En-route Sector Complexity Control Strategies in Air Traffic Management

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Abstract: Along with the rapid development of air traffic, the contradiction between conventional air traffic management (ATM) and the increasingly complex air traffic situations is more severe, which essentially reduces the operational efficiency of air transport systems. Thus, objectively measuring the air traffic situation complexity becomes a concern in the field of ATM. Most existing studies focus on air traffic complexity assessment, and rarely on the scientific guidance of complex traffic situations. According to the projected time of aircraft arriving at the target sector boundary, we formulated two control strategies to reduce the air traffic complexity. The strategy of entry time optimization was applied to the controllable flights in the adjacent upstream sectors. In contrast, the strategy of flying dynamic speed optimization was applied to the flights in the target sector. During the process of solving complexity control models, we introduced a physical programming method. We transformed the multi-objective optimization problem involving complexity and delay to single-objective optimization problems by designing different preference function. Actual data validated the two complexity control strategies can eliminate the high-complexity situations in reality. The control strategy based on the entry time optimization was more efficient than that based on the speed dynamic optimization. A basic framework for studying air traffic complexity management was preliminarily established. Our findings will help the implementation of a complexity-based ATM.

Key words: air traffic management (ATM); air traffic situation; air traffic control; complexity-based management; traffic complexity

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0 Introduction

The existing air traffic control service (ATCS) focuses on the separation maintenance and conflict resolution between two aircraft in local sector as well as other tactic deployment behaviors, but cannot macroscopically understand air traffic situation evolution. Consequently, conflict chain reaction may occur during conflict resolution, and even the surrounding sectors will be adversely affected[1-3]. Data suggest that under current complex environments with high traffic density, the operational error probability of controllers is gradually rising[4]. When adverse saturations occur, the capability of controllers to recover traffic situations is also severely declining[5]. The major influence factor on the workload of managers is the complexity degree of air traffic situations. Based on the concept of air traffic complexity, researchers should be able to effectively judge the complexity of air traffic situations.

Since Schmidt proposed the concept of air traffic complexity based on the "index of difficulty" in 1976, air traffic complexity has been closely related with the workload of controllers and the sector ca-

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pacity and has been treasured by researchers of ATM[6]. Meckiff defined the complexity as the measuring difficulty faced by air traffic controllers when specific traffic conditions occur, and described it as a three-element function, including the geometrical characteristics of air traffic, the operational procedures of traffic processing, and the individual characteristics and behaviors (experiences, habits) of controllers[7]. Since the concept of "free flight" was put forward, NASA and other organizations have proposed the concept of dynamic density that reflects the degree to which the characteristics of air traffic flow affect the workload of controllers. Based on dynamic density, researchers have continually modified the selection of complexity parameters and the determination of weights, and further expanded its application fields[8-11]. However, "dynamic density" is faced with two limitations. First, the weights of factors can only be applied to specific airspaces, not in a common use[12]. Second, relevant studies yet depend on observable behaviors as the standards to measure the workload of controllers[13]. Some researchers tried to compute complexity by directly using the position and speed of aircraft as well as other inherent factors[14-17]. Though they could effectively describe the historical evolution trend and process of air traffic situations, they focused on the conflicts between air traffic flows and ignored the influence relationships among flight individuals. Moreover, due to the large amount of calculations, they cannot adapt to the real-time and fast computation of air traffic complexity. Zhu et al. proposed a new model to measure air traffic complexity based on small samples[18]. Wee et al. developed a dynamic tactical complexity model, known as conflict activity level (CAL) that evaluates the likely aircraft flight shape profile based on its current and projected position and trajectory[19].

As for the problem of air traffic complexity control, Yousefi et al. proposed a complexity control method based on airspace reconfiguration. With this method, each sector was redivided so as to ensure the complexity balance among different sectors[20]. Under the fixed space structure, however, this method cannot diminish the complexity in the space.

In this study, the air traffic complexity objective measuring methods proposed in our previous research are introduced[21-23]. Then, we further propose complexity control strategies for scientific guidance of air traffic situations. Since multiple objectives, including complexity, flight delay and flight adjustment quantity, should be considered during air traffic complexity management, physical programming is introduced. Further, two complexity control models are designed, including (1) a complexity control model based on the sector entry time optimization used for controllable flights in adjacent upstream sectors, and (2) a complexity control model based on flying speed dynamic optimization used for within-sector flights. Finally, the algorithm to solve the complexity control models is presented. Based on the actual radar data of four sectors, the simulations are conducted to verify the effectiveness of the models and the algorithm.

1 Models and Algorithm

1.1 Air traffic complexity measuring models

Air traffic complexity originates from the dynamic multi-factor interaction of air traffic situations under the influence of various random factors. For this reason, we incorperated the features of complex networks in our previous research and built air traffic situation dynamic weighting network models. Then based on the interrelations among the network elements, we proposed an air traffic complexity measure algorithm. The basic computational steps are listed below[23].

