scheduled air transportation due to the high degree of uncertainty, variability in demand, and the need for operational flexibility. These models provide a robust framework for making informed decisions in the face of imprecise data, making them a valuable tool for improving efficiency and responsiveness in the non-scheduled air transport sector.

In this regard, it should be noted that it is very necessary to conduct research with the participation of fuzzy models in creating an optimal forecasting model for non-scheduled passenger air transportation.

The methodology

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, they 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 are reflected in the non-scheduled air transportation sector as well as in other areas. As a result, non-scheduled passenger air transportation for each country is country-specific, which complicates the application of classical methods. The fact that the changes are different in nature makes it difficult to apply the same classic forecast model to all countries. With this in mind, a fuzzy approach is applied to overcome this problem. Fuzzification of intra-line changes in non-scheduled passenger air transportation was carried out based on the statistical indicators of the line. Fuzzification can also be applied to other approaches, such as interval estimation, scale estimation, etc.

Another problem encountered in studies is the lack of data. 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 trend changes 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 a fleet of aircraft that remains stable for a certain period of time and carries out transportation based on it. This feature allows us to build forecasting models in a fuzzy approach based on actual time series data. In the conducted research, we have implemented the construction of the time series forecasting model of non-scheduled passenger air transportation using statistical indicators.

Solution method

Based on the supporting facts mentioned above, we propose to build a forecast model using a fuzzy approach, using the randomness of the intra-series changes of the statistical indicators of non- scheduled passenger air transportation to solve the problem.

Let's enter the following notation to build the model:

– *n:* the number of years involved in the research;

– x_{kj}: the amount of non-scheduled passenger air transportation in the j-th month of the k-th year (i=1, n;j =1,12)

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

$$M_{kj} = x_{kj} - x_{(k-1)} \quad (k = 2, n; j = 1,12) \tag{1}$$

In the time series calculated by the formula (1), the thresholds are positive (the case of increases in non-scheduled passenger air transportation) ($M^+ k_j$) and negative (the case of decreases) ($M^- k$j). 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 ($M^+ k_j$) or ($M^- k_j$) 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 ($MAX\pm(j)$, $MIN\pm(j)$ and S±(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, we can construct 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").

As we mentioned above, numerous factors affecting the time series of non-scheduled air transportation lead to the fact 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:

$$\mu^+(x,j) = \left\{ \begin{matrix} x: M\dot{I}N^+(j)/little\ growth\,, S^+_{average}(j)/average\ growth\,, \\ MAX^+(j)/too\ much\ growth \end{matrix} \right\} \tag{2}$$

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

Let's determine the characteristics of intra-series changes using the above formulas. For this, let's use the weighting coefficient of for each month, the mean square deviation, and intra-series fractal changes during the years in which the increase or decrease characteristics of intra-series changes were involved in the study.

$$\delta_j^{\pm} = \frac{\sum_{i=1}^{n^{\pm}} M_{ij}^{\pm}}{\sum_{i=1}^{n} |M_{ij}|}, \qquad j = \overline{1,12} \tag{3}$$

$$\sigma_j^{\pm} = \sqrt{\frac{\sum_{i=1}^{n^{\pm}} (M_{ij}^{\pm} - S_{ij}^{\pm})^2}{n^{\pm}}}, \quad j = \overline{1,12} \tag{4}$$

$$\nu_j^{\pm} = \frac{\sigma_j^{\pm}}{S_{average}^{\pm}} \quad , j = \overline{1,12} \tag{5}$$

Based on the base year, let's calculate the indicators for the forecast year as follows. Since the membership function characterizes the changes in the months of all years, its product with the weight coefficient can be used as the main indicator of the changes in the months of the years involved in the study.

$$Q^{\pm}(x,j) = \mu^{\pm}(x,j) * \delta^{\pm}(j) \tag{6}$$

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

$$P^{\pm}(j) = \sigma^{\pm}(j) * \nu^{\pm}(j) \tag{7}$$

We can accept the numerical value of the changes from the selected base year for the forecast year based on the formula (8):

$$R(x,j) = \left(Q^{+}(x,j) + P^{+}(j)\right) + \left(Q^{-}(x,j) + P^{-}(j)\right) \quad j = \overline{1,12} \tag{8}$$

Thus, using the indicators of the base year (n – 1) of the time series, we determine the forecast values for the next year. The prediction *(x_{nj}^{P})* is given as the sum of the corresponding threshold and the R(j) parameter calculated by the formula (8):

$$x_{nj}^{P} = x_{n-1j} + R_j(x_{n-1}) \ , \ j = \overline{1,12} \tag{9}$$

Statistics covering the years 2020-2023 were used to build a forecasting model based on fuzzy time series (Table 1). Based on the given statistical indicators, a forecast for 2023 is made based on the years 2020-2022, and the results will be compared with the actual indicators of 2023.

