Forecast of Air Traffic Controller Demand Based on SVR and Parameter Optimization

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Abstract: As the main body of air traffic control safety, the air traffic controller is an important part of the whole air traffic control system. According to the relevant data of civil aviation over the years, a mapping model between flight support sorties and air traffic controller demand is constructed by using the prediction algorithm of support vector regression (SVR) based on grid search and cross-validation. Then the model predicts the demand for air traffic controllers in seven regions. Additionally, according to the employment data of civil aviation universities, the future training scale of air traffic controller is predicted. The forecast results show that the average relative error of the number of controllers predicted by the algorithm is 1.73%, and the prediction accuracy is higher than traditional regression algorithms. Under the influence of the epidemic, the demand for air traffic controllers will decrease in the short term, but with the control of the epidemic, the demand of air traffic controllers will return to the pre-epidemic level and gradually increase. It is expected that the controller increment will be about 816 by 2028. The forecast results of the demand for air traffic controllers provide a theoretical basis for the introduction and training of medium and long-term air traffic controllers, and also provide method guidance and decision support for the establishment of professional reserve and dynamic control mechanism in the air traffic control system.

Key words: air traffic controller; demand forecast; support vector regression (SVR); grid search; cross-validation

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0 Introduction

As the frontline personnel in the air traffic control system, air traffic controllers play a direct role in maintaining traffic order, ensuring flight safety and improving operation efficiency. In recent years, the civil aviation industry has developed rapidly. However, the insufficient and unbalanced development relationship between the increasing demand for flight services and the supporting air traffic controllers leads to low control efficiency, increased flight delays and even serious accidents. Therefore, forecasting the demand of air traffic controllers based on the air traffic and its future development is of great significance for improving the ability of air traffic control management and achieving high-quality development of air traffic control.

Air traffic controller demand refers to the number of controllers required to meet the flight support demand for a flight. Air traffic controller increment refers to the number of new controllers required to meet the increased flight support demand. With regard to prediction algorithms, scholars in domestic and international regions have invented and improved various prediction methods. He et al.[1] used the improved grey prediction based on the Markov chain theory to predict the increment of air traffic controllers. The experimental results show that the improved prediction algorithm has higher prediction accuracy than the traditional grey prediction, whereas the grey prediction is not suitable for long-term prediction. Kong et al.[2] collected the controller

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load related data through the control simulation experiment, and used the BP neural network algorithm to predict the controller load, while the neural network is prone to fall into the local minimum value. Ashley et al.[3] proposed an autoregressive summation moving average model to predict the traffic flow through the economic evaluation of airlines and airports, and speculated the long-term development plan in the future. Takashi et al.[4] utilized the deep belief network formed by multi-layer limited Boltzmann to capture features of time series, which could be used for short-term prediction. This algorithm has certain advantages in prediction accuracy, but it also increases the complexity of the algorithm.

The commonly used forecasting models include gray forecasting models, time series models, regression analysis models, Markov models, neural network models, etc. In order to obtain better prediction results under the premise of reducing the algorithm parameters and complexity, and avoid falling into the local optimal solution, this paper chooses the support vector regression (SVR) combined with parameter optimization. The main methods of SVR parameter selection mainly include grid search algorithms, genetic algorithms and chaos optimization. Gao et al.[5] adopted the grid search algorithm to optimize parameters in order to improve the accuracy of prediction and reduce computing load. Experimental results show that the method is more effective than the genetic algorithm and the particle swarm optimization algorithm. Gencoglu et al.[6] used the chaos theory to determine the optimal input variables by reconstructing the saturated embedding dimension of phase space, while the time series processed was required to be chaotic. Since the data processed in this paper are small samples, the chaos of time series is not obvious, so grid search is used to optimize parameters. In order to improve the robustness of the algorithm and avoid over-fitting, cross-validation is combined with grid search, which reduces the error caused by the random parameter selection and improves the generalization ability of the model[7].

