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Abstract
Purpose – Air traffic resources mainly include two parts, namely, air traffic controller (ATC) and physical system resources, such as airspace. Reasonable assessment and effective management of ATC and airspace resources are the premise and foundation of ensuring the safety and efficiency of air traffic management systems. The previous studies focussed on subjective workload control and the statistics of control communication time; they revealed the lack of kinetic universality analyses of controlling actions. Although frequency distribution patterns were generated by controlling the timing sequence, the correlation between the controlling actions and terminal airspace (TMA) sector capacity was not revealed. The paper aims to discuss these issues.
Design/methodology/approach – Thus, given the immeasurable complexity of controlling actions and statistical features of the controlling communications, a dynamical model of ATC was built in this study to identify the frequency distribution patterns generated by controlling the timing sequence. With the Directorate of Operational and Analysis Task method, TMA sector capacity was estimated through multiple linear regression analysis.
Findings – With data from the Kunming sector, the power exponent was calculated as 2.55, and the mathematical expectation was determined to be 47.21 s. The correlation between controlling actions (workload) and sector capacity was obtained. Finally, the data were integrated in the verification of the model and its feasibility.
Originality/value – Airspace capacity is an index to measure the ability of the airspace system to deliver services to meet the air traffic demand. A scientific and accurate forecast of airspace capacity is a foundation of the effective management and rational allocation of the airspace resources. The study is of great significance for the efficient use of airspace resources, controller resources.
Keywords Behaviour, Action research, Mathematical modelling, Statistical analysis
Paper type Research paper

1. Introduction
The rapid development of the air transport industry has resulted in increased air traffic congestion and prominent contradictions between limited airspace resources and traffic demands. Increased traffic congestion leads to substantial flight delays, large economic losses, and increased safety issues in air transportation systems. Estimations (Olaf *et al.*, 2007) indicate that by 2025, global air traffic could be triple the present amount. Improving the capacity of air transportation systems is thus urgent. Single European Sky ATM Research (Olaf *et al.*, 2007) and Next-Generation Air Transportation System (Swenson *et al.*, 2006) forecast that an air transportation system with a capacity that is triple the present amount will be developed in the next 10-15 years. For this purpose, the

This work was supported by the National Science Foundation of China (U1233101, 71271113, 60979018) and by the Fundamental Research Funds for the Central Universities (NS2016062).

Kybernetes
Vol. 45 No. 6, 2016
pp. 884-899
© Emerald Group Publishing Limited
0368-492X
DOI 10.1108/K-12-2014-0308

effective management of air traffic resources is a key aspect. Air traffic resources include two parts, namely, air traffic controller (ATC) and physical system resources, such as airspace. Reasonable assessment and effective management of ATC and airspace resources are the premise and foundation to ensure the safety and efficiency of air traffic management systems.

Airspace capacity estimation is a key technology in the implementation of effective management and rational allocation of air traffic resources. Currently, many new airports are being built, and existing airports are being expanded to meet growing traffic demands. How to accurately estimate the terminal airspace (TMA) capacity of airports is the first question to be addressed by civil aviation planning and construction departments. TMA refers to low and medium airspace at the center of airports, and its capacity indicates the number of aircraft in service or can provide services in unit time with a certain systematic structure, control rules, and security level under the effect of variable factors (human, weather, etc.) (Schuen-Medwed, 2003). TMA consists of several control sectors. A sector is the minimum service unit of air traffic control. Airspace capacity can be identified by analyzing the controlling workload level in a sector (Schuen-Medwed, 2003).