Step 1 Complexity measurement for aircraft and aircraft relationship

Let $E_{i,j}(t)$ be the ellipsoid distance between aircraft i and j at time t, and it can be calculated as

$$E_{i,j}(t)=\sqrt{\left(\frac{\Delta x_{i,j}^2(t)}{a^2}+\frac{\Delta y_{i,j}^2(t)}{a^2}+\frac{\Delta z_{i,j}^2(t)}{b^2}\right)} \quad (1)$$

where $\Delta x_{i,j}(t)$, $\Delta y_{i,j}(t)$, $\Delta z_{i,j}(t)$ are the longitudinal, the lateral and the vertical separations between aircraft i and j at time t, respectively; and a and b the semi-major axis and the semi-minor axis of the ellipsoid model, respectively. In this model, a and b can be set according to the sensitive degree of conflict risks, and in this study, they are set to be 5 n mile and 1 000 ft, respectively, according to the minimum separation.

Let $V_{i,j}^{A}(t)$ be the spatial approaching rate, and it can be computed as

$$V_{i,j}^{A}(t)=\frac{E_{i,j}(t)-E_{i,j}(t-1)}{E_{i,j}(t-1)} \tag{2}$$

Let $C_{i,j}^{A}(t)$ be the complexity relationship between aircraft i and j at time t. It can be computed as

$$C_{i,j}^{A}(t)=\begin{cases}\left(\dfrac{1}{E_{i,j}(t)}\right)^{1+\beta_A V_{i,j}^{A}(t)} & E_{i,j}(t)\geqslant 1\\ \left(\dfrac{1}{E_{i,j}(t)}\right)^{1-\beta_A V_{i,j}^{A}(t)} & E_{i,j}(t)<1\end{cases} \tag{3}$$

where β_A is the adjustment coefficient for between-aircraft spatial proximity.

Step 2 Computation of sector complexity

Let the situation complexity at time t be $C(t)$, and it can be computed as

$$C(t)=\sum_{i=1}^{N(t)-1}\sum_{j=i+1}^{N(t)} C_{i,j}^{A}(t) \tag{4}$$

where $N(t)$ is the number of aircraft in the air traffic situation at time t.

1.2 Physical programming algorithm for multi-objective optimization

Multiple objectives, including complexity, flight delay and flight adjustment quantity, should be considered during ATM. The interrelationship among different objectives is essentially a multi-objective optimization problem. Physical programming (PP) is a classical optimization design algorithm proposed by Messac. It has been used as an efficient algorithm to solve multi-objective optimization problems in various fields[24]. The basic steps of optimization via PP are listed below.

Step 1 Set preference structures. The boundary values of preference functions are determined, or namely the values of design objectives at the ends of preference ranges with different satisfaction degrees.

Step 2 Solve preference functions. With the given boundary values of the preference functions, the parameters of the preference functions are solved, and thus the curves of the preference functions can be completely described.

Step 3 Optimization. The objective functions are solved, and thereby the preference function values are reverse-calculated. After that, the overall preference of the PP problem is clarified and further optimized by using an appropriate optimization algorithm.

The key of the above steps is to design a suitable preference function. But existing studies provide very strict requirement on the mathematical nature of the preference functions, which complicates their construction and hinders the application of PP[24]. We have simplified the traditional preference functions according to the core thoughts of PP. According to the basic characteristics of preference functions, we established simple the preference functions according to the piece-wise functions of preference boundary points[25]

$$P(g)=\begin{cases}\lambda(i)+\dfrac{(\lambda(i+1)-\lambda(i))\times(g-g_i)}{g_{i+1}-g_i}\\ \qquad g_i\leqslant g\leqslant g_{i+1};\ i=1,2,3,4\\ \lambda(5)\times \mathrm{e}^{\frac{g-g_5}{g_5-g_4}} \qquad g\geqslant g_5\end{cases} \tag{5}$$

where g is the target value; g_i (i=1, 2, 3, 4, 5) are the boundary points of preference ranges; and $\lambda(i)$ is the preferred value at each boundary point and can be set to certain values according to the concrete application scenarios. The value of a preference function is decided without strict restrictions, and it is acceptable as long as the designer is satisfied with the target values in different preference ranges. According to the physical meanings of complexity and other indices as well as the monotonous progressive increase of the exponential function, we have presented the preference value of the exponential function[25].

$$\lambda(i)=\sqrt{e^{i-5}} \quad i=1,2,3,4,5 \tag{6}$$

In this way, a preference function is constructed. And for any target value, the corresponding value of the preference function can be determined from Eq.(5). For m objectives, let $P_j(g)$ be the jth objective ($j\in[1,m]$). Then the overall preference P_{T} of PP or namely the optimized target function can be determined.

$$P_{\mathrm{T}}=\ln\left(\sum_{j=1}^{m} P_j(g)/m\right) \tag{7}$$

At this moment, the multi-objective optimization problem can be transformed to single-objective optimization problem.

During air traffic complexity control, the preferred compromise solution to the optimization objective from controllers can be truly uncovered by using PP, according to the boundary points of preferences provided by air traffic controllers. And the compromise solution is contained in the non-inferior solution set of the multi-objective optimization problem. Thus, PP can be used to determine the non-inferior solution that reflects the preference of ATM. This meets the real requirements of traffic complexity control and avoids the difficulty of selecting weights for different objectives.