At present, there are few researches on the forecasting of controller demand. This paper proposes a method for forecasting controller demand based on SVR and parameter optimization. In order to select the parameters of kernel function, according to historical data of flight support sorties and controller demand, an SVR model based on grid search and cross-validation is established to predict the demand for controllers in seven regional air traffic control bureaus. The prediction results show that the prediction algorithm in this paper has higher prediction accuracy than other prediction algorithms. Then, the forecast results are adjusted according to the impact of the outbreak of COVID-19 epidemic on the civil aviation industry. Finally, based on the adjusted prediction results and the training proportion of controllers in the three civil aviation colleges, the training scale of controllers in Nanjing University of Aeronautics and Astronautics (NUAA), Civil Aviation University of China (CAUC) and Civil Aviation Flight University of China (CAFUC) is determined, which provides reference for the training mode and strategy of air traffic controllers in universities in the future.

1 SVR Principle

SVR is a supervised learning algorithm and a regression algorithm derived from the classification algorithm of support vector machine (SVM). The idea is to first map the low-dimensional nonlinear data to the high-dimensional space through the nonlinear mapping function $\phi(x)$ for a group of data samples $(y_1, x_{11}, \cdots, x_{1n}), \cdots, (y_m, x_{m1}, \cdots, x_{mn})$, as shown in Fig.1[8].

Then the linear regression is carried out in this high-dimensional space to construct an optimal hyperplane to minimize the distance between data sam-

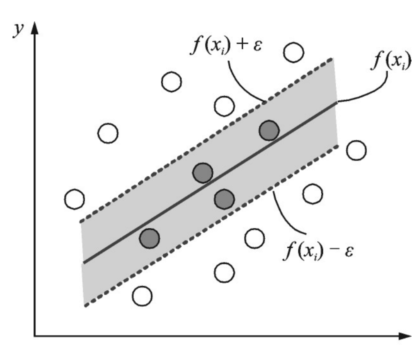

Fig.1 SVR diagram

ples and the hyperplane, so as to solve the linear indivisibility problem of the original space[9]. The objective function and constraint conditions are shown as

$$\min_{w,b,\sigma_i,\tilde{\sigma}_i} \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{m}(\mu_i + \tilde{\mu}_i) \tag{1}$$

$$\text{s.t.}\begin{cases} f(\boldsymbol{x}_i) - y_i \leqslant \varepsilon + \mu_i \\ y_i - f(\boldsymbol{x}_i) \leqslant \varepsilon + \tilde{\mu}_i \\ \mu_i, \tilde{\mu}_i \geqslant 0 \quad i = 1, 2, \cdots, m \end{cases} \tag{2}$$

where $\boldsymbol{w}$ is the weight vector, C the penalty factor, and ε the upper limit of error. μ_i, $\tilde{\mu}_i$ are the relaxation factors.

Lagrange multiplier is introduced to substitute the constraint conditions into the objective function, and the partial derivative of $\boldsymbol{w}, b, \mu_i, \tilde{\mu}_i$ is made to be zero by KKT condition, and the regression function is obtained [10].

$$f(\boldsymbol{x}) = \sum_{i=1}^{m}(\tilde{\alpha}_i - \alpha_i)K(\boldsymbol{x}, \boldsymbol{x}_i) + b \tag{3}$$

where $\tilde{\alpha}_i, \alpha_i$ are Lagrange multipliers. $K(\boldsymbol{x}, \boldsymbol{x}_i)$ is the kernel function, and b the offset.

Kernel function is used to calculate the dot product of nonlinear mapping between two vectors, which can simplify the calculation of inner product in the mapping space. Therefore, the selection of kernel function and its parameters has an important impact on the performance of the prediction model of support vector regression algorithm. The kernel functions commonly used in the process of solving practical problems are shown in Table 1.

