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Enhancing Insight into Air Traffic Controller Fatigue: A Dynamic Quantitative Examination through Biological Rhythms

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To scientifically and effectively predict fatigue risk among air traffic controllers, the authors developed a dynamic evaluation model tailored to the routine activities of traffic controllers. By considering biorhythms and workload, we identified causes of fatigue and quantitatively analyzed their impact. Our study involved 24-hour sleep deprivation experiments, collecting electroencephalogram (EEG) data to track fatigue over time. Expert scoring determined workload coefficients for different periods and positions. Using experimental data, we established and validated a mathematical model for dynamic fatigue risk assessment during various work periods. Results align with controllers' actual fatigue levels and self-assessment scores, indicating the proposed method's effectiveness in early fatigue detection and ensuring aviation safety.

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Introduction

As air traffic continues to surge, so does the strain on air traffic management, with human factors emerging as a pivotal concern for civil aviation safety. The rotating day-night shift system and relentless mental and physical workload have spotlighted controller fatigue as a critical issue in human factors research. The International Civil Aviation Organization (ICAO) defines fatigue as a physiological condition in which the ability to perform mental or physical activities is reduced due to lack of sleep, prolonged periods of wakefulness, or excessive physical activity (ICAO, 2016). In two recent studies conducted by Lu and his research team, fatigue emerged as a significant causal factor contributing to undesirable events in aviation, especially amidst the challenges posed by the unexpected pandemic (Lu et al., 2023; Lu et al., 2024). Fatigue compromises attention, alertness, judgment, and decision-making, culminating in cognitive and operational errors. According to the U.S. Federal Aviation Administration (FAA), approximately 21% of annual aviation accidents stem from controller fatigue (ICAO, 2016). Hence, establishing a scientifically robust and effective method for predicting controller fatigue and implementing corresponding preventive measures holds paramount importance in safeguarding aviation operations.

Present studies on assessing controller fatigue methods classify into subjective and objective evaluation techniques. Subjective methods involve fatigue scales completed by subjects to gauge their fatigue status and severity, such as the Multidimensional Fatigue Inventory developed by Professor Smets at the University of Amsterdam in the Netherlands (Smets et al., 1995) and the MFI-16 Multidimensional Fatigue Self-Rating Scale (Sun et al., 2016). The objective evaluation method employs a range of instruments and techniques to gather physiological, biochemical, behavioral, or human factors engineering indices associated with fatigue, forming a comprehensive fatigue evaluation system. Commonly utilized approaches involve collecting subjects' electroencephalogram (EEG), electrocardiograph (ECG), Electrodermal, and other indicators to delineate fatigue. Foreign scholars Lal and Craig (2001) believe that EEG signal is one of the most reasonable indicators for testing fatigue. Chen and Wang (2017) collected the EEG data of controllers and used EEG indicators to compare the fatigue differences of controllers under different shift systems. Some scholars also analyze fatigue by monitoring subjects' blinking, yawning, and other behaviors. Chen (2015) proposed controller fatigue status monitoring based on eye movement data. The fatigue state of controllers was evaluated by collecting the eye tracking data and analyzing the fixation state, pupil changes, blink time, and other indicators combined with PERCLOS (Chen, 2015). Based on facial recognition technology, Sun et al. (2014) used the OpenCV development platform to identify controller fatigue status through the eyelid opening and closing rate and mouth opening frequency.

While the aforementioned method accurately gauges controller fatigue, its implementation entails a complex measurement process, prolonged testing duration, and requires installing cameras in control positions, potentially amplifying the psychological burden on controllers. Moreover, fatigue is subject to biological rhythms, work content, and dynamic time variability. Consequently, existing research solely evaluates personnel's current fatigue status, lacking predictive capabilities for preemptive fatigue risk assessment and proactive control measures in response to dynamic fatigue fluctuations (Li et al., 2017).