1.3 Complexity control model based on flying speed dynamic optimization

1.3.1 Problem description

Controllers usually adopt speed adjustment, altitude adjustment and heading adjustment to avoid potential conflicts or address high-complexity situations. Despite the higher promptness and larger deployment redundancy, the altitude adjustment and heading adjustment are more likely to affect the surrounding aircraft and thereby cause a chain reaction of potential conflicts. Thus, the complexity control strategy based on speed adjustment is discussed. First, the study period T is separated into n^W time windows at the length of T^W (T^W is also the period of dynamic optimization). Then the flight velocities in the time windows are optimized at the period of T^W until all windows are optimized. The goal is to provide controllers, according to the predicted air traffic complexity in the time window, with the dynamic adjustment schemes of within-sector flight velocities, so as to decrease the complexity as much as possible. To avoid workload imposed on controllers by excessive adjustment, we should consider the times of adjustment and the quantity of speed adjustment when using the speed dynamic adjustment strategy.

1.3.2 Optimization objectives

Dynamic adjustment of cruising velocities of aircraft is a multi-objective optimization problem, and the objectives include overall complexity, times of speed adjustment, and speed adjustment quantity. Decreasing the within-sector complexity is an important objective of complexity control strategies, and can be achieved reasonably by dynamic speed adjustment. Further, if excessive flights are involved in speed adjustment, controllers will face extra working pressures, so that the speed adjusting scheme cannot decrease the workload, but instead intensify it. Thus, decreasing the number of flights involved in speed adjustment as much as possible is one of the objectives of the complexity control strategy. From the aspect of passenger comfort and fuel saving, the speed adjustment strategy should also avoid large-amplitude adjustment, that is, the total speed change of aircraft should be the smallest.

(1) Total quantity of speed adjustment

$$J_s=\sum_{i=1}^{N_{W^j}}|s_i| \tag{8}$$

where N_{W^j} is the number of flights in window W^j; and s_i the speed adjustment quantity of the i-th flight. Positive s_i means the flight is accelerating, while negative s_i means it is decelerating.

(2) Proportion of flights with speed adjustment

$$J_f=\left(\sum_{i=1}^{N_{W^j}} f_i\right)\Big/N_{W^j} \tag{9}$$

where f_i is the mark of speed adjustment of each flight and is computed as

$$f_i = \begin{cases} 1 & |s_i| > 0 \\ 0 & |s_i| = 0 \end{cases} \tag{10}$$

Eq.(10) means if the absolute value of speed adjustment of flight i is 0, then f_i is 0; otherwise, it is 1.

(3) Complexity

$$J_c = \sum_{t \in T_{W^j}} C(t) \tag{11}$$

where T_{W^j} is the length of the jth time window. After the flight speed is adjusted, the interrelation among new 4D trajectories will change, which causes a variation in the within-sector complexity.

(4) Overall objective

It is known from Eqs.(8, 9, 11) that when the aircraft in a given window are dynamically velocity-adjusted, the selection of a specific scheme may correspond to different total adjusted quantities, proportion of flights with speed adjustment, and complexity. Given their differences in physical meaning and dimensions, the three objectives cannot be directly added together. PP is used here. The objective of each adjustment scheme is substituted into the corresponding PP function curve. As for the PP algorithm, one typical method is that the common logarithm of the average value from the preference function of a certain design target is chosen as the comprehensive preference function[26]. Then the overall preference value, namely the optimized value of the target function, can be obtained as

$$\min J = \lg((P_1(J_s) + P_2(J_c) + P3(J_f))/3) \tag{12}$$

1.3.3 Constraint conditions

(1) Constraints of speed adjusted quantity

To avoid excessive speed adjustment of single flight, we should set the range of speed adjustment.

$$s_{\min} \leqslant s_i \leqslant s_{\max} \tag{13}$$

where s_i is the decision-making variable defined as the speed adjustment quantity of flight i (the positive and the negative values mean acceleration and deceleration, respectively); $s_{\min}$ and $s_{\max}$ are the largest and the smallest speed adjustment ranges, respectively. $s_{\min}$ is negative and its absolute value means the largest limit value of speed change when the flight is decelerating; $s_{\max}$ is positive and means the largest limit value of speed change when the flight is accelerating. According to general speed adjustment rule, the step length of adjustment by s_i is 20 km/h.

(2) Constraint of aircraft performance

Given the aeroplane performances, the cruising speeds of aircraft can be adjusted only within a certain range.

$$v_{i,\min} \leqslant v_i(t) + s_i \leqslant v_{i,\max} \tag{14}$$

where $v_i(t)$ is the speed of flight i at time t; $v_{i,\min}$ and $v_{i,\max}$ are the minimum and the maximum cruising speeds of the same type of aircraft as flight i, respectively.

(3) Conflict-free constraints

When an aircraft flies at the adjusted velocity, it theoretically does not conflict with other aircraft, so a conflict-free constraint is set as

$$E_{i,j}(t) > \sqrt{3} \quad \forall t \in T \tag{15}$$

where $E_{i,j}(t)$ is the ellipsoid distance of aircraft i, j at time t. According to Eq.(1), when the between-aircraft ellipsoid distance is larger than $\sqrt{3}$, no conflict between aircraft will occur.