Studies on airspace capacity estimation date back to the theoretical research on runway capacity estimation conducted by Bowen and Pearcey (1948) in the late 1940s. Since then, scholars have successively proposed runway (Bowen and Pearcey, 1948), airport (Hockaday and Kanfani, 1974), terminal area (Boesel and Bodoh, 2004; Hah *et al.*, 2006; Basu *et al.*, 2009; Zhang *et al.*, 2010), and regional (Milan and Vojin, 1991) capacity estimation theories. Among them, in the field of sector capacity estimation of terminal area airspace, Boesel and Bodoh (2004) considered ATC ability and other factors and adopted track fusion technology to estimate the Detroit-Wayne terminal area sector capacity according to the flight ratio of entrance and departure sites of the terminal area. Hah *et al.* (2006) explored the effect of the growth of air traffic load on the controlling workload. Basu *et al.* (2009) proposed the automatic division of the TMA sector according to the controlling workload. Zhang *et al.* (2010) regarded the controlling workload as the constraint and conducted integrated capacity estimation of TMA and airport surface. In the late 1980s, with the rapid development of computer technology, simulation evaluation software, such as total airspace and airport modeler (TAAM), FAA airport and airspace simulation model (SIMMOD), and reorganized ATC mathematical simulator were invented. The TMA simulation method gradually became a key method of airspace capacity estimation (Majumdar *et al.*, 2005). Irvine *et al.* (2015) conducted a Monte Carlo simulation to quantify and compare the relative capacity enhancements that may be provided by the construction of a new hub airport in the Thames Estuary and additional runways at Heathrow, Gatwick, and Stansted as well changing the operating practices at Heathrow. However, this research only conducted correlation analysis between TMA capacity and air traffic based on simulation data. As for simulation research on airspace capacity, the simulation methods of air traffic can be generally divided into macroscopic and microscopic models according to the degree of detailed description of the air traffic system. In the macroscopic model, the description of air traffic flow takes the unit of flow velocity or density. The description of details of elements and actions of the air traffic system is at a comparatively low degree. The traffic flow description in microscopic air traffic simulation regards the individual aircraft as a basic unit; this method can truly reflect microscopic behaviors, such as speed, height, and heading regulation of aircraft on airways. Thus, among all methods, simulation is the closest to reality. Microscopic simulation strives to reproduce actual constraints and limitation conditions. In the simulation process, many operation details, such as conflict resolution, selection of taxiways and gate positions, and promotion of procedures, are described. Microscopic models include the 2D node model and the 3D spatial model. The 2D node model includes Airport Machine and SIMMOD. The 3D spatial model includes Heuristic Runway Movement Event Simulation and TAAM.

Existing TMA capacity estimation methods can be divided into four categories, namely, mathematical modeling and analysis, controlling workload assessment, historical statistical data analysis, and computer simulation. With the development of airspace capacity estimation technology, several disadvantages of existing methods have been gradually revealed. First, although mathematical analysis or mathematical modeling is simple, quick, and invests less in capacity estimation, it neglects the effect of ATC ability and intention on sector capacity. Second, although capacity estimation by controlling workload can reflect the human resource limitation in the system, it might yield certain subjective evaluation results because of insufficient controlling workload statistics and measurement method. Third, although capacity estimation based on historical statistical data analysis is convenient for operation, data collection is difficult, and the size of the data are large. The quantity and quality of sample data directly influence the correctness of the results. Fourth, although computer simulation produces relatively accurate results, it requires substantial technology support and capital investment in the simulation modeling and long assessment periods. Obviously, simple reliance on a certain assessment method can hardly realize accurate estimation of TMA sector capacity. Accurate estimation of TMA sector capacity can be accomplished by combining several estimation methods.

ATC provides air traffic control services for airspace, and accurate assessment of the workload is the premise and foundation of the identification of TMA sector capacity (Schuen-Medwed, 2003). The study of ATC workload dates back to the 1960s and mainly involves three aspects: acquiring the intensity of controlling workload through the assessment of ATC physiological and behavioral indicators, assessing the controlling workload through observation and questionnaires, and acquiring the ATC loading level by controlling airspace complexity in the assessment.

For the assessment of physiological and behavioral indicators of controlling workload, the objects of research are several physiological and behavioral indicators. Through the measurement and analysis of indicator changes under different traffic characteristics, the variation relationship between physiological and behavioral indicators and the controlling workload has been analyzed. Physiological and behavioral indicators involve a massive range (Brookings *et al.*, 1996; Tobaruela *et al.*, 2014) from pacemakers, brain voltage, ECG, blood pressure, pupil size, biochemical indicators of body fluids, and so on. Literature shows that this assessment is an effective means to identify controlling workload. However, the human body is a complex system. Various factors, such as the importance degree of extensive physiological and behavioral indicators and the correlation among indicators, determine the difficulty of assessment.

Meanwhile, subjective assessment of controlling workload can be divided into self-assessment and expert assessment of workload intensity. Self-assessment (Mogford, 2001) requires the compilation of questionnaires suitable for controlling workload as well as a questionnaire assessment to accomplish workload assessment. The expert evaluation method mainly refers to Directorate of Operational and Analysis Task (DORATASK) and Messerschmidt, Bolkow and Blohm, which are subjective capacity estimation methods recommended by the International Civil Aviation Organization (2010) through normative documents for different countries. DORATASK identifies the sector capacity and its capacity threshold by collecting statistical data on ATC operation and communication time; the collected operation and communication time must be smaller than the controlling work time by 80 percent. In addition, the operation and communication time in the peak period should reach 90 percent of the working time. The overall time should not exceed 2.5 percent of the statistical time. With these expert methods, several scholars established controlling workload assessment methods to realize capacity estimation. For example, Han *et al.* (2000) analyzed the human factors that affect sector capacity during controlling. They applied the DORATASK method to identify the correlations between workload and capacity and those between workload and communication devices. Leiden *et al.* (2003) established an airspace sector capacity estimation method based on ATC workload through the analysis of ATC work and estimated the sector capacity through simulation. Subjective assessment of workload is easy to implement and has been acknowledged by many experts in practical applications. However, this method has limitations in the subjective measurement of workload.