Table 1 Common kernel functions

Kernel function	Formula	Parameter
Polynomial kernel	$k(\boldsymbol{x}, \boldsymbol{x}_i) = (\boldsymbol{x}^{\mathrm{T}} \cdot \boldsymbol{x}_i)^d$	$d \geqslant 1$ is the degree of the polynomial
Gaussian kernel	$k(\boldsymbol{x}, \boldsymbol{x}_i) = \exp\left(-\frac{\|\boldsymbol{x} - \boldsymbol{x}_i\|^2}{2\sigma^2}\right)$	$\sigma > 0$ is the bandwidth of the Gaussian kernel
Linear kernel	$k(\boldsymbol{x}, \boldsymbol{x}_i) = \boldsymbol{x}^{\mathrm{T}} \cdot \boldsymbol{x}_i$	
Sigmoid kernel	$k(\boldsymbol{x}, \boldsymbol{x}_i) = \tanh(\beta \boldsymbol{x}^{\mathrm{T}} \cdot \boldsymbol{x}_i + \theta)$	$\tanh(\cdot)$ is the hyperbolic tangent function, $\beta > 0, \theta > 0$

2 Parameter Optimization of SVR

In order to transform the original nonlinear separable feature space into a high-dimensional space and make the problem linearly separable in the high-dimensional space, the kernel function is used to map the data into the high-dimensional space, so that it is linearly separable[11-13]. The Gaussian kernel function is used in this paper because it rarely has dimensional disaster and the number of hyperplane parameters is less than that of polynomial kernel function.

The penalty parameter C and kernel parameter σ in the Gaussian kernel function are very important to the prediction results of the model. In practical application, $g = \frac{1}{\sigma^2}$ is used to find the optimal parameter combination (C, g) of the algorithm by combining grid search and cross-validation.

2.1 Grid search

Grid search is commonly used in dealing with nonlinear optimization algorithms. The basic idea is that based on the set parameter search range, several grids are divided within the parameter variable range to form grid points, and all the crossing points in the grid are all the parameter combinations to be searched. Then, each parameter combination in the grid is calculated to select the optimal parameter combination[14]. The density of grid points determines the calculation time and accuracy. Generally, the smaller the mesh size is, the higher the prediction accuracy will be, but the model calculation time will increase. The larger the mesh size is, the shorter the model calculation time will be, but the prediction accuracy may not be high enough. Therefore, when using the grid search, it is necessary to comprehensively consider the calculation accuracy and time, so as to ensure the practical application effect of the prediction model.

Cross-validation is a method used to eliminate model training bias caused by sampling randomness[15]. The demand prediction model in this paper adopts the K-fold cross-validation method to find the optimal parameter combination. The original data are evenly divided into K parts, and $K-1$ parts of them are selected as training data to build the model, while the remaining part is used as test data to test the model. After training K times, K models are obtained, and the average prediction accuracy of the test data of the models is used as the performance index of the model.

When evaluating the training data of the model, the parameters of SVR with the highest prediction accuracy are taken as the optimal parameters to improve the effectiveness and generalization ability of the prediction model. In the process of model training, the model accuracy is represented by the minimum mean square error[12]. The mean square error η_{MSE} is expressed as

$$\eta_{\mathrm{MSE}}=\frac{1}{n}\sum_{i=1}^{n}(y_i-\bar{y}_i)^2 \tag{4}$$

where y_i, $\bar{y}_i$ are the true value and the predicted value of the data, respectively.

2.2 Parameter optimization steps

The grid search method can traverse every possible parameter combination of C and g in the search range, and combine with cross-validation to find the optimal parameter with the smallest mean square error, thus avoiding the emergence of local optimal solution[16]. The basic steps of grid parameter optimization based on the K-fold cross-validation are described as follows.

Step 1 Establish parameter search grid. Let $x=[-a,a]$, $y=[-b,b]$, and all step size be λ, then the grid point of the parameter is $C=2^x$, $g=2^y$.

Step 2 The prediction error value is obtained based on K-fold. Divide the original data set into K parts, select one subset as the test set and the remaining $K-1$ parts as the training set, and train to get the best (C,g) of the model. Based on this model, the one test set is predicted, and the prediction error value is obtained. K models can be obtained by repeating the above steps, so that each piece of data has been tested, and the mean value of prediction error values of all models is taken as the final prediction error η_{MSE} corresponding to the set of parameters.