Controller fatigue primarily stems from endogenous biological rhythms and exogenous workload and pressure. Biological rhythms, such as the 24-hour circadian rhythm, dictate inherent patterns in physiological states characterized by fluctuations between high and low periods. Shift workers often find themselves operating during these low periods, such as late afternoon and midnight, exacerbating fatigue. Consequently, fatigue prediction models for controllers must comprehensively account for the influence of biological rhythms. Many scholars in relevant research domains have thus developed mathematical models for fatigue prediction grounded in human sleep homeostasis, circadian rhythm, and working hours. For example, the Three Process Model of Alertness (TPMA) proposed by Akerstedt and Folkard (2004) calculates the alertness value through the start and end time of work/sleep; in 2001, the Sleep Research Center of the University of South Australia proposed the Fatigue Audit Inter Dyne (FAID) model, which calculated the output fatigue value through duty/rest time (Roach et al., 2004). Rosa (2004) proposed the CAS model, which calculated alertness through circadian rhythm and sleep homeostasis. Based on the above studies, Li (2019) established a fatigue prediction model aiming at the work characteristics of subway attendants, considering factors such as the time domain of personnel operation, working hours, work breaks, and shift patterns. However, all parameters in the model were determined by subjective methods, lacking objective accuracy. Wu (2018) collected PVT reaction time data of subjects through a sleep deprivation experiment, established the change function of quantified alertness value with wake time, and combined it with the controller's workload to calculate the fatigue prediction curve. Workload denotes the volume of work the human body can handle within a given timeframe. A higher workload accelerates fatigue accumulation, resulting in an earlier onset of fatigue (Wu, 2018). Arico et al. (2015) analyzed the EEG signals of twelve (12) school control students, established the mental load coefficient of control work, and proposed a workload model based on EEG. Shou and Lei (2013) found that the frontal theta wave of controllers changes sensitively and significantly with the working load and working time.

The aforementioned research acknowledges the influence of sleep and circadian rhythm on fatigue and establishes a quantitative fatigue prediction model through experimentation and mathematical analysis, providing a basis for the present study. Nonetheless, existing studies on dynamic quantification of fatigue often overlook the specific work characteristics of air traffic controllers. Thus, this paper aims to address these limitations by introducing enhancements and additions derived from a comprehensive examination of current research gaps:

1) Considering both endogenous biological rhythm and exogenous workload, this study identified factors influencing controller fatigue: circadian rhythm, work content, and work hours. Through experimentation and mathematical calculations, a quantitative fatigue prediction model was subsequently developed.

2) Perform a controlled simulator test under conditions of sleep deprivation. Collect EEG signals from the subjects during the test and process the data to derive EEG fatigue values. Utilize regression analysis to determine the changes in the fatigue value curve over the course of 24 hours with respect to awakening time.

3) Utilize the expert scoring method to ascertain the workload coefficient for each control seat

and working period. Compute the controller's workload implementation curve and determine the parameters of the fatigue quantitative assessment model through mathematical calculations.

Experimental Design

Experimental Materials and Contents

The experiment utilized the MFI-16 fatigue scale, a unique adaptation of the Multidimensional Fatigue Scale (MFI-20) developed by the University of Amsterdam in the Netherlands. This revised version, developed by the Safety Science Institute of the Civil Aviation University of China, is specifically tailored to the professional characteristics of controllers. The scale, comprising 16 items, yields a total score ranging from 16 to 80 points, and a higher score indicates a greater degree of fatigue (Lal. & Craig, 2001). The scale score is recorded and can be compared with subjective scale scores to validate the effectiveness of physiological index data in representing fatigue.

The equipment used to collect physiological data is the Manglod-10 multi-channel physiological instrument produced by Mind Media. This equipment is used for recording human physiological signals and consists of a multi-channel analog signal collector, a signal processing unit, and computer software. During the experiment, physiological sensors were installed on various parts of the subjects' bodies to capture up to 10 signals, including electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), and electrodermal response (EDA). These signals were then collected by a multichannel analog signal collector and transmitted to the signal processing unit. Following amplification, filtering, and interference removal, the data was sent to the computer for further processing and analysis.

Experimental Process and Content

A total of 12 air traffic controller students from the Civil Aviation University of China were selected before and after the experiment. They were all male, with normal naked or corrected vision, no smoking or drinking, self-reported no sleep disorders, and no history of neurological or psychiatric medication or medical history. All subjects studied radar control-related courses and passed the assessment of subject scores. All subjects were informed in advance of the experiment's content, method, and purpose and participated in the experiment voluntarily.

In this experiment, the subjects were deprived of sleep for 24 hours under the supervision of the experimenter, who ensured that the subjects did not sleep throughout the study. They were regularly tested. In terms of good health, an adult is recommended to sleep for seven to eight hours per night (Healthy China Action Promotion Committee, 2019; Napoli, 2023). Therefore, all subjects were asked to sign a pledge to get eight hours of sleep the night before and set an alarm for 7 a.m. on the day of the experiment to ensure uniform sleep conditions (no analysis of the subject’s sleep status was involved) before the test. Testing commenced at 9 a.m. and occurred every two hours until 7 a.m. the following day, totaling 12 tests per individual, as outlined in Table 1. During the intervals between tests, under the supervision of the researchers, the participants refrained from engaging in strenuous activities that would deplete physical energy and were prohibited from consuming stimulating beverages like coffee or strong tea. Additionally, the staff provided the diet during the experiment to ensure that meals did not affect the participants' state.