Assessment of controlling workload based on airspace complexity explores traffic characteristics in different airspaces, such as flights of aircraft surveillance, amount of coordinated actions, effectiveness of commands, airspace limitations, and number of conflicting points in unit time. Thus, the level of workload can be identified. For example, French scholars Athenes *et al.* (2002) analyzed the relationship between airspace complexity and controlling workload and presented a set of airspace complexity factors. Pawlak *et al.* (1996) presented the assessment results of 15 aspects of airspace complexity. Corker *et al.* (1999) measured airspace complexity, such as the mixing ratio of aircraft and increasing communication time, to obtain the controlling workload. Zhao *et al.* (2011) created and analyzed a quantitative analysis chart of airspace complexity based on the air traffic situation to estimate the traffic complexity level of airspace. Delahaye *et al.* (2004) presented the concept of traffic randomness and applied geometric measurement and dynamical system models in the estimation to objectively describe the complexity of traffic situation evolution.

In addition to the three types of controlling workload studies mentioned above, comprehension and mastery of the law of dynamics in the controlling behaviors of air traffic systems can serve as a basis for the accurate identification and assessment of controlling workload as well as the foundation of realizing airspace sector capacity estimation. In 2005, Barabasi published an article in the magazine *Nature* showing that the time pattern of human behaviors has a high degree of non-uniformity; within a period of time, no record of behavior and activity may exist. However, at long time intervals, intensive activities based on intermittency can be observed. Barabasi and others initiated the new research direction of "human dynamics," which soon attracted attention from scientists in the fields of mathematics, system science, statistical mechanics, and nonlinear sciences. Substantial quantitative research on human activities in real life and work, such as commercial transactions (Vazquez *et al.*, 2006), human space activity (Brockmann *et al.*, 2006), SMS (Hong *et al.*, 2009), and e-mail communication (Oliveira and Barabasi, 2005), continued to emerge. In air traffic systems, based on their cognitive competence and experiences, ATC perceives and makes a preliminary judgment of the traffic situation and sends instructions to air traffic command through communication behaviors according to the rules of air traffic control. Wang *et al.* (2013) conducted a dynamic analysis of the traffic control instructions of Europe and US control sectors through statistics. However, their study only identified the dynamical model of control acts through the data fitting method and did not involve correlation studies between the dynamical model of traffic control acts and the control sector capacity.

Increased knowledge and research on controlling workload indicate that the single airspace sector capacity estimation method presents certain limitations. Estimation of controlling workload is the basis of the accurate acquisition of TMA sector capacity. The abovementioned studies focussed on the investigation of subjective controlling workload and the statistics of control communication time and reveal the lack of kinetic universality analyses of controlling acts. Despite the frequency distribution patterns generated by controlling the timing sequence, the correlation between controlling acts and TMA sector capacity has not been revealed. Thus, given the immeasurable complexity of controlling acts and statistical features of controlling communications, a dynamic model of ATC was built in this study to identify the frequency distribution patterns generated by controlling the timing sequence. On this basis, TMA sector capacity was estimated through multiple linear regression analysis according to the DORATASK method.

2. Solution of power-law distribution-based maximum likelihood estimation (MLS) and application to ATC controller workload

Power-law distribution has diverse manifestations, which can be extensively observed in many disciplines (White *et al.*, 2008). The specific expression is:

$$f(x) = Cx^{-\alpha}. \tag{1}$$

We took the logarithm on each side of Equation (1) and found that $\ln y$ and $\ln x$ have a linear relationship, that is, the relationship presents a straight line with the gradient of $-\alpha$ in the double logarithmic coordinates. Thus, empirical studies utilize a linear regression model and least square method to obtain the regression equation of the straight line and the power-law relationship of y and x. However, many studies have revealed comparatively significant differences between the power exponent and true value obtained with this method. To acquire a relatively accurate α, frequent solutions often involve the linear binning method, the logarithmic binning method, cumulative distribution function fitting, and MLS. Previous studies (White *et al.*, 2008) revealed that the linear binning method requires the support of substantial data, and the required binning width should be precise. This is difficult to realize in practical applications (generally, the set binning width is relatively random). Thus, it is not an optimal solution process. Although the logarithmic binning method solves the data needs, it still has high requirements for the selection of the binning width. The cumulative distribution function fitting method mainly analyzes the cumulative distribution function of the variables and avoids binning selection. However, it cannot directly lead to the value of α and relies on the solution of $\alpha+1$. This reliance may inevitably result in certain errors. MLS can avoid these problems. Thus, the MLS method was adopted for the solution in this study.