1.4 Complexity control model based on entry time optimization

1.4.1 Problem description

At present, when a flight is transferred from an adjacent upstream sector to the target sector, it may affect other aircraft in the target sector, decreasing the safe level and enhancing complexity[27]. To avoid this, controllers usually give some urgent instructions before the transfer, such as sudden heading, altitude or speed adjustment. Such instructions inevitably complicate the works of upstream sector controllers within a short period of time and increase their workload. The primary causes of the transfer-induced conflicts are that the controllers do not fully understand the complexity changing trend in the sector and thus give the instructions very late. For this reason, we discuss the comprehensive evaluation and prediction of within-sector traffic complexity, and the complexity control strategy for promptly adjusting the entry time of the flight at the sector. Our aims are to control the complexity of the target sector at a reasonable level by adjusting the entry time of the flight, to enhance the system operational efficiency and thus to permit the upstream sector controllers with enough time to easily respond to such time adjustment.

1.4.2 Optimization objectives

The allocation of sector entry time among flights is a multi-objective optimization problem and the objectives include overall complexity, and delay of sector entry. Excessive complexity will easily cause potential operational risks, but too low complexity will waste the airspace resources. The main aim of complexity control is to smooth the post-control traffic situation complexity, so controllers can respond more easily. The minimum delay of sector entry is another key aim of complexity control. First, as for the entire air traffic system, the basic principle of improving operational efficiency is to try to accelerate the air traffic flows under the premise of safety. Second, if the outcome of strategy execution is to detain numerous flights in the upstream sector, it will largely increase the work pressures on the upstream sector controllers and reduce the operational efficiency of the entire air traffic system. Thus, aircraft entrance delay should be avoided as much as possible during complexity control.

(1) Flight delay

$$J_d = \sum_{i=1}^{N_{\text{in}}^T} d_i \tag{16}$$

where N_{in}^T is the number of flights arriving at the sector within this period; d_i the delay time of flight i. Positive d_i means the flight will delay for a certain time, and negative means the flight will advance by a certain time. d_i is the only decision-making variable of this model, and from d_i and $t_{\text{in}i}^{\text{p}}$ (time of flight i predicted to arrive at the sector), we can determine $t_{\text{in}i}^{\text{o}}$ (optimized time of flight i to arrive at the sector) of flight i after adjustment.

(2) Complexity

$$J_c = \sum_{t \in T} C(t) \tag{17}$$

When $t_{\text{in}i}^{\text{o}}$ is assigned to the flight, a new 4D flight trajectory will be generated. After the execution, each flight will fly along the new 4D trajectory, and the positional relationship among flights will certainly change largely, leading to a variation of within-sector complexity.

(3) Overall objective

It is known from Eqs.(16, 17) that when the aircraft arriving at the sector are dynamically adjusted, the selection of different schemes may result in different adjusted quantities of delay and complexity. Because of differences in physical meaning and dimensions, the delay and complexity cannot be directly added together. Thus, they are processed by PP. The delay and complexity after each adjustment scheme are substituted into the corresponding PP function curve. Then the overall preference value, that is the optimized value of the target function, can be obtained as

$$\min J = \lg((P_1(J_d) + P_2(J_c))/2) \tag{18}$$

1.4.3 Constraint conditions

(1) Constraint on quantity of speed adjustment in adjacent upstream sectors.

After the flight entry time at the sector is adjusted, controllers from adjacent upstream sectors will adopt speed modulation, flight trajectory alteration or the holding pattern so as to make the flight delay or advance. Due to the impacts of airspace environment, the time consumption differ among different sectors. To simplify the problem, we hypothesize that the adjacent upstream sectors will adopt the speed adjustment strategy to meet the limitations from the target sector. However, if the time adjustment over a certain flight is too large, the cruising speed of this flight in the upstream sector will overly deviate from that in the main traffic flows, which will severely interfere with other traffics and may force the upstream sector controllers to query or even reject the implementation of this strategy. Thus, to ensure the feasibility of this scheme, we should take into account the constraint on the mainstream cruising speed in the upstream sector, and estimate the largest consumable time variation in this sector, according to the range of allowed maximum speed adjustment. Let S^i be the target sector of flight i; S_p^i be the sector where the flight is when the decision is made, or namely the upstream sector of S^i. Statistics show the cruising speeds of within-sector flows mostly obey a normal distribution. Let the cruising speeds of aircraft within sector S_p^i obey a normal distribution with the mean of $V_{S_i^p}$ and standard deviation of $\sigma_{S_i^p}$. Let the acceptable range of speed adjustment be $(-2\sigma_{S_i^p}, 2\sigma_{S_i^p})$, and the decision-making time of the scheme be t_d. Admittedly, when the decision-making time is earlier (namely t_d is larger), the largest time variation that can be consumed by the flight will increase. Thus, based on the mean cruising speed in the upstream sector, the range of speed adjustment, and the decision-making time, the range of acceptable time change in this sector can be estimated. The time adjustment quantities, namely the delay time, of all flights in this sector meet this constraint

$$\frac{-2\sigma_{S_p^i} \times t_d}{V_{S_p^i} + 2\sigma_{S_p^i}} \leqslant d_i \leqslant \frac{2\sigma_{S_p^i} \times t_d}{V_{S_p^i} - 2\sigma_{S_p^i}} \tag{19}$$

(2) Constraint of aircraft performance

The time variation quantity of a flight is also affected by the aircraft type and performances, in addition to the unified constraint offered by the upstream sector. According to the adjustable speed range and the distance from the aircraft to the boundary points of the target sector, we can determine the range of time variation of each aircraft under the performance constraint.

$$\frac{D_i(t_d)}{v_i} - \frac{D_i(t_d)}{v_{i,\min}} \leqslant d_i \leqslant \frac{D_i(t_d)}{v_i} - \frac{D_i(t_d)}{v_{i,\max}} \tag{20}$$

where $D_i(t_d)$ is the distance of flight i from the boundary of the target sector at time t_d; v_i the current speed of flight i; $v_{i,\min}$ and $v_{i,\max}$ are the minimum and the maximum cruising velocities of the same type of aircraft as flight i, respectively.

(3) Conflict-free constraint

When an aircraft arrives at the sector at the adjusted time, it theoretically does not conflict with other aircraft, so a conflict-free constraint is set as

$$E_{i,j}(t) > \sqrt{3} \qquad \forall t \in T \tag{21}$$

where $E_{i,j}(t)$ is the ellipsoid distance of aircraft i, j at time t. When the between-aircraft ellipsoid distance is larger than $\sqrt{3}$, no conflict between aircraft will occur.

2 Experiment and Result

2.1 Data preparation

We selected four sectors S1, S2, S3, S4 in China airspace. In these sectors, the altitude ranged within 6 000—7 800 m, 5 400—7 800 m, 7 800—12 000 m and 7 800—12 000 m. And the numbers of altitude layers were 7, 9, 13 and 13 accordingly. The horizontal separation standards were all 10 km, and the vertical separation standards were all 300 m. Original radar data were collected at 13:00—14:00 on 1 February 2015, which was the peak period for all sectors. The number of flights per minute during this period, namely instantaneous traffic count, was shown in Fig.1. Clearly, the peak volumes of the four sectors exceeded the capacity to different extents, which caused severe control pressures and operational risks.

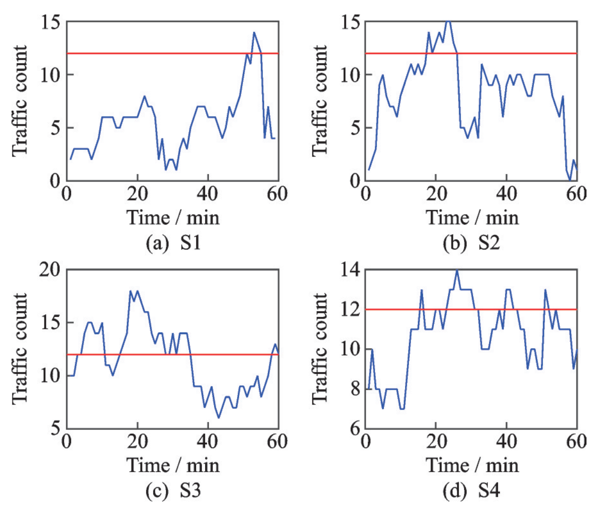

Fig.1 Number of flights per minute in each sector

2.2 Parameter setting

2.2.1 Setting of preferred range of proportion of adjusted flights

The preferred boundary point of proportion of adjusted flights was set as {0, 0.25, 0.5, 0.75, 1}. Then the preferred range was substituted into the preference function, forming a preference function curve of proportion of adjusted flights (Fig.2).

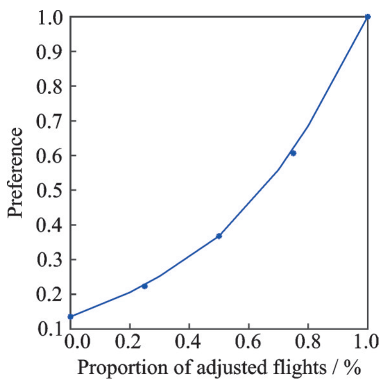

Fig.2 Curve of preferred range of proportion of adjusted flights

2.2.2 Setting of preferred range of speed adjustment quantity of flights

Data analysis and preliminary investigation showed the maximum speed adjustment quantity at the deceleration was $s_{min}=-100$ km/h, and the maximum speed adjustment quantity at acceleration was $s_{max}=100$ km/h, and the expected aircraft speed adjustment range was [-100, 100]. Thereby, the preference boundary point of the absolute value of speed adjustment quantity was set as {0, 25, 50, 75, 100}. Then the preferred range was substituted into the preference function, forming a preference function curve of within-sector speed adjustment (Fig.3).

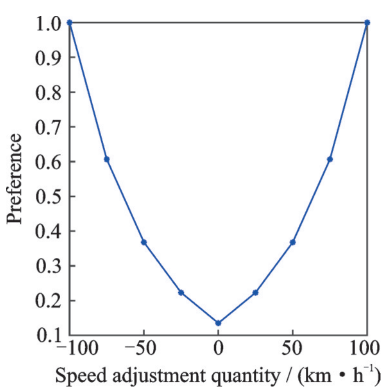

Fig.3 Curve of preferred range of quantity of aircraft speed adjustment

2.2.3 Preferred interval of complexity

With lower complexity, the safe pressure imposed on controllers is less, and the corresponding safety is higher. Then the historical data based on reality were used to compute the preferred boundary points of complexity. Firstly, the complexity per minute in each of the four sectors from 1 to 7 February 2015 was computed and then divided into five clusters by the K-means clustering method. The results were used as the preferred boundary points of complexity and substituted into the preference function, forming the preference curves of the four sectors (Fig.4).

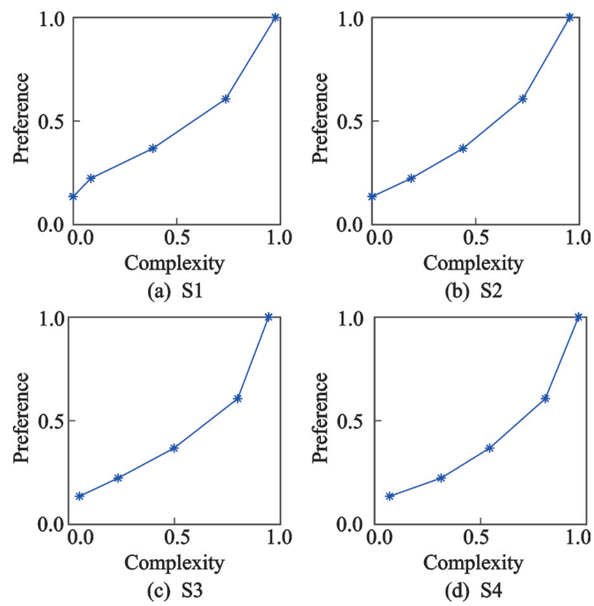

Fig.4 Complexity preference curves

2.2.4 Setting of time window T^W

If the time window was too large, the total times of speed adjustment would be decreased, but the impact on the predicted trajectory errors would be larger, which lowered the effect of complexity adjustment. If the time window was too small, though the effect on the predicted trajectory errors would be less, the times of speed adjustment would be too frequent, which intensified the workloads on the controllers. Given the mean flight time in the sectors, we set T^W at 5 min.

2.2.5 Setting of preferred flight entry time adjustment quantity

As stated above, the flight time adjusted quantity was constrained by the speed distribution and decision-making time in the sector. The time adjustable range under different decisions in the study airspace calculated by Eq.(19) was listed in Table 1. Clearly, at longer decision-making time, the adjustable range of flights was broader, and the model optimized result was better. As for effectiveness validation, we set the decision-making time at t^d= 10 min. Thus, the flights can arrive at the sector earlier by up to 2 min, and later by up to 3 min. As for operational efficiency of air traffic control, flight delay should be decreased and traffic flow be accelerated as much as possible. Thus, within the time interval, the common delay preference boundary points {−2, −0.75, 0.5, 1.75, 3} among the four sectors were selected. Then the preferred range was substituted into the preference function, forming a preference function curve of sector entry time adjustment (Fig.5).

Table 1 Ranges of time adjustment corresponding to different decisions

Sector	Mean speed/ (km•h^{-1})	Standard deviation of speed	Range of speed/ (km•h^{-1})	t^d=10 min		t^d=15 min		t^d=20 min	
				d_{min}	d_{max}	d_{min}	d_{max}	d_{min}	d_{max}
Upstream sector of S1	720	89	542—908	−2.0	3.3	−3.0	4.9	−4.0	6.6
Upstream sector of S2	707	99	509—905	−2.2	3.9	−3.3	5.8	−4.4	7.8
Upstream sector of S3	762	96	570—954	−2.0	3.4	−3.0	5.1	−4.0	6.7
Upstream sector of S4	768	102	564—972	−2.1	3.6	−3.1	5.4	−4.2	7.2

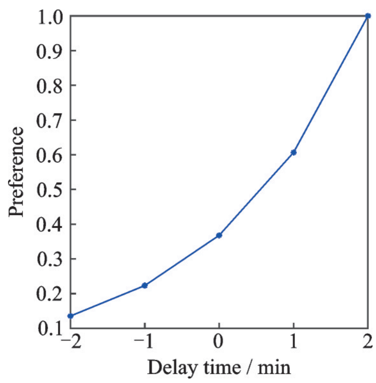

Fig.5 Preference function curve of delay time

2.3 Dynamic optimization of aircraft flight speed

The flight dynamic speed modulation of the four sectors was shown in Table 2. Clearly, the number of flights in the four sectors at corresponding time periods were 35, 56, 69, 50, and the total times of speed adjustment were 4, 17, 34, 11.