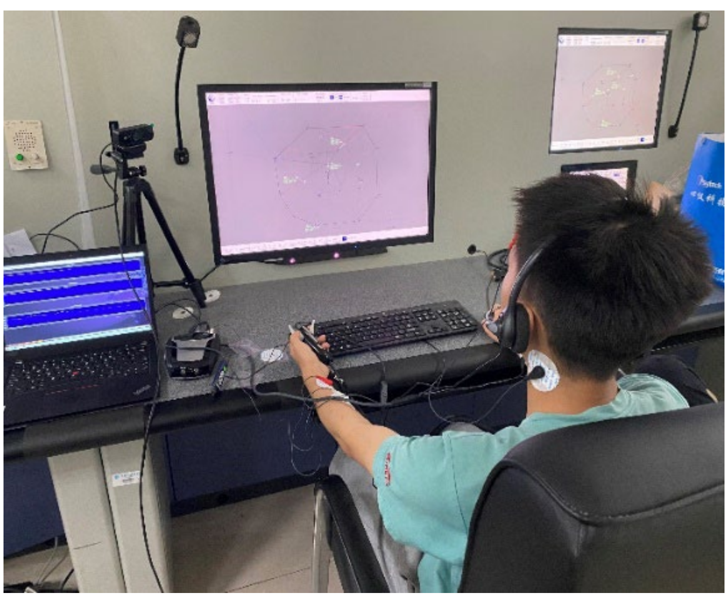
Table 1
Test Schedule

Number of Experiments	1	2	3	4	5	6	7	8	9	10	11	12
Time	09	11	13	15	17	19	21	23	01	03	05	07

The test contents include the approach radar simulator test and the MFI-16 fatigue scale filling (PVT test). Before conducting the radar simulator test, the subjects first filled out the fatigue scale to record their subjective fatigue value at the current moment. Each simulator test lasted 30 minutes.

The whole test process's EEG data were recorded. The multi-channel physiological instrument was connected to the controller's left forehead, wrist, ear, elbow joint inside, index finger, and middle finger through electrodes. The EEG unipolar lead method was used to record the EEG signals of the controller's left forehead during the simulation. Figure 1 shows the scenario during the test.

Figure 1
Experimental Scene Diagram



Workload Evaluation Indicators

Understanding the intricate relationship between workload and fatigue among air traffic controllers is crucial. The time between waking and sleeping represents a period of energy expenditure, where fatigue accumulates as energy is depleted. However, workload is also a key factor in this equation (Wu, 2018).

Given the inherent variations in workload and specific tasks, the accumulation of fatigue among controllers on duty varies significantly across different types of control, positions, and periods. These control types include airport control, approach control, and area control. Airport control oversees aircraft movements within the airport's jurisdiction, including taxiing, take-off, landing, and related maneuvers. Approach control manages aircraft approaches and departures. Area control provides air traffic control services for aircraft within a designated airspace. Control positions typically comprise director, coordinator, and supervisor roles. The director organizes air command and deployment, the coordinator facilitates coordination and handover, monitors flight dynamics, and oversees the director's commands for errors or omissions, while the supervisor manages on-site operations, coordinates with other units, and ensures overall operational efficiency (Li, 2000). Due to the workloads being different in different positions, general units will arrange for controllers to rotate positions for duty.

While the air traffic control industry operates continuously, controllers are mandated to be on duty around the clock. Flight volumes exhibit time-varying patterns, fluctuating throughout the day. Consequently, controllers contend with varying work pressures and loads as they manage different numbers of flights at different times. Ultimately, a controller's workload is shaped by the specific tasks and complexity of their position, as well as the workload during their designated working period.

Data Processing and Model Processing

EEG Data

The four fundamental rhythm waves of the EEG signal can be collected using a multichannel physiological instrument: fast waves α, β and slow waves θ, δ. According to scientific research in related fields, when a normal adult is clear-headed and alert, the brain waves are mainly α waves and β waves; on the contrary, when a person's alertness decreases, operational ability deteriorates, and fatigue increases, θ waves will appear in the brain, and δ waves will appear when a person is anesthetized or asleep (MOT, 2017). As adults shift from a normal to a fatigued state, the slow wave signal in the brain's electrical activity gradually intensifies while the fast wave signal weakens. Consequently, the energy ratio between slow waves and fast waves serves as an indicator to assess fatigue status (Chen, 2017), as illustrated in the following formula (1):

$$F_1 = \frac{E_\theta}{E_\alpha + E_\beta} \tag{1}$$

In the formula, F_1 is the fatigue value, E_α is the energy of α wave, E_β is the energy of β wave, