An Controller Workload Forecasting Method Based on Flight Plan

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Abstract. The significant growth of air traffic volume in the next few years requires a more accurate method of controller load assessment. Under the current framework of pre flight plan management, the most important thing is to quantify the control work of controllers according to the flight plan and find a reasonable method to evaluate their work. We present a controller load evaluation method based on flight plan. The first part aims to analyze the elements of the flight plan that affect the work of the controller, and the second part will be devoted to evaluating the controller load according to the flight plan. Finally, the practical application will be discussed.

Keywords: Controller workload · NNET · SVM · Random forest · Flight plan

1 Introduction

In recent years, with the rapid increase of air traffic flow, air traffic management (ATM) system is also constantly improving its capacity to cope with the increasing flight flow. The control seat has been overloaded for a long time. Accurate evaluation and prediction of controller load has become an urgent research task. In recent years, the frequency and frequency of air traffic unsafe incidents have increased significantly, most of which are caused by control reasons. Therefore, the prediction of controller load is of great significance to accurately grasp air traffic safety. We take the evaluation of controller load as the gateway premise, eliminates the hidden dangers in advance and increases the response ability.

The research on controller load is mainly different in the evaluation methods of workload, mainly focusing on the following two aspects: subjective evaluation and objective evaluation. The subjective evaluation method is to evaluate the work of the controller, the number of calls per unit time, duration and other behaviors. In this regard, the "DORATASK" method [1] proposed by the British operations research and Analysis Council and the "MBB" method [2] proposed by German scientist Messerschmidt are listed as publicly recommended methods by ICAO [2]. Reid and Nygren [3] proposed SWAT method in 1988, and Hart and Staveland [4] of NASA Ames Research Center proposed NASA-TLX (National Aeronautics and space administration task loading index) method. With the development and maturity of related technologies, the research on objective

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evaluation methods is also developing and improving. Zhao and others [5] analyzed and studied the variation law of ECG signal with working time by using principal component analysis, and came to the conclusion that rrmean and SDNN can evaluate the fatigue state. In 2020, Wang and Chen [6] proposed the method of evaluating load by EEG signal. Friedrichs and Yang [7] used eye movement recognition technology to identify and evaluate the controller load. However, the above subjective method has the problems of strong subjectivity and weak timeliness, and the objective method will interfere with the normal work of the controller because of wearing measuring equipment. However, from the perspective of cognition, as the core of the air traffic system, the controller needs to understand the airspace and its situation evolution including aircraft location and other information with the help of equipment, and make adjustments in case of emergencies, which is also the main cause of the workload of the controller. Therefore, Delahaye et al. [8, 9] proposed to establish a controller load evaluation system based on four indicators: traffic density, convergence, dispersion and sensitivity through the analysis of aircraft position and heading in airspace.

In recent years, with the development of machine learning and its application in the field of air traffic control, scientific research achievements continue to emerge. Zhang and others [10] took the lead in applying BP neural network to the field of air traffic control, and built a universal and feasible air traffic control operation quality evaluation system based on the universal collectability of data; Wen and Wang [11] used the ridge regression BP neural network model to predict and evaluate the controller load by analyzing and calculating the air traffic complexity evaluation index. Subsequently, Yue and others [12] proposed to use the machine learning model to cluster analyze and predict the health status of the control seat through the exercise data.

To sum up, domestic scholars' research on the workload of controllers mostly starts from objective data and does not consider the subjective factors of controllers in the process of control. We analyze the flight plan data and forecasts the controller load through the of machine learning model. It is helpful to fully grasp the operation of air traffic control system and provide basis for controller scheduling management and dynamic capacity management.

2 Flight Plan Index Selection

According to the requirements of relevant specifications [13], the flight plan usually needs to include dozens of items, including route direction, flight altitude and waypoints in and out of the flight area. The actual data summarized by the air traffic control department also includes the number of aircraft and the flow of sectors at peak hours. In actual control, there are many indicators that will not affect the controller load, such as the maximum takeoff and landing weight of aircraft. Therefore, through the questionnaire survey of front-line controllers, 10 factors in the flight plan that will affect the controller load are obtained as the analysis data of this paper, as shown in Table 1.

3 Controller Load Evaluation Method

The European aviation safety organization [14] puts forward the relationship model between controller workload and control work, as shown in Fig. 1.

Table 1. Flight plan index and meaning.

Index	Index name	Index meaning
C1	Number of aircraft in sector	Total number of aircraft operating in sector
C2	Peak value of aircraft number in time period	The maximum number of aircraft in the sector in all time nodes in the time period
C3	Number of aircraft whose control power is transferred	The number of aircraft entering and leaving sectors handed over within the time period
C4	Number of aircraft with altitude change	The number of altitude changes of all aircraft in the sector in the time period
C5	Number of aircraft in conflict	The number of times all aircraft in the sector have conflicts in the time period
C6	Number of aircraft with changed course	The number of heading changes of all aircraft in the sector within the time period
C7	Number of aircraft with speed change	The number of speed changes of all aircraft in the sector in the time period
C8	Number of inbound and outbound paths	The number of arrival and departure paths used by all aircraft in the sector within the time period
C9	Number of inbound and outbound points	The number of arrival and departure points used by all aircraft in the sector within the time period
C10	Model mixing factor	The number of aircraft types in operation in the sector within the time period

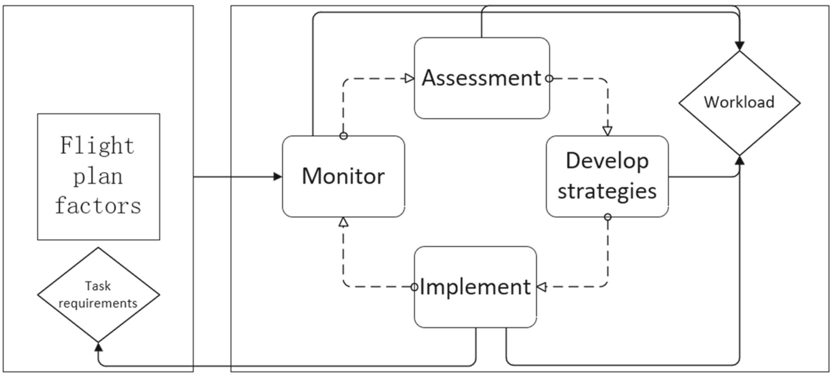


Fig. 1. Controller workload model

The model divides the generation of controller workload into two parts: task demand of external factors (i.e. the influencing factors of controller workload) and the processing process of internal factors. The approved flight plan triggers the mission requirements. The controller circularly monitors, evaluates, formulates control strategies and executes four processes according to the mission requirements obtained from observation. It can be seen that the controller's physiological and thinking load generated by executing four processes through observing task requirements is the controller's workload.

Based on the above analysis, "Doratask" method is selected as the evaluation method of controller load. In this method, the work of the controller is divided into three categories. One category is the invisible work, that is, the executive part in the figure above, including the routine control work of the controller, the communication of conflict resolution and filling in the progress sheet, which can be recorded and timed by the observer; The second category is invisible work, that is, the part of monitoring, evaluation and strategy formulation in the above figure, which mainly refers to the work of the controller monitoring the radar screen, comparing the progress sheet and thinking; These two types of work occupy most of the working time. In addition, the work of the controller also includes the third part, namely the recovery time. The workload evaluation for specific sectors and air traffic conditions is the sum of visible and invisible working hours, plus the recovery time, which is the workload of the controller. The visible part should account for about 50% of the whole workload, that is, the total workload is about twice the visible workload.

4 Controller Load Forecasting Based on Machine Learning

4.1 Data Acquisition

Xiamen Gaoqi International Airport is located in Xiamen, Fujian Province. As a 4E Civil International Airport, it plays an important role as a regional aviation hub in the southeast coastal area of China. In the whole year of 2020, Gaoqi airport has completed 16 710 197 passenger throughput, 278 336.4 tons of cargo and mail throughput, and 139 827 take-off and landing sorties, all of which are in the forefront of China. Its relevant data are highly representative.

