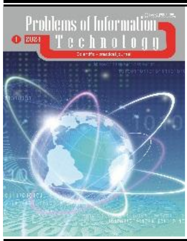

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# Support vector machines for forecasting non-scheduled passenger air transportation

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ABSTRACT

Forecasting non-scheduled passenger air transportation demand is essential for effective operational planning and decision-making. In this abstract, we explore the use of Gaussian Support Vector Machines (SVM) methods in forecasting non-scheduled passenger air transportation processes. SVM is a type of supervised machine learning algorithm that can be applied to various domains, including non-scheduled passenger air transportation. In classification and regression tasks, SVMs are considered especially useful. SVMs can be used to forecast passenger demand for specific routes or flights. By analysing historical data, including factors such as time of day, day of the week, etc., SVMs can help airlines estimate future passenger demand. This method is crucial for optimising ticket pricing and managing seat inventory. This research proposes the implementation of different Gaussian SVM methods for the forecasting of non-scheduled passenger air transportation.

## 1. Introduction

Non-scheduled air transportation is considered a type of commercial air transportation service. Unlike scheduled international air services, which are primarily regulated on the basis of bilateral agreements between states, non-scheduled international air services are generally authorised on the basis of national regulation. Although aviation regulators sometimes also regulate commercial non-transport operations (such as aerial crop dusting and surveying) as well as operations such as overflight and landing by private, corporate, military, and state aircraft, whether for transport or not, (ICAO, 2004). Non-scheduled air services may be performed by all types of air carriers and may be distinguished from scheduled services by the following characteristics: They are usually operated on:

- According to the charter agreement, several lessees can use the capacity of the aircraft on the relevant route.
- It is not subject to certain public service obligations imposed on scheduled air carriers, regardless of the load factor.
- with the financial risk of an underutilised payload being assumed by the charterer rather than the aircraft operator;
- In many cases, the aircraft's commercial capacity is sold by the carrier to tour operators, freight forwarders, or other entities. For this reason, the airline does not

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exercise any direct control over retail prices.

Overall, non-scheduled air transportation offers flexibility, convenience, and customisation for both passengers and cargo, catering to specific needs and preferences outside the realm of traditional commercial aviation. (ICAO, 2004).

Forecasting methods play a crucial role in the air transportation industry by providing insights into future demand, operational requirements, and market trends. Forecasting helps airlines, airports, and aviation authorities estimate future passenger demand. This is essential for optimising route planning, scheduling flights, and determining the need for infrastructure upgrades. Nowadays, machine learning algorithms are used for classification and regression tasks. In the context of air transportation, SVMs can be applied in various ways for tasks such as forecasting, classification, and optimisation.

## 2. Related work

In the context of air transportation, SVMs can be applied in various ways for tasks such as forecasting, classification, and optimization. In addition to the research conducted in this field, the SVM models also provide effective forecasting results in the air transportation field, as in Heng et al. (2009) and Shabri (2015).

Huang, Kecman, and Kopriva (2006) proposed an approach based on kernel-based algorithms for mining large data sets.

Platt (1999) proposed a fast algorithm for training support vector machines. In Fan et al. (2005) and in Fan et al. (2006), working set selection using second order information for training support vector machines and SMO-type decomposition methods for support vector machines were proposed.

Suykens and Vandewalle (1999) proposed least squares support vector machine classifiers, which solve a system of equations instead of a quadratic programming (QP) problem and lead to optimal results in calculations.

In Xie et al. (2013), hybrid approaches based on the LSSVR model for container throughput forecasting were proposed, and this research has brought effective solutions to cargo transportation.

It is clear from the research conducted on air transportation forecasting that the applied methods are based on regular air transportation. Research on non-scheduled passenger air transportation forecasting is scarce. For this reason, this research proposes different Gaussian kernel functions for forecasting passenger demand in non-scheduled air transportation. Unlike regular passenger air transportation, the time sequence of non-scheduled passenger air transportation varies within a certain limited time, although it is a random process. Regardless of how it changes in this limited area, a forecasting model for a specific airport can be built based on SVM methods.

## 3. Proposed approach

Non-scheduled air transportation is formed depending on the technical equipment of the existing aircraft fleet, the economic situation in the country, the demographic indicators of the population, the characteristics of the environment and many other factors. For this reason, the basic model of the process of non-scheduled air transportation should be created individually for each specific case (in our case, airports). In our case, different Gaussian kernel functions were used to define the base model. It should be noted that during the construction of the models, the time of flights and the number of passengers are taken as dependent and independent variables, respectively. Data for 12 months of 2022 and 9 months of 2023 were included in the study. Based on the data for 2022, the base model was selected, and based on the data for 2023, the kernel function (Medium Gaussian SVM) that provided the most optimal results was selected. Forecasting results for November, December 2023, January, February, and March 2024 are given based on the selected basis and optimal kernel function.

### 3.1. *Selection of a base model based on different Gaussian kernel functions*

Let's denote the kernel function by G to start calculations. It should be noted that, depending on the data involved in the study, different kernel functions are applied. In this research, we propose the selection and comparison of three Gaussian kernel functions for SVM methods. The $G(x_i, x_j)$ is considered the kernel function. There is a class of capacities $G(x_i, x_j)$ associated with the accompanying property. (Lin, 2021) This class of capacity incorporates the following features:

- Gaussian function (radial basis)

$$G(x_i, x_j) = exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) = exp\left(-r\|x_i - x_j\|^2\right) \quad (1)$$

Here, $r$ is a coefficient and its value is equal to $r = \frac{1}{2\sigma^2}$. Where $\sigma$ represents the width of the kernel. If the parameter $\sigma$ is close to zero, in this case, the SVM is overfitting. If $\sigma$ is large, it may lead to underfitting, resulting in the inability to classify all categories. Thus, parameter selection is crucial, and a suitable value must be selected for the kernel width. In order to achieve nonlinear separation in the kernel space, the SVM Gaussian kernel maps the data from the feature space to the higher-dimensional kernel space. According to our proposed approach, we can easily say that different Gaussian kernel functions can achieve different levels of classification accuracy. In the analysis, the Gaussian kernel function parameter G in Equation (1) is adjusted to different values according to the following assumptions:

$r_{fG} = \sqrt{p/4}$ for fine Gaussian,

$r_{mG} = \sqrt{p}$ for medium Gaussian, and

$r_{cG} = 4\sqrt{p}$ for coarse Gaussian,

where p is the number of features or the dimension size of in Equation (1). In terms of forecasting non-scheduled passenger air transportation, we can note that medium Gaussian has the ability to classify more complex data, coarse Gaussian has the ability to classify medium complexity data, and fine Gaussian has the ability to classify low complexity data. Thus, this research leads to the non-scheduled passenger air transportation forecasting results of the classification of these three Gaussian kernel functions and discusses their classification accuracy rates.

### 3.2. *Statistical analysis of the obtained results*

The root mean square error (RMSE) is

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y_i}-y_i)^2}{n}} \quad (2)$$

Here,

$\hat{y_i}, \hat{y_2}, \ldots, \hat{y_n}$ are predicted values; $y_1, y_2, \ldots, y_n$ are observed values; and $n$ is the number of observations.

The mean squared error (MSE) is

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y_i} - y_i)^2 \quad (3)$$

The average sum of all absolute errors (MAE) is

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y_i} - y_i| \quad (4)$$

R-squared ($R^2$) is a statistical measure that reflects the ratio of variance for the independent variable and the dependent variable (for which the forecasting results are determined) in computational models.

$$R^2 = 1 - \frac{\sum(\hat{y_i}-y_i)^2}{\sum(y_i-\bar{y})^2} \quad (5)$$

Here $\bar{y}$ is the mean of the y value.

## 4. Experimental results

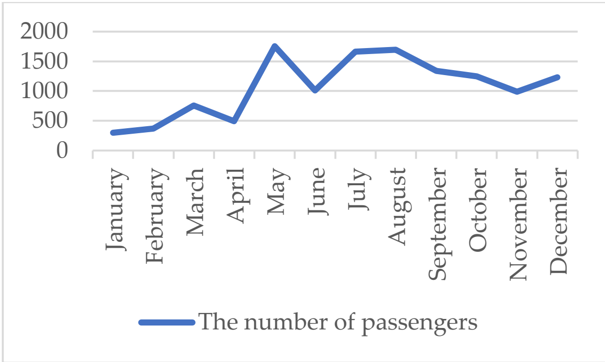


**Fig. 1.** Monthly statistics of non-scheduled passenger air transportation at Heydar Aliyev International Airport for 2022

In Fig. 1, SVM models with different Gaussian kernel functions are built based on monthly data for 2022. In formula (1), fine, medium, and coarse Gaussian SVM models are built. The results are plotted in Fig. 2-10. As an observation, for all three models, the actuals and predictors based on the monitoring points are given first. Then, one can discover how effective the relationship between the actual data and the forecasting data is. So, the points close to the straight line are accurately determined. The last step is the fact of errors between the obtained result and the outputs. As observed, points close to 0 are considered more effective; that is, the error is at a lower level. As it moves away from 0, the error increases, which affects the accuracy of the forecast. (Fig. 4), (Fig. 7), and (Fig. 10).

### 4.1. *Fine Gaussian SVM model and basic indicators*

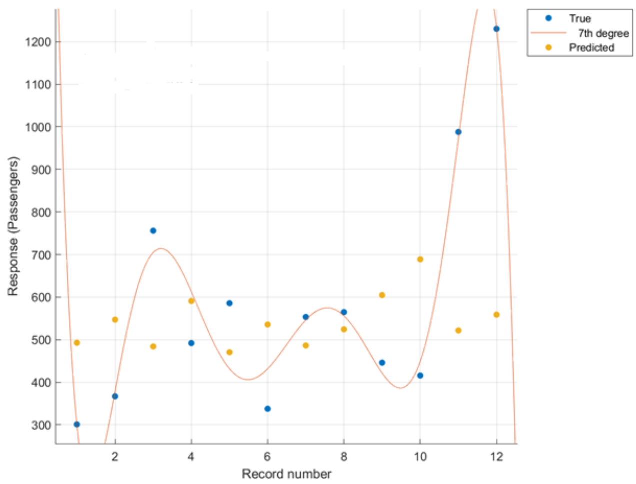


**Fig. 2.** Fine Gaussian SVM (Response-record number)

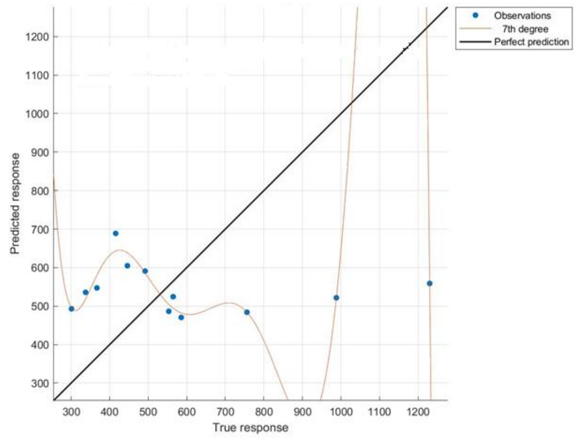


**Fig. 3.** Fine Gaussian SVM (observations-perfect prediction)

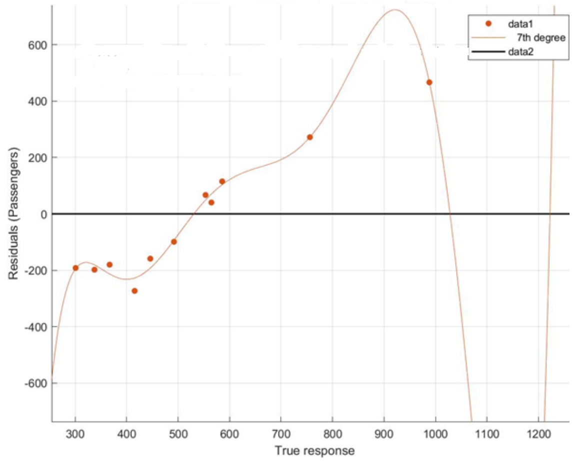


**Fig. 4.** Fine Gaussian SVM (residuals)

$$y = -495.8z^7 - 30.57z^6 + 2022.7z^5 + 118.4z^4 - 2085.2z^3 + 9.25z^2 + 452.04z + 488.7 \quad \text{(Fig. 2)} \qquad (6)$$

$$z = \frac{(x-\mu)}{\sigma} \qquad (7)$$

here, $\mu$- the mathematical expectation, $\sigma$- is mean-square bias.

where z is centred and scaled:

$\mu = 6.5$ , $\sigma = 3.6056$ (Fig. 2)

$$y = -325.37z^7 + 823.97z^6 + 539.57z^5 - 1658.4z^4 - 230.66z^3 + 722z^2 - 103.13z + 481.8 \text{ (Fig. 3)} \qquad (8)$$

where z is centred and scaled:

$\mu = 586.42$ , $\sigma = 278.81$ (Fig. 3)

$$y = 325.37z^7 - 823.97z^6 - 539.5z^5 + 1658.4z^4 + 230.6z^3 - 722z^2 + 381.9z + 104.6 \text{ (Fig. 3)} \qquad (9)$$

where z is centred and scaled:

$\mu = 586.42$ , $\sigma = 278.81$ (Fig. 4)

### *4.2. Medium Gaussian SVM model and basic indicators*

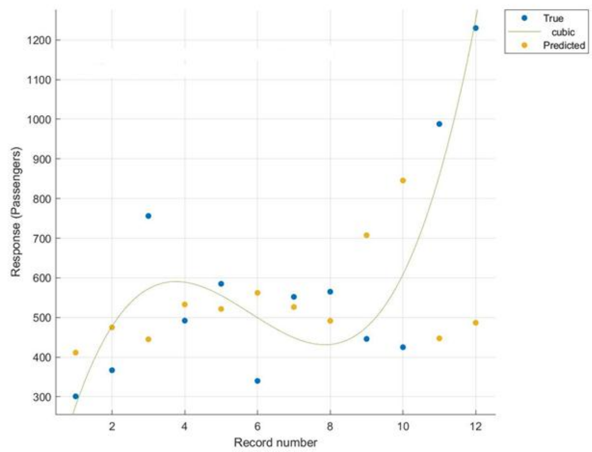


**Fig. 5.** Medium Gaussian SVM (Response-record number)

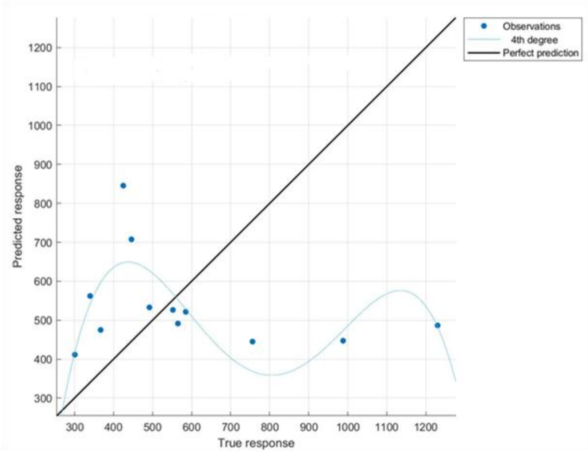


**Fig. 6.** Medium Gaussian SVM (observations-perfect prediction)

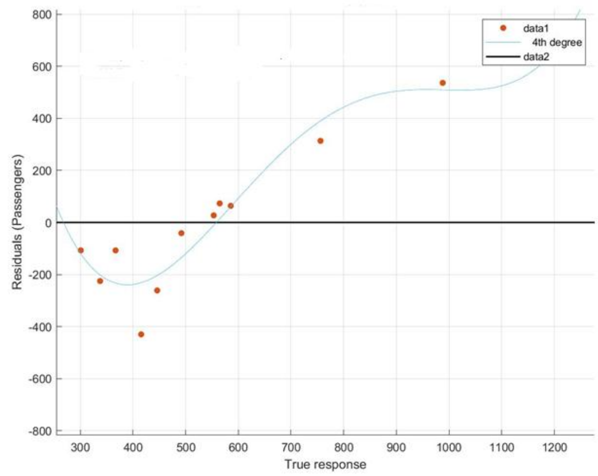


**Fig. 7**. Medium Gaussian SVM (residuals)

$$y = 217.25z^3 + 125.8z^2 - 186z + 471 \qquad (10)$$

where z is centred and scaled:

$\mu = 6.5$ , $\sigma = 3.6056$ (Fig. 5)

$y = -102.51z^4 + 302.3z^3 - 12.237z^2 - 339.66z + 525.66$ (Fig. 6) (11)

where z is centred and scaled:

$\mu = 586.42$ , $\sigma = 278.81$ (Fig. 6)

$y = 105.92z^4 - 309.43z^3 + 7.8659z^2 + 624.47z + 62.346$ (Fig. 7) (12)

$\mu = 586.42$ , $\sigma = 278.81$ (Fig. 7)

### 4.3. *Coarse Gaussian SVM model and basic indicators*

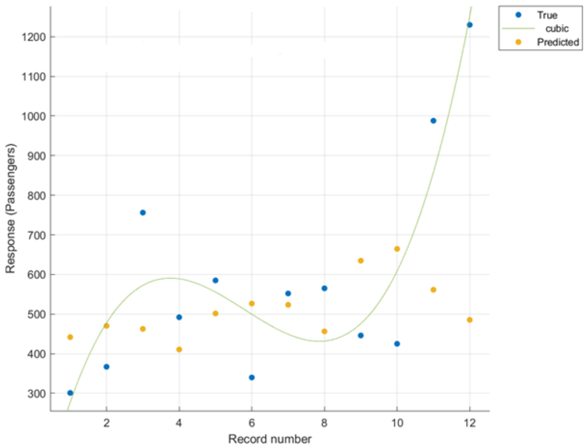


**Fig. 8.** Coarse Gaussian SVM (Response-record number)

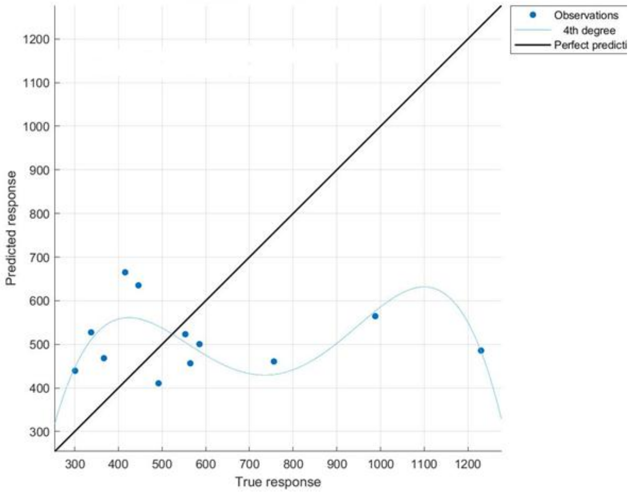


**Fig. 9.** Coarse Gaussian SVM (observations-perfect prediction)

**Table 1**. Resulting trained models

| | **Fine Gaussian SVM** | **Medium Gaussian SVM** | **Coarse Gaussian SVM** |
|---|---|---|---|
| RMSE | 238.812177 | 189.983185 | 216.7506 |
| MSE | 57031.256 | 36093.6106 | 46980.84 |
| MAE | 202.474872 | 146.322682 | 186.6744 |
| R-Squared | 0.747722 | 0.84739815 | 0.985924 |

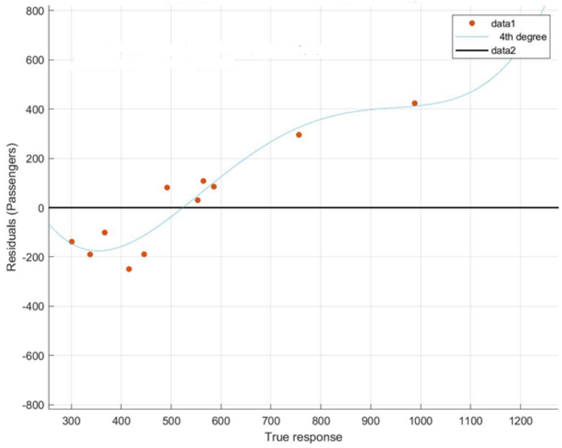


**Fig. 10.** Coarse Gaussian SVM (residuals)

$y = 217.25z^3 + 125.8z^2 - 186z + 471$ (13)

where z is centred and scaled:

$\mu = 6.5$ , $\sigma = 3.6056$ (Fig. 8)

$y = -76.193z^4 + 181.8z^3 + 61.919z^2 - 174.27z + 483.33$ (Fig. 9) (14)

where z is centred and scaled:

$\mu = 586.42$ , $\sigma = 278.81$ (Fig. 9)

$y = 76.193z^4 + 181.8z^3 - 61.919z^2 + 453.08z + 103.08$ (Fig. 10) (15)

where z is centred and scaled:

$\mu = 586.42$ , $\sigma = 278.81$ (Fig. 10)

The classification learner toolbox of Matlab has been used to design our SVM-based classifier, with training and forecasting steps.

Furthermore, the resulting SVM model of the fine Gaussian kernel function is presented in

Fig. 2-4. From these figures, we show that we have 12 observations. Additionally, equations and coefficients are defined in (6), (8), and (9). From the obtained results, the error rate for forecasting non-scheduled passenger air transportation using the Fine Gaussian SVM model is 26%, hence the necessity to test another kernel function (Table 1).

Next, the resulting SVM model of the medium Gaussian kernel function is presented in Fig. 5-7. From these figures, we show that we have 12 observations. Additionally, equations and coefficients are defined in (10), (11), and (12). From the obtained results, the error rate for forecasting non-scheduled passenger air transportation using the Medium Gaussian SVM model is 16%, hence the necessity to test another kernel function. (Table 1) Finally, the resulting SVM model of the coarse Gaussian kernel function is presented in Fig. 8-10.

From these figures, we show that we have 12 observations. Additionally, equations and coefficients are defined in (13), (14), and (15). From the obtained results, the error rate for forecasting non-scheduled passenger air transportation using the coarse Gaussian SVM model is 2%. We note that coarse Gaussian SVM gives the best results compared to fine Gaussian SVM (Table 1).

As can be seen from Table 2,3 and 4, the variation of the absolute error in the Fine Gaussian SVM model is relatively higher than in other models. The variation interval of the relative errors of the models is more satisfactory for the fine Gaussian and medium Gaussian SVM models.
The correlation coefficients R and standard error of the models were calculated to determine which of these models (fine and medium) to use in future forecasting calculations. (Table 1).

**Table 2.** Dynamics of absolute and relative errors in a fine Gaussian SVM

| Month/ Year | Actual data | Fine Gaussian SVM | Absolute error | Relativ e error |
|---|---|---|---|---|
| Jan-2023 | 770 | 592.6986 | 177.3014 | 23.02616 |
| Feb-2023 | 710 | 532.1904 | 177.8096 | 25.0436 |
| Mar-2023 | 886 | 530.6827 | 355.3173 | 40.10353 |
| Apr-2023 | 855 | 530.6795 | 324.3205 | 37.93222 |
| May-2023 | 932 | 530.6795 | 401.3205 | 43.06013 |
| Jun-2023 | 370 | 530.6795 | 160.6795 | 43.4269 |
| Jul-2023 | 495 | 530.6795 | 35.67954 | 7.207988 |
| Aug-2023 | 623 | 530.6795 | 92.32046 | 14.81869 |
| Sep-2023 | 250 | 530.6795 | 280.6795 | 112.2718 |
| Oct-2023 | 550 | 530.6795 | 19.32046 | 3.51281 |

**Table 3**. Dynamics of absolute and relative errors in a medium Gaussian SVM

| Month/ Year | Actual data | Medium Gaussian SVM | Absolut e error | Relative error |
|---|---|---|---|---|
| Jan-2023 | 770 | 748.1827 | 21.81729 | 2.833414 |
| Feb-2023 | 710 | 717.5672 | 7.567168 | 1.065798 |
| Mar-2023 | 886 | 665.562 | 220.438 | 24.88013 |
| Apr-2023 | 855 | 614.5275 | 240.4725 | 28.12544 |
| May-2023 | 932 | 577.4228 | 354.5772 | 38.04476 |
| Jun-2023 | 370 | 555.985 | 185.985 | 50.26621 |
| Jul-2023 | 495 | 545.8379 | 50.83788 | 10.27028 |
| Aug-2023 | 623 | 541.8392 | 81.16078 | 13.02741 |
| Sep-2023 | 250 | 540.5147 | 290.5147 | 116.2059 |
| Oct-2023 | 550 | 540.1437 | 9.856307 | 1.792056 |

**Table 4.** Dynamics of absolute and relative errors in a coarse Gaussian SVM

| Month/ Year | Actual data | Coarse Gaussian SVM | Absolute error | Relative error |
|---|---|---|---|---|
| Jan-2023 | 770 | 608.9622 | 161.0378 | 20.91401 |
| Feb-2023 | 710 | 616.3133 | 93.68668 | 13.19531 |
| Mar-2023 | 886 | 621.6296 | 264.3704 | 29.83864 |
| Apr-2023 | 855 | 624.917 | 230.083 | 26.91029 |
| May-2023 | 932 | 626.2451 | 305.7549 | 32.80632 |
| Jun-2023 | 370 | 625.7401 | 255.7401 | 69.11895 |
| Jul-2023 | 495 | 623.5751 | 128.5751 | 25.97478 |
| Aug-2023 | 623 | 619.9597 | 3.040318 | 0.488012 |
| Sep-2023 | 250 | 615.128 | 365.128 | 146.0512 |
| Oct-2023 | 550 | 609.3277 | 59.32767 | 10.78685 |

Consequently, we can conclude that the medium Gaussian kernel function has the best classification accuracy compared to the fine and coarse kernels. The obtained results show that the best model in terms of standard error is the medium-gaussian SVM model.

The forecasting results obtained based on the Medium Gaussian SVM model, which provides the most optimal results, are listed in Table 5.

**Table 5.** Forecasting results of non-scheduled passenger air transportation based on the Medium-Gaussian SVM model

| Months/year | The number of passengers |
|---|---|
| Nov-2023 | 557 |
| Dec-2023 | 535 |
| Jan-2024 | 537 |
| Feb-2024 | 541 |
| Mar-2024 | 525 |

## 5. Conclusions and future works

As a result of the conducted research, a basic model for non-scheduled passenger air transportation was established at Heydar Aliyev International Airport. According to the results of calculations based on different Gaussian kernel functions, the medium Gaussian SVM model provided effective results. With the application of the model, an effective forecasting model for non-scheduled passenger air transportation was established. Forecasting results were obtained based on the mentioned model. In future works, this model can serve as a basis for applying neural network models by adaptively changing the coefficients as the actual values are known for each year.

## References

ICAO. (2004). Manual on the Regulation of International Air Transport, Doc 9626, Second Edition. http://www.icao.int/meetings/atconf6/documents/doc%209626_en.pdf

Xie, G., Wang, S., Zhao, Y., & Lai, K. K. (2013). Hybrid approaches based on the LSSVR model for container throughput forecasting: A comparative study, Applied Soft Computing, 13(5), 2232–2241. http://doi.org/10.1016/j.asoc.2013.02.002

Suykens, J. & Vandewalle, J. (1999). Least squares support vector machine classifiers. Neural Processing Letters, 9, 293–300. https://doi.org/10.1023/A:1018628609742

Heng, H. J., Zheng, B. Z., & Li, Y. J. (2009). Study of an SVM-based air cargo demand forecast model. International Conference on Computational Intelligence and Security (CIS'09), Beijing, China, December (pp. 53–55). http://doi.org/10.1109/CIS.2009.180

Shabri, A. (2015). Least square support vector machines as an alternative method in seasonal time series forecasting, Applied Mathematical Sciences, 9 (124), 6207–6216. http://doi.org/10.12988/ams.2015.58525

Huang, T. M., Kecman, V., & Kopriva, I. (2006). Kernel-based algorithms for mining huge data sets: supervised, semi-supervised, and unsupervised learning. New York: Springer. https://doi.org/10.1007/3-540-31689-2

Platt, J. (1999). Sequential Minimal Optimisation: A Fast Algorithm for Training Support Vector Machines. Technical Report MSR-TR-98–14.

Fan, R. E., Chen, P. H., & Lin, C. J. (2005). Working set selection using second order ınformation for training support vector machines, The Journal of Machine Learning Research, 6, 1871–1918.

Fan, R. E., Chen, P. H., & Lin, C. J. (2006). A study on SMO-type decomposition methods for support vector machines, IEEE Transactions on Neural Networks, 17:893–908. https://doi.org//10.1109/TNN.2006.875973

Lin, S. L. (2021). Application of machine learning to a medium gaussian support vector machine in the diagnosis of motor bearing faults, Electronics, 10, 2266. https://doi.org/10.3390/electronics1018226