Constant C was normalized. The normalization equation is:

$$1 = \int_{x_{\min}}^{\infty} f(x)dx = C\int_{x_{\min}}^{\infty} x^{-\alpha}dx = \frac{C}{1-\alpha}\left[x^{-\alpha+1}\right]_{x_{\min}}^{\infty}. \tag{2}$$

if $\alpha > 1$, the above equation can be simplified as:

$$C = (\alpha-1)x_{\min}^{\alpha-1}, \tag{3}$$

where x_{min} is the (necessarily positive) minimum possible value of X. The power-law distribution is:

$$f(x) = Cx^{-\alpha} = \frac{\alpha - 1}{x_{\min}} = \left(\frac{x}{x_{\min}}\right)^{-\alpha}. \tag{4}$$

Given a set $\{x_i\}$ composed by n x_i, the probability of x_i in the distribution is positively correlated with:

$$P(x|\alpha) = \prod_{i=1}^{n} p(x_i) = \prod_{i=1}^{n} \frac{\alpha - 1}{x_{\min}} \left(\frac{x_i}{x_{\min}}\right)^{-\alpha} \tag{5}$$

The resulting figure is referred to as the likelihood value of the data set. Meanwhile, the value that we truly require is the probability value of α based on set $\{x_i\}$. Bayes Law shows that:

$$P(\alpha|x) = P(x|\alpha)\frac{P(\alpha)}{P(x)}. \tag{6}$$

The prior probability $P(x)$ of data were 1 in the set $\{x_i\}$. Generally, in a case that does not satisfy the condition, the prior probability $P(\alpha)$ of α is unified, that is, a constant. Thus, $P(\alpha|x) \propto P(x|\alpha)$. For convenience, the logarithm of the maximum likelihood function L, $\log L$, is often utilized to replace the log value of $P(\alpha|x)$. They have equal values. Specifically:

$$\begin{aligned} L = \ln P(x|\alpha) &= \sum_{i=1}^{n} \left[\ln(\alpha - 1) - \ln x_{\min} - \alpha \ln \frac{x_i}{x_{\min}}\right] \\ &= n \ln(\alpha - 1) - n \ln x_{\min} - \alpha \sum_{i=1}^{n} \ln \frac{x}{x_{\min}}. \end{aligned} \tag{7}$$

The most possible value of α is calculated through the MLS value of α. L is a monotonically increasing function. We let $\delta L/\delta\alpha = 0$; we thus obtain:

$$\frac{n}{\alpha - 1} = \sum_{i=1}^{n} \ln \frac{x_i}{x_{\min}} = 0. \tag{8}$$

Namely:

$$\alpha = 1 + n\left[\sum_{i=1}^{n} \ln \frac{x_i}{x_{\min}}\right]^{-1}. \tag{9}$$

Definition 1. A control event comprises a consecutive series that includes verbal communication of one or several control commands (including the ATC controller issuing an instruction and listening to the repeated instruction from the ATC controller).

By analyzing the recording data of a sector in TMA, the interval time X of the consecutive control event was obtained. The corresponding α was obtained with the above method to acquire the corresponding ATC controller workload equation.

The mathematical expectation of the sample was acquired according to the nature of the power-law function (Habibullah and Ahsanullah, 2000):

$$E(X) = \left(\frac{C}{\alpha-1}\right)^{\frac{1}{\alpha-1}} \frac{\alpha-2}{\alpha-1} (\alpha > 2) \tag{10}$$

3. Sector capacity estimation based on ATC dynamics

The activation of control events is necessarily related to the number of aircraft within the airspace. Thus, we used regression analysis to establish the corresponding sector capacity estimation model:

(1) *Determine the required independent and dependent variables*: for different airspaces, different sectors exhibit differences. A proper independent variable can be selected according to sector and traffic flow characteristics. For example, the number of aircraft passing different corridors in the airspace during a certain time interval can be selected as well as the flight time or aircraft model. ATC workload is regarded as the dependent variable, and the specific workload can be further categorized into small loading groups.

The independent variable is an explanatory variable of workload. It involves entities that generate the workload of the investigated individuals, leading to the production of ATC workload:

Definition 2. Dependent variable y refers to the number of control events that occurred in unit time.

Independent variables $x_1, x_2, x_3, \ldots, x_n$ show the number of aircraft of different traffic flows (arrival, departure, etc.) in the airspace during a unit time. e is a random error term. The regression equation of control events and air traffic flow (Laudeman *et al.*, 1998) was then established as follows:

$$y = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n + e. \tag{11}$$

Each variable value required in the regression equation was obtained by collecting and processing the sector data. Through multiple linear regression, regression coefficients $\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_n$ were solved to obtain the corresponding regression equation. Based on the produced regression equation, the ATC workload within a sector was analyzed. In addition, with reference to DORATASK, sector capacity (number of control events that occurred within one hour of the estimation time) was estimated as follows:

$$y = \frac{2880}{E(X)}. \tag{12}$$

In this equation, given that DORATASK set up the threshold criterion of 80 percent, the reasonable controlling workload time should be 3,600×80 percent = 2,880 seconds within one hour or 3,600 seconds.

With this constraint, Equation (12) is substituted in Equation (11) to identify TMA sector capacity C_s in the corresponding sector as follows:

$$C_s = x_1 + x_2 + \ldots + x_n. \tag{13}$$

(2) *Use of proper data acquisition and processing methods*: time series analysis, which is a work measurement technique, was adopted. Its principle is to identify the required time to accomplish a given task based on the measurement of actual workload to accomplish this task. For data collection, the multi-channel digital radar voice recorder (MDR) was utilized to acquire work elements of work. This device can easily acquire time study data within a short time, even though such working elements occur according to a foreseeable order. For other elements, such as control behaviors, timing field measurements were used. Hence, the duration of each element and frequency was recorded. The data source processing mainly includes two parts: MDR data processing (to acquire the dependent variable) and actual flight data processing. The specific processing was achieved through computer programming.

(3) *Regression analysis*: through such an analysis, the number of control events that occurred in the unit time was correlated with the potential independent variable calculation method to determine the exact measurement method that can conduct the optimal estimation of ATC work of air traffic.

(4) *Computer-implemented process of regression analysis*: the following content illustrates the processing of parameters, such as independent and dependent variables, in the ATC workload assessment model as well as the computer implementation of the analysis process. The entire system consists of a database, the control module, the ATC voice communication time statistics module, the independent variable production module through regression analysis, the regression analysis algorithm implementation module, and the result output module. The data mainly include detailed flight information and MDR aircraft voice communication logging saved in the information system of the air traffic control center. The database is the basis of the system. The master module is the one where various modules are manipulated by the system to facilitate data transmission and calling. The transmission module of regression analysis was used for data analysis and fitting. Programming was applied to realize multivariate regression analysis and was the core of the entire system. The output module received the result of regression analysis and was the basis of diagnostic analysis of the regression results. All system modules and their logical relationships are shown in Figure 1.

4. Analysis of examples

4.1 Identification of the ATC dynamical model

Radiotelephony records of 1,000 control events in the third sector of Kunming TMA on January 21, 2014 were collected as experimental data by a voice recording equipment of the air traffic control department. Data statistics were made with MATLAB (Figure 2). After obtaining the power exponent, the distribution, and density distribution of the experimental data were compared with the theoretical curve (heavy-tailed distribution curve) by using MATLAB. The results are shown in Figures 3 and 4. The experimental data agree with the distribution characteristic of the heavy-tailed curve.

The time interval of the 1,000 consecutive events on a certain day was obtained by analyzing the recorded data. Some of the data are shown in Table I.