Table 1. Statistical indicators of non-scheduled passenger air transportation for 2020-2023

Months	Years			
	2020	2021	2022	2023
January	238	135	301	470
February	162	257	367	490
March	230	769	756	886
April	298	534	492	855
May	366	527	585	932
June	433	610	340	370
July	501	557	552	495
August	569	631	565	623
September	637	599	446	475
October	749	596	425	550
November	483	609	523	746
December	584	601	465	790

Note: by the author himself

Taking 2023 as the base year, the linguistic terms of fuzzy changes were determined as a result of the reports carried out according to formulas (1)–(2), and appropriate membership functions were constructed. According to Table 1, the characteristics of intra-row changes were calculated. The calculated membership function is defuzzified based on the statistical indicators calculated according to the formulas (3)–(5), and the forecast for 2023 is given according to the formulas (8)–(9) (Table 2).

Table 2. Forecast prices of non-scheduled passenger air transportation for 2023

Months	Rj	Forecast- 2023	Fact- 2023
January	14.63938	316	470
February	6.830616	374	490
March	95.53741	852	886
April	17.76326	510	855
May	24.19093	613	932
June	-13.6998	326	370
July	1.018109	553	495
August	-0.17134	565	623
September	38.11782	481	475
October	-15.3145	409	550

November	2.771475	525	746
December	-6.06723	458	790

Note: by the author himself

In order to compare the proposed model with models based on trend changes, reference is made to the literature by [1], [3] (Figure 1).

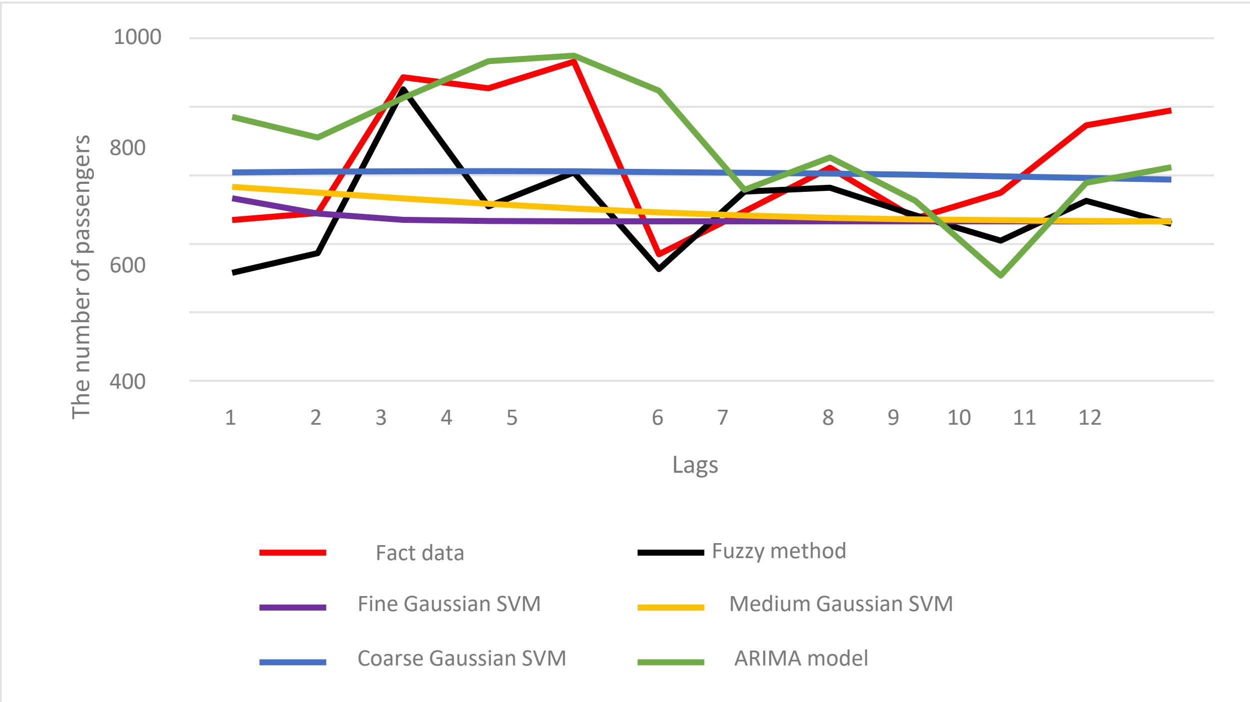

Figure 1. Comparative forecasting results of fuzzy, SVM, and ARIMA models

Note: by the author himself

In order to compare the obtained forecast results with our proposed results, let's look at the changes in the relative error of the forecast indicators with the actual values for the selected year (Figure 2). As can be seen from the figure, in all cases, the proposed model gives better results than the others. The average relative error of the studied models is 15.18% for the fuzzy method, 25.77% for the fine Gaussian SVM, 25.93% for the medium Gaussian SVM, 26.67% for the coarse Gaussian SVM, and 30.92% for the ARIMA model.