We select the complete flight activity data in Xiamen air traffic control station system for statistics. Among them, the flight plan data includes the number of aircraft in the sector executing the flight plan, the peak number of aircraft in the time period, etc.; The radar track mainly records the longitude and latitude, altitude, heading, flight speed and other flight information during flight; The land air communication data is the audio file for command transmission and information transmission between the controller and the pilot. After analyzing such data, the controller workload can be obtained according to the "DORATASK" method. In this paper, the actual time span is two hours, and the data in the actual work of the controller in this stage are collected. 2 043 groups of effective data are obtained from the system, of which 80% and 1 634 items are used for the construction of the training set of the machine learning model, and the remaining 20% and 409 items are used for the verification and analysis of the model.

4.2 Model Building

Machine learning refers to automatically summarizing and sorting out some laws from massive data by computer, and obtaining a certain prediction model. The unknown data can be predicted by constructing a machine learning model. In the process of building machine learning model, we need to preprocess the collected data, and divide the data set into two parts: training set and test set. The training set is used to build the machine learning model, and the test set is used to verify the model. Because this paper has collected data and built the model through the data, this method belongs to supervised learning. Therefore, this paper selects three common supervised learning models: support vector machine [15], random forest [15] and neural network [15]. The model construction process can be summarized as follows:

(1) Data collection
The data collected in this article has been introduced in the previous section.
(2) Data processing
Because the collected data will inevitably have problems such as incompleteness and inconsistent format, it is necessary to process the data, including normalization, standardization, discretization and so on. In this paper, the normalization method is used to preprocess the data, and the formula is:

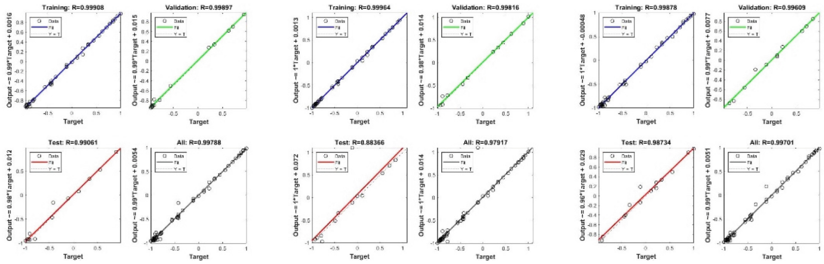
$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

where $X_{\max}$ and $X_{\min}$ are the maximum and minimum values respectively; X is the original value; X_{norm} is the normalized value.
(3) The training and testing model
The training set and test set are constructed for the processed data. In this paper, 10 indicators collected from the flight plan are selected as the input and the controller load as the output to build the model. In the construction of the SVM, the Gaussian inner product kernel function is selected, and the parameter gamma in the kernel function is 0.14 and the penalty coefficient is 1; The parameters of random forest are the default values; The number of neurons in the hidden layer of NNET is 30, and the weight attenuation parameter is 0.001.
(4) Model evaluation
Through the analysis of the test results of the model, the prediction effect of the model is evaluated.

4.3 Comparative Analysis of Models

Through the analysis of the calculation results, the accuracy of the training set and test set of the three models can be obtained, as shown in Fig. 2.

The results of training set show that the prediction accuracy of support vector machine is lower than that of neural network and random forest. The results of the test set show that the prediction effect of neural network is the best among the three models.



(1) Prediction results of NNET (2)Prediction results of SVM (3)Prediction results of random Forest

Fig. 2. Prediction results of machine learning models

5 Conclusion

This paper proposes to evaluate the controller load based on flight plan. Firstly, the factors affecting the controller load in the flight plan are screened in the form of questionnaire. Secondly, the "DORATASK" method is used to evaluate the controller workload. Finally, three machine learning models of SVM, random forest and NNET are introduced to predict the controller load. The effect of neural network is the best in the overall performance. In the process of model construction, we choose to build the model based on the data in the actual flight control process, and the results have a good guiding role for the actual control. The prediction results of the model prove the feasibility and rationality of the prediction method.

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