Fig.6 shows the traffic count and speed adjustment times in each window of the four sectors. The proportion of speed adjusted flights among total flights was computed to be very small as 0.04, 0.11, 0.18, 0.07. The results of optimized complexity were shown in Fig.7. Clearly, the optimization strategy based on dynamic speed adjustment can eliminate the peak complexity in all four sectors and decrease the initial complexity to some extent. Moreover, during the peak-flow period, controllers often preferentially choose to guarantee safety, but pay less attention to the flight efficiency. Thus, we did not consider the shortest flight time as the optimization objective. Nevertheless, the optimized flight time was shorter than the actual one in all cases, or namely the new strategy can decrease com-

Table 2 Optimization of dynamic speed adjustment strategy

Sector	Number of flights	Times of speed adjustment	Mean complexity		Maximum complexity		Mean flying time/s	
			Real	After adjustment	Real	After adjustment	Real	After adjustment
S1	35	4	0.23	0.21	0.94	0.71	529	521
S2	56	17	0.33	0.32	0.87	0.78	522	520
S3	69	34	0.45	0.43	0.94	0.79	552	547
S4	50	11	0.34	0.30	0.92	0.49	721	718

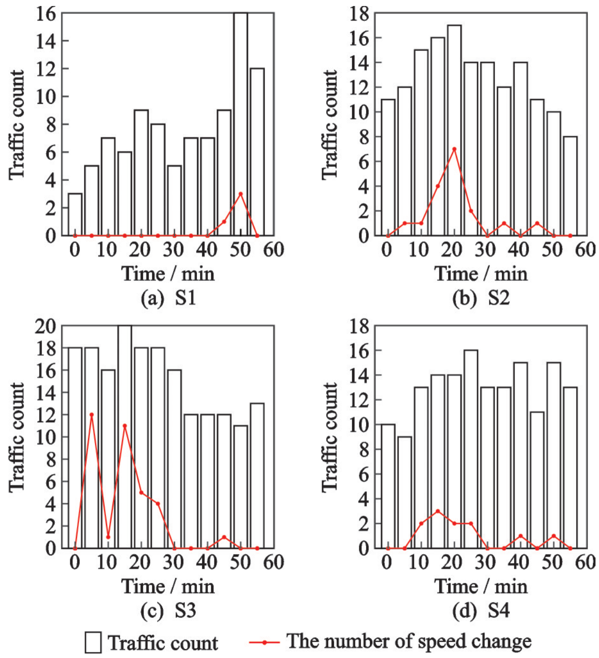

Fig.6 Traffic count and speed adjustment times in each window

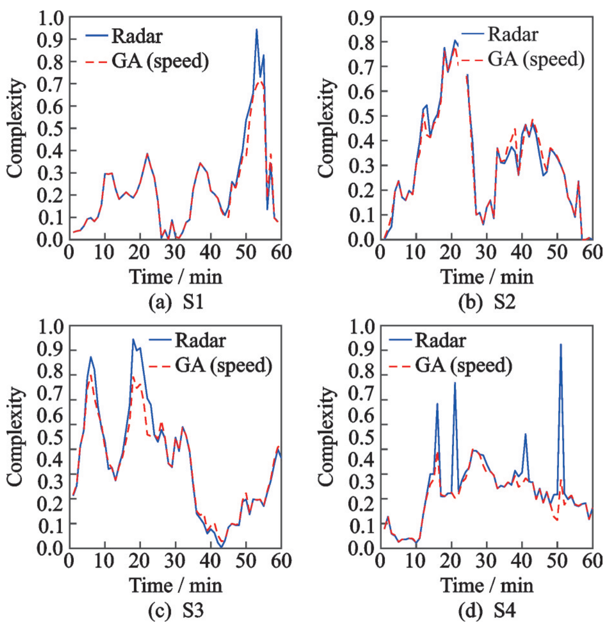

Fig.7 Complexity optimization based on speed adjustment strategy

plexity without raising extra delay. In a nutshell, the dynamic speed adjustment strategy can effectively decrease the within-sector complexity and save controllers much time in tactic adjustment upon the peak complexity, under the minimum interference to controllers.

2.4 Optimization of entry time of aircraft

Table 3 lists the results of optimized flight entry time in the four sectors. Clearly, the number of flights in the corresponding periods of the four sectors were 35, 56, 69 and 50, the adjusted number of flights upon the arrival time were 24, 34, 41 and 31, the numbers of delayed flights were 9 (26%), 18 (32%), 15 (22%), and 12 (24%), and the numbers of earlier flights were 15 (43%), 16 (29%), 26 (38%), and 19 (38%). The average delay time was negative in all four sectors (−0.7, −0.4, −0.7, and −0.8 min), indicating the average entry time after optimization was earlier than the real time, that is, the time adjustment made the most flights arrive earlier.

Fig.8 compares the situation complexity per minute before and after optimization. Clearly, the optimized complexity was smoother, since the real high-complexity situations were all eliminated. Compared with the dynamic optimization strategy based on aircraft flying velocity, the optimization efficiency was higher, and the final average complexity and maximum complexity were both slightly lower. This was because the preset objectives of the flying speed dynamic optimization strategy included the minimization of the number of flights and speed adjustment in all cases in addition to the minimum expected complexity, which excluded some schemes that decreased complexity through excessive speed adjustment. Such consideration is consistent with the practical situations, since the dynamic speed adjustment strategy directly serves the controllers and

Table 3 Optimized results of the entry time adjustment strategy

Sector	Number of flights	Number of delayed flights	Number of earlier flights	Average delay time/min	Mean complexity		Maximum complexity	
					Actual	After adjustment	Actual	After adjustment
S1	35	9	15	−0.7	0.23	0.16	0.94	0.36
S2	56	18	16	−0.4	0.33	0.31	0.87	0.78
S3	69	15	26	−0.7	0.45	0.41	0.94	0.86
S4	50	12	19	−0.8	0.34	0.29	0.92	0.45

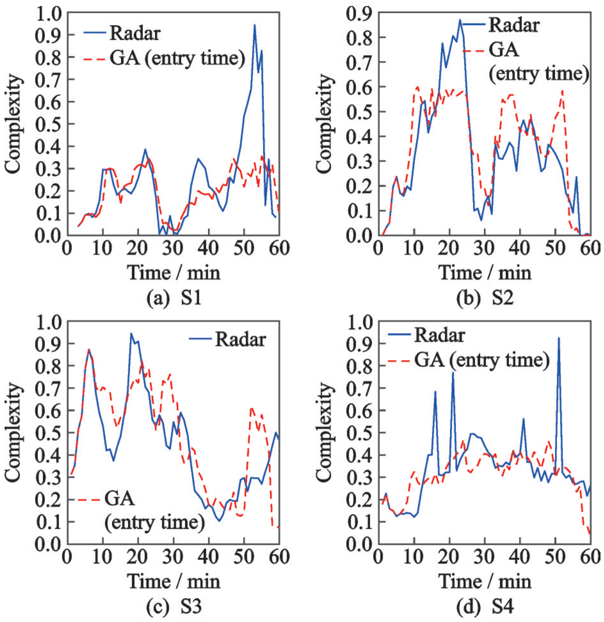

Fig.8 Complexity optimization based on the entry time adjustment strategy

is featured by shorter decision-making time and higher timeliness. The entry time adjustment strategy is a more strategic behavioral decision-making, as the controller can adopt many ways, e.g. changing the flying path, adjusting the flying height and velocity, to achieve goals, and thus, this strategy is more capable of controlling air traffic complexity. Moreover, comparison of different sectors indicated the duration time of high-complexity situations were shorter and the optimized results were significantly better. For instance, the maximum complexity of S1 and S4 was decreased from 0.94 to 0.36 and from 0.92 to 0.45, respectively. The optimized results of high-complexity situations with longer duration time were relatively unfavorable, such as S2 and S3. In a nutshell, the within-sector complexity was appropriately decreased by adjusting the flight entry time, and the high-complexity situations were avoided. Namely, the high-pressures and high risks of management in response to high-complexity situations were decreased, and air traffic control operational efficiency was appropriately enhanced.

3 Conclusions

Along with the rapid air traffic growth, the complexity of air traffic situations is increasingly intensified. The contradiction between conventional ATM and the increasingly complex air traffic situations is more significant, which largely weakens the ATM system capacity and reduces the operational efficiency of civil aviation transportation systems. Thus, based on objective quantification of complexity of air traffic situations and scientific guidance for complex traffic situations, the workload of tactic allocation for air traffic control can be decreased and thereby the air traffic system capability can be improved by the provision of lower-complexity and more manageable air traffic situations. For this reason, we propose two air traffic complexity control strategies depending on whether flights arrive at the sector. The flying speed dynamic adjustment strategy is applied to the within-sector flights, while the sector entry time adjustment strategy is applied to the flights arriving at the sector. We introduce PP and preference functions, transform the multi-objective problem involving complexity and delay to single-objective optimization problems. The actual data of four sectors at the peak period are simulated so as to validate the effectiveness of the models and the algorithm. Our approach are verified to be applicable to real air traffic management.

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空中交通管制扇区复杂性控制策略研究

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摘要:随着空中交通的快速发展,传统空中交通管理手段与日益复杂的空中交通态势之间的矛盾越发明显,这从根本上降低了航空运输系统的运行效率。因此,客观地衡量空中交通态势的复杂性成为空中交通管理领域的研究热点。现有研究主要集中在空中交通复杂性评估方面,而对复杂交通态势的科学引导和合理控制相关研究较少。本文根据飞机到达目标扇区边界的预计时间,制定了两种降低空中交通复杂性的控制策略。将进入扇区时间优化策略应用于相邻上游扇区内可控航班,将飞行速度动态优化策略应用于目标扇区内的航班。在复杂性控制模型的求解过程中,引入了物理规划方法。通过设计不同的偏好函数,将具有复杂度、延误等的多目标优化问题转化为单目标优化问题进行求解。实际数据验证结果表明,两种复杂性控制策略都能够消除实际中的高复杂性态势,且基于扇区进入时刻优化的控制策略比基于速度动态优化的控制策略更有效。本文尝试建立了空中交通复杂性控制的基本研究框架,研究成果有助于实现基于复杂性的空中交通管理,从而缓解空中交通管制员的工作负荷、提高空中交通系统容量,最终适应航空运输的快速增长。

关键词:空中交通管理;空中交通态势;空中交通管制;基于复杂性的管理;交通复杂性