Step 3 Traverse all the grids to select the optimal parameter combination (C,g). Select another parameter combination in the search grid, and repeat Step 2. The prediction error η_{MSE} about all parameter combinations can be calculated, and sorted in descending order to select the optimal parameter combination (C,g) corresponding to the minimum η_{MSE}.

3 Forecast Results and Analysis of Air Traffic Controller Demand

3.1 Forecast of air traffic controller demand

3.1.1 Dataset and experimental settings

According to the civil aviation air traffic management statistical report which issued by Air Traffic Management Bureau of Civil Aviation Administration of China, the flight support sorties and air traffic controllers' quantity from 2010 to 2019 in north China, northeast China, east China, central south, southwest, northwest and Xinjiang can be obtained, which are collected by year. Due to the large order of magnitude difference between national flight support sorties and air traffic controller demand, direct training the model with raw data will result in large model prediction errors.

Therefore, in order to improve the calculation accuracy of the prediction model, while retaining data features and preventing over-fitting, the data are firstly normalized into $[0,1]$, so that data with different representations are set to the same scale. The normalization calculation formula is

$$\tilde{x}=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \tag{5}$$

where $x_{\min}$, $x_{\max}$ are the minimum and the maximum values in the same group of data, respectively.

In this paper, search grid ranges of C and g are $C\in[2^{-10},2^{10}]$, $g\in[2^{-10},2^{10}]$, and parameter search step-size is 0.1. In K-fold cross-validation, set $K=5$.

3.1.2 Experimental results and analysis

The number of air traffic controllers is predicted based on the SVR model of grid search and 5-fold cross-validation. The experiment is implemented based on Python3.8. The optimal parameter combination and the mean relative error (MRE) are shown in Table 2.

Table 2 Optimal parameter combinations and errors of regional forecast from 2010 to 2019

Region	Optimal parameter combination	MRE/%
North China	(8.574 2, 2.639 0)	2.67
Northeast China	(724.077 3, 0.038 5)	7.62
East China	(1.624 5, 45.254 8)	1.80
Central south	(445.729 1, 0.071 8)	5.95
Southwest	(22.627 4, 0.134 0)	10.74
Northwest	(103.968 3, 1.231 1)	1.63
Xinjiang	(1.624 5, 8)	3.63

The prediction results show that SVR has the best effect on the prediction of the number of air traffic controllers in northwest China. Forecasts for the number of air traffic controllers in the southwest are poor. There are two reasons: Firstly, the statistical error of the data of original flight support sorties or air traffic controllers in the region is large; Secondly, the error caused by the limitation of the prediction model itself. The outbreak of COVID-19 in 2020 had an impact on the aviation industry. In order to control the spread of the epidemic, many flights were delayed at the airport, and the demand for air traffic controllers was also affected. Therefore, it is necessary to adjust the air traffic controller demand according to the development trend of civil aviation industry under the influence of the epidemic. According to data released by the National Civil Aviation Work Conference and the National Civil Aviation Safety Work Conference in 2021, affected by the epidemic, civil aviation carried 420 million passengers in 2020, equivalent to 63.3% of that in 2019. In 2021, China's civil aviation passenger traffic was expected to return to about 90% of that before the epidemic. It was estimated that by the end of 2022, China's civil aviation passenger traffic would basically recover to the pre-epidemic level. According to the reduction of civil aviation in China, it was estimated that the number of air traffic controllers in 2020 would decrease by about 37% compared with that in 2019, increase by 43% in 2021 and 11% in 2022. So far, the number of air traffic controllers basically restores to the pre-epidemic level. The adjusted air traffic controller number demand predictions in 2021—2028 are shown in Table 3.

Table 3 Forecast of the number of regional air traffic controller demand in 2020—2028

Year	The number of controller in different regions							
	North China	Northeast China	East China	Central south	Southwest	Northwest	Xinjiang	Total
2020	1 018	505	1 313	1 358	905	590	179	5 868
2021	1 456	722	1 877	1 942	1 294	844	256	8 391
2022	1 616	801	2 084	2 156	1 436	937	284	9 314
2023	1 655	868	2 116	2 387	1 577	972	283	9 858
2024	1 724	936	2 163	2 564	1 707	1 032	278	10 404
2025	1 799	1 011	2 215	2 756	1 849	1 102	274	11 006
2026	1 879	1 094	2 272	2 964	2 003	1 181	291	11 684
2027	1 966	1 185	2 334	3 189	2 171	1 272	295	12 412
2028	2 059	1 286	2 401	3 433	2 354	1 375	320	13 228

At present, the overall age structure of controllers is stable, and the retirement of controllers has little impact on the turnover of front-line personnel in the next 5—10 years, which can be ignored. Therefore, the controller demand of the current year can be obtained by subtracting controller demand of the previous year, as shown in Table 4.

In order to further analyze the prediction accuracy of the regression model proposed in this paper, a comparison experiment of unary linear regression (ULR), time series forecasting and SVR is carried out. Based on the historical data of flight support sorties in seven regions from 2010 to 2019, different regression models are verified, as shown in Fig.2.

Table 4 Forecast of air traffic controller increment from 2022 to 2028

Year	The number of controller increment
2022	923
2023	544
2024	546
2025	602
2026	678
2027	727
2028	816

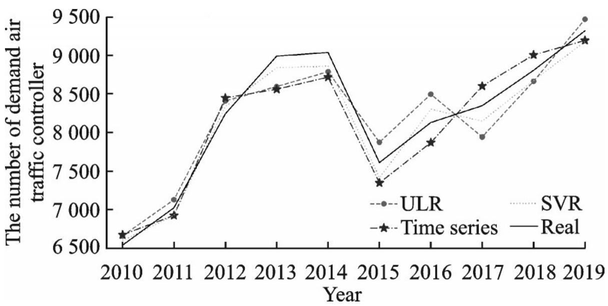

Fig.2 Comparison of three regression methods

According to Fig.2, the average relative error of ULR is 2.86%, the average relative error of time series prediction is 2.77%, and the average relative error of SVR is 1.73%. During the experiment, the calculation time of the SVR algorithm is shorter than that of the other two algorithms based on the same platform. The comparison results verify the effectiveness of the model in this paper.

Due to the impact of COVID-19, the number of national flight support sorties decreases, and the demand for controllers reaches a trough in 2020. After that, with the control of the epidemic, the civil aviation industry gradually recovers. In 2022, the demand for controllers will increase significantly and basically recover to the pre-epidemic level. In the post-epidemic era, the number of flight support sorties will increase steadily, and the demand for controllers will gradually increase from 2023 to 2028. With the dynamic change of civil aviation industry, the demand for controllers also may have a dynamic change. When the demand for controllers decreases, it is necessary to optimize the structure of the controller team, and reasonably adjust the working time and shift frequency to reduce the unnecessary waste of resources. When the demand for controllers gradually increases, human resources should be guaranteed to ensure that there are enough positions to introduce new controllers.

3.1.3 Ablation study

The above experiments determine the optimal parameter combination of Gaussian kernel function. The flight support sorties in each region in 2020—2028 are predicted by the grey prediction method. Then the predicted number of air traffic controllers in the corresponding year can be obtained by substituting it into the regression prediction model. In order to compare the effects of different kernel functions (Table 1) on the regression model and on the forecast of the number of controllers, based on the data of the flight support sorties and the number of controllers in seven regions from 2010 to 2019, the statistical average relative errors are shown in Table 5.

Table 5 Kernel function comparison test error %

Kernel function	Polynomial kernel	Gaussian kernel	Linear kernel	Sigmoid kernel
MRE	6.63	4.86	5.09	5.67

According to the error judgment in the Table 5, the Gaussian kernel function is relatively stable in SVR, and the regression model training effect is good. When predicting the number of controllers, the average relative error is 4.86%, which is smaller than that of the other three kernel functions. In addition, the Gaussian kernel function seldom has the disaster of dimensionality while realizing the nonlinear mapping. Compared with the polynomial kernel function, the number of hyperplane parameters is less and the numerical calculation is reduced. Therefore, this paper finally chooses the Gaussian kernel function.

3.2 Forecast of scale of college air traffic controller training

The main source of new controllers recruited by the Civil Aviation Administration of China (CAAC) is the students who major in control and the in-service personnel of control units who have been both systematically trained in universities with training qualifications. At present, there are three major universities in China with training qualifications and certain recruitment scale: NUAA, CAUC and CAFUC. According to the increase in demand for controllers predicted in this paper and the proportion of students from different universities working for CAAC, the scale of controller training in different universities can be predicted, so as to provide reference for the teaching and enrollment of universities. The training number of college controllers from 2022 to 2028 is shown in Table 6.

Table 6 Training number of air traffic controller from 2022 to 2028

Year	Training number of different universities		
	NUAA	CAUC	CAFUC
2022	69	435	419
2023	40	257	247
2024	41	258	248
2025	45	284	273
2026	50	320	308
2027	54	343	330
2028	61	385	370

According to the forecast results of the training scale of controllers, the number of controllers needed to be trained by the three universities will reach the peak of recent years in 2022, and the total number is expected to 923. After 2023, it will fall back to the basic level of pre-epidemic, and then increase steadily year by year. With the expansion of the scale of controller training in universities, the improvement of education resources allocation and the construction of high-level teachers also need to be speeded up to meet the requirements of controller training in the new situation.

4 Conclusions

SVR and parameter optimization algorithm are adopted to predict the future demand and the training scale of air traffic controllers in universities based on the national flight support data and the existing controller data. The main conclusions are as follows:

(1) Using grid search and 5-fold cross-validation can improve the performance of the optimal solution. The accuracy of prediction algorithm can be improved highly by using SVR that also can reduce the difficulty of algorithm design and the complexity of algorithm parameters. In the future, the SVR algorithm can be improved and combined with other prediction algorithms to achieve better prediction performance.

(2) The demand for controllers in the future will change in a U-shape. Affected by the epidemic, the number of national flight support sorties will be reduced. The demand for controllers will reach a trough in 2020 and recover from 2021. It is expected that it will return to the pre-epidemic level in 2022. After that, the demand for controllers will keep rising steadily.

(3) The training scale of controllers in universities will be gradually expanded. With the improvement of the epidemic situation and the recovery of civil aviation, more controllers will be needed. It is expected that the training scale of controllers will reach the peak in 2022 when the civil aviation industry fully recovers. Then it will fall back to the normal level and expand year by year.

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Author contributions Ms. **ZHANG Yali** designed the study, complied the models and wrote the manuscript. Prof. **ZHANG Honghai** contributed to complying the models and data selection for analysis and simulation design. Dr. **LI Shan** contributed to adding supplement for revised version and adjusting the paper format. All authors commented on the manuscript draft and approved the submission.

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基于支持向量回归机和参数优化的空中交通管制员需求量预测

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摘要：空中交通管制员作为落实空管安全工作的主体，是整个管制系统的重要环节。本文根据历年民航局相关数据，首先采用基于网格搜索和交叉验证的支持向量回归机(Support vector regression, SVR)预测算法，构建了飞行保障架次与管制员需求量之间的映射模型；然后通过模型预测了7个地区空管局的管制员需求量；最后根据各民航高校就业数据，对未来高校管制员的培养规模进行预测。预测结果表明：本文算法预测的管制员数量平均相对误差为1.73%，相比传统回归算法精度有所提高。受疫情影响，短期内管制员需求量将有所下降，但随着疫情得到控制，管制员需求量将回升至疫情前的水平并逐步提升，预计到2028年的管制员增量约为816人。管制员需求量的预测结果为中长期空管人员的引进和培养提供了理论依据，也为空管系统建立专业人员储备和动态调控机制提供了方法指导和决策支持。

关键词：空中交通管制员；需求预测；支持向量回归机；网格搜索；交叉验证