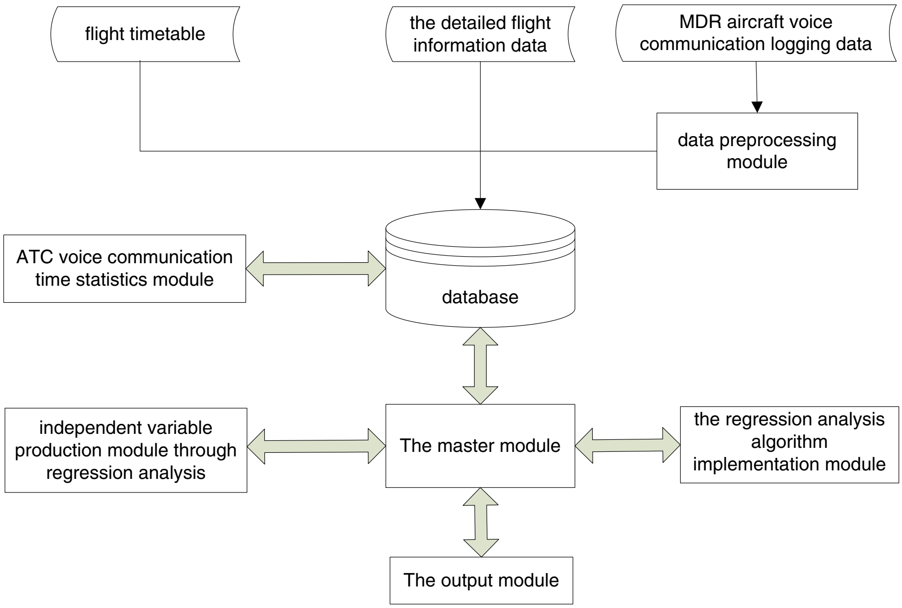

Figure 1.
System modules and their logical relationships

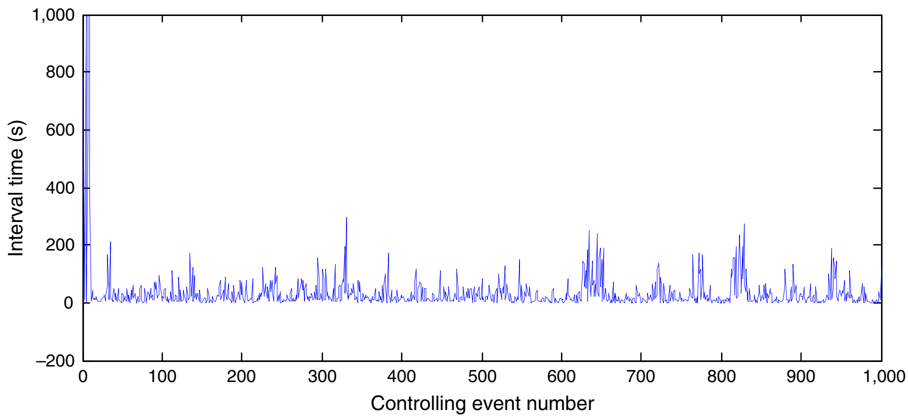

Figure 2.
Time intervals of 1,000 consecutive control events

The data in the table indicate that the control events exhibit intermittency, that is, they occur in several time frames with short interval and high frequency (e.g. 8-11 h, 14-17 h, 19-21 h) and in the rest of the time frames with long interval. Such distribution is consistent with the actual working condition. The time frame with high frequency of control events is the busy time frame of the actual operation unit. Figure 2 directly shows that the above features can be observed. In several intervals (e.g. the horizontal interval between 100 and 300), the interval time of control events is small. The corresponding interval is the busy time frame of a sector. Meanwhile, in several other intervals, the time is relatively long, and the corresponding interval is a relatively idle time frame (e.g. the horizontal interval between 600 and 700).

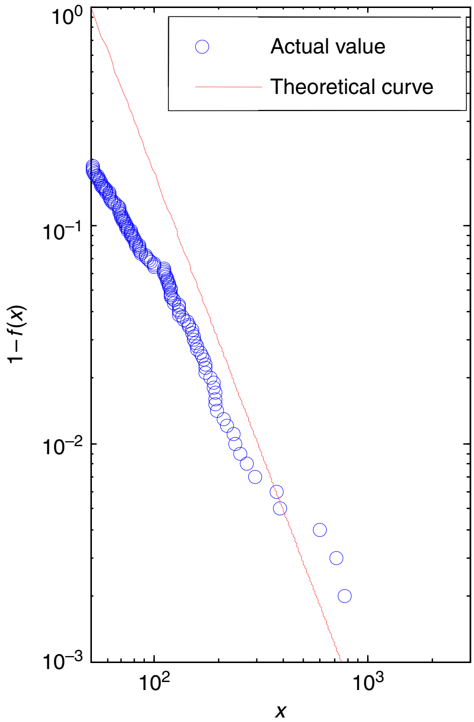

Figure 3.
Time interval distribution of control events

Together with the analysis of known data, the MLS method was utilized to calculate the power exponent $\alpha = 2.55$ in accordance with Equation (9). With the theoretical curve of the given power exponent and the power exponent of the data, we established the analogy. The data distribution and density distribution are shown in Figures 3 and 4, respectively. Figure 3 shows that the density distribution of the interval time of control events has the obvious characteristic of heavy tail, thereby verifying its consistency with the power-law distribution.

With further fitting, the density function of the control events in this sample is:

$$f(x) = 122.36x^{-2.55}. \tag{14}$$

Equation (10) allows for the calculation of $E(X) = 47.21$ s.

Figures 3 and 4 verify that the time interval of the control events conforms to the heavy-tailed distribution. Intuitively, Figure 3 shows that the time interval of the control events is consistent with the heavy-tailed (power-law) distribution. In other words, a linear time interval relationship exists among the log-log coordinates. Figure 4 shows the heavy-tailed distribution feature of the time interval of control events. The density distribution function has a "power-law tail" under the log-log coordinates.

Special attention should be paid to the extensive use of the concept of "heavy-tailed distribution" in human dynamics without strict differentiation from the power-law distribution. Generally, distributions with evident deviation from the Poisson distribution and a broad tail are viewed as heavy-tailed distributions. Except

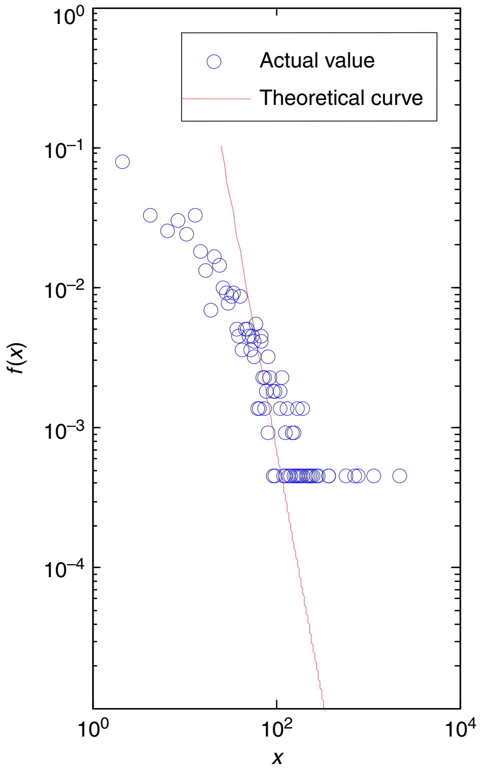

Figure 4.
Density distribution of time interval of control events

Table I.
Time interval of 1,000 consecutive controlling events (part)

Time frame	6-7 h	7-8 h	8-9 h	9-10 h	10-11 h	11-12 h
Interval time (s)	373	711	5	14	9	65
	777	46	9	6	11	96
	–	–	–	–	–	–
	69	384	13	5	7	115
	1,141	23	17	9	23	84
Time frame	12-13 h	13-14 h	14-15 h	15-16 h	16-17 h	17-18 h
Interval time (s)	118	61	15	14	9	59
	131	99	13	8	31	24
	–	–	–	–	–	–
	79	68	22	23	16	72
	36	74	18	19	7	33
Time frame	18-19 h	19-20 h	20-21 h	21-22 h	22-23 h	After 23 h
Interval time (s)	63	13	16	35	99	38
	25	21	5	51	118	129
	–	–	–	–	–	–
	113	17	23	118	75	81
	73	19	35	67	53	56

for single distributions, such as power-law distribution, they also include mixed distributions (e.g. power exponent distribution) although they cannot strictly meet the definition that no exponential order matrix exists in heavy tail. This explains why the heavy-tailed distribution and power-law distribution in this study are the same.

4.2 Sector capacity transformed from the frequency of occurrence of control events

For the specific conditions of the Kunming TMA01 Sector, three types of estimation methods of explanatory variables (shown below) were used:

(1) total number of departing aircraft in 1 h;

(2) total number of arriving aircraft in 1 h; and

(3) total number of flyover aircraft in 1 h.

By analyzing and processing the raw data sets, the following models were extracted for the solution of variables: the number of control events in a time frame and the number of departing, arriving, and flyover aircraft of the sector in a corresponding time frame. The response variable of the regression model is the number of control events in a time frame. Alternative predictive variables include the number of departing, arriving, and flyover aircraft of the sector in a corresponding time frame.

The required variables in regression equation were analyzed. Among them, the data of 75 samples are shown in Table II (duration of 1 h).

Regression analysis was conducted on all samples. According to the results of the multiple linear regression analysis, the ultimate model was obtained as follows:

$$y = 1.385x_1 + 2.768x_2 + 1.75x_3. \tag{15}$$

From the perspective of the coefficient model, departing aircraft have the maximum influence on the number of control events, followed by flyover aircraft. In actual control, the ATC controller in the regional control room spends most of his/her energy approving or modifying the height of Reduced Vertical Separation Minimum implemented by departing aircraft handed over from the adjacent sector of arrival as well as the handover of overflying aircraft among sectors. Hence, the coefficient size in the regression model is reasonable.

With the consideration of the actual working conditions of ATC in the Kunming radar control area, the core of the work of ATC controllers is controlling events. Most of their working time is utilized for voice communications with aircraft, including issuing commands to the captain and listening to the captain repeat the commands. In addition, a very few ATC controllers have subjective workloads, such as dragging caution plates. As influenced by the behavioral habits of each ATC, the manifested subjectivity is relatively significant. Thus, these factors were not considered in the regression model. Finally, radar control was used, and the commanding ATC needs to pay

Case	Arrival	Departure	Fly over	Number of control events
1	7	9	3	43
2	6	10	8	56
3	7	9	10	57
4	7	8	14	56
5	8	8	5	47
6	11	8	7	61
7	6	13	9	48
8	4	9	6	49
9	10	8	10	45
10	6	7	4	30

Table II. Control events and corresponding flight data (part) attention to the radar screen. As long as an aircraft is in the controlling area, ATC abides by rules to supervise it. In many cases, the supervision is concurrent to the control events. Thus, the control event is included the workload. In this study, the model does not include the effect of supervision.

The ATC workload in the sector can be analyzed according to Equation (13). The frequency of control events in the evaluation time is $2{,}880/47.21 = 61$ times/hour because the DORATASK method set the threshold criterion of 80 percent. According to the actual operation statistics in Kunming TMA, the ratio between the approach and departure is roughly 1:1 (i.e. $x_1 = x_2$). If the number of flyover aircraft in the sector accounts for 30, 40, and 50 percent of the control events in the total number of aircraft in the sector, the sector capacity can be identified as follows. When the number of flyover aircraft accounts for 30 percent of all aircraft in the sector, the sector capacity is 31 flights/h. When the number of flyover aircraft accounts for 40 percent of all aircraft in the sector, the sector capacity is 32 flights/h. When the amount of flyover aircraft accounts for 50 percent of all aircraft in the sector, the sector capacity is 33 flights/h. The details are shown in Table III.

Table III shows that the number of control events is proportional to sector capacity, which agrees with the practical situation. Large sector capacity means that many flights in the sector exist, and many controllers are needed to communicate with pilots. This scenario increases the number of control events.

According to human dynamics analysis, limiting the number of control events per unit time actually limits the ultimate sector capacity from the perspective of controller workload. Table III shows that the higher the percentage of flyover aircraft in all aircraft of the sector, the higher the ultimate sector capacity is. In other words, given a limited number of control events, the controller can command numerous aircraft. This scenario also agrees with the practical situation. Compared with arriving and departing aircraft, controllers send and receive the least commands to and from flyover aircraft, generally including the arrival of aircraft, adjusting or maintaining certain flying heights, pilots reporting their location, and handover of aircraft control. For arriving and departing aircraft, controllers also have to adjust their flying heights several times according to the practical situation. This action will

Total flights in the sector	Number of control events When 30% are flyover aircraft	When 40% are flyover aircraft	When 50% are flyover aircraft
25	50	49	47
26	52	51	49
27	54	53	51
28	56	55	53
30	58	57	55
31	60	59	57
32	62	61	59
33	64	63	61
34	66	65	63
35	68	67	65
36	70	69	67
37	72	71	69
38	74	73	71

Table III.
Evaluation results of sector capacity

shorten the time interval of control events, that is, increase the number of control events. With a limited number of control events per unit time, a high percentage of arriving and departing aircraft in the sector will result in small ultimate sector capacity. In other words, a high percentage of flyover aircraft in the sector is accompanied by high ultimate sector capacity.

5. Conclusion

In this research, sector capacity estimation based on ATC workload was explored, and relevant studies on human dynamics were applied in the evaluation and research of ATC workload assessment. The seemingly random regularity of ATC workload was revealed. In addition, the regression analysis method was utilized to establish a model of TMA sector capacity estimation. Finally, the feasibility of the model was verified with actual data on the control area of Kunming TMA.

The power exponent calculated in this study may present certain limitations because of the constraint posed by the specific sample size of control sectors. Future studies should further explore the power exponent and analyze other influential factors of ATC workload to build a more complete model of sector capacity estimation.

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