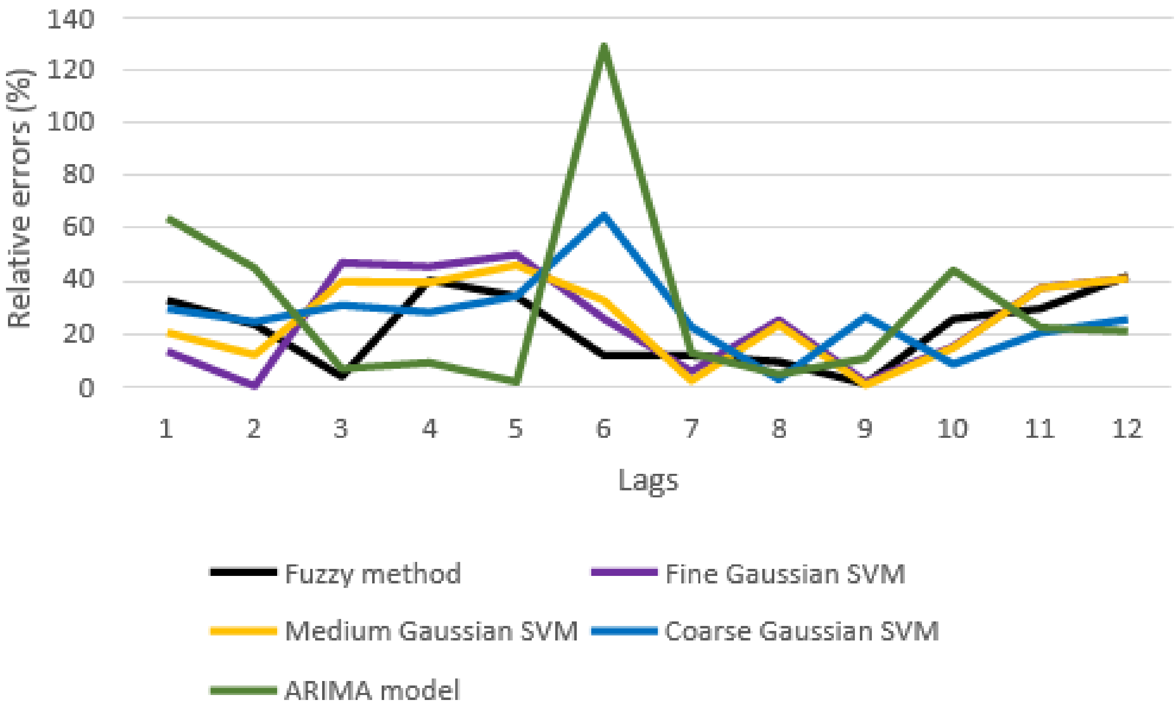

Figure 2. Relative error of forecast results of fuzzy, SVM, and ARIMA models based on actual indicators

Note: by the author himself

Findings/Discussion

Non-scheduled air transportation is formed depending on many internal and external factors. Some of these factors include the country's economic situation and social events. All other factors are formed completely randomly. In this case, the construction of the forecasting model is different from regular air transportation. Our research results show that the fuzzy method is more effective and optimal than other traditional methods. This method, suitable for the characteristics of non-scheduled air transportation, can be applied in future research in a hybrid form or in the construction of machine learning methods. Additionally, it should be noted that there is very little research on the forecasting of non-scheduled passenger air transportation. Applying forecasting models here by studying the characteristics of this type of air transportation and obtaining effective results is a scientific innovation. Other researchers can also apply predictive models using these results as a baseline.

Conclusion

A new approach to building a fuzzy forecasting model for classical time series with intra-series multiplicative changes is proposed. The method is based on the procedure for calculating forecast indicators from membership functions constructed using statistical indicators of intra- series changes in classical time series. The proposed method was applied to the time series of non-scheduled passenger air transportation. The results obtained on the basis of the computational experiment were compared with the average relative error between the forecast indicators calculated for the classical forecast models (ARIMA, SVM) and the actual indicators. The analysis of the results revealed that the proposed model gives 10–15% better results than the classical models.

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Бұлыңғыр тәсілдегі тұрақты емес жолаушыларды әуе тасымалының болжау моделі

Аңдатпа. Бұл жұмыста біз анық емес логиканың концептуалды негіздерін және оның жоспарлы емес жолаушыларды әуе тасымалы контекстінде болжау үшін қолдану мүмкіндігін қарастырамыз. Біз дәстүрлі болжау әдістерінің шектеулерін және анық емес тәсілді қабылдаудың негіздемесін көрсете отырып, тиісті әдебиеттерді қарастырамыз. Сонымен қатар, біз болжамды болжаудың ұсынылған моделін әзірлеуде қолданылатын әдістемені сипаттаймыз, оның өзгермелі операциялық жағдайларға бейімделуіне және оның авиациялық индустрияда шешім қабылдау процестерін жақсартуға арналған әлеуетіне баса назар аударамыз. Жүргізілген зерттеулерде қатар ішілік мультипликативтік өзгерістері бар тұрақты емес жолаушыларды әуе тасымалының уақыттық қатары үшін анық емес тәсілді пайдалана отырып болжау моделін құрудың жаңа әдісі ұсынылды. Әдіс жол ішілік өзгерістердің статистикалық көрсеткіштеріне негізделген болжамдық мәндерді есептеуде мүшелік функцияларды қолдануға негізделген. Тұрақты әуе тасымалы кезінде уақыттық қатарлардың статистикалық көрсеткіштерінің қатар ішілік өзгерістері тұрақты. Чартерлік рейстерде бұл өзгерістер тұрақсыз. Бұл чартерлік рейстердің қалыптасуына сыртқы факторлардың (рейстерге сұраныстың кенеттен өсуі, экономикалық өзгерістер және т.б.) күшті кездейсоқ әсерлеріне байланысты. Осы себепті чартерлік авиатасымалда болжамдық үлгілерді құру кезінде тренд өзгерістеріне негізделген үлгілерді қолдану жеткілікті жақсы нәтиже бермейді. Сондықтан, мәселені шешу үшін біз анық емес тәсілді пайдалана отырып, тұрақты емес жолаушыларды әуе тасымалының болжау моделін құруды ұсынамыз. Зерттелетін әдіс чартерлік рейстердің уақыттық қатарының нақты деректері негізінде тексерілді. Алынған нәтижелер классикалық болжау үлгілерімен (ARIMA, Fine, Medium және Coarse SVM) салыстырылды және нәтижелердің қолайлы шектерде алынғаны атап өтілді.

Түйін сөздер: жоспарлы емес әуе тасымалы, болжау, анық емес логика, уақыттық қатарларды талдау, оңтайлы модель, классикалық болжау модельдері, статистикалық талдау, SVM әдісі, ядро функциясы

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Нечеткий подход к модели прогнозирования нерегулярных пассажирских авиаперевозок

Аннотация. В этой статье мы углубляемся в концептуальные основы нечеткой логики и ее применимость к прогнозированию в контексте нерегулярных пассажирских авиаперевозок. Мы рассматриваем соответствующую литературу, подчеркивая ограничения традиционных методов прогнозирования и обоснование принятия нечеткого подхода. Кроме того, мы описываем методологию, используемую при разработке предлагаемой нечеткой модели прогнозирования, подчеркивая ее адаптивность к изменяющимся эксплуатационным условиям и ее потенциал

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для улучшения процессов принятия решений в авиационной отрасли. В этом исследовании был предложен новый метод построения модели прогнозирования с использованием нечеткого подхода для временного ряда нерегулярных пассажирских авиаперевозок с внутрирядными мультипликативными вариациями. Метод основан на использовании функций принадлежности при расчете прогнозных значений на основе статистических показателей внутрирядовых изменений. В регулярных авиаперевозках внутрирядовые изменения статистических показателей временных рядов устойчивы. В чартерных авиаперевозках эти изменения неустойчивы. Это обусловлено сильным случайным воздействием внешних факторов (резкий рост спроса на авиаперевозки, экономические изменения и т. д.) на формирование чартерных авиаперевозок. По этой причине использование моделей, основанных на трендовых изменениях, не дает достаточно хороших результатов при построении моделей прогнозирования в чартерных авиаперевозках. Поэтому для решения поставленной задачи предлагается построить модель прогнозирования нерегулярных пассажирских авиаперевозок с использованием нечеткого подхода. Исследуемый метод был протестирован на фактических данных временных рядов чартерных авиаперевозок. Полученные результаты были сопоставлены с классическими моделями прогнозирования (ARIMA, Fine, Medium и Coarse SVM), и было отмечено, что результаты были получены в приемлемых пределах.

Ключевые слова: нерегулярные авиаперевозки, прогнозирование, нечеткая логика, анализ временных рядов, оптимальная модель, классические модели прогнозирования, статистический анализ, метод SVM, функция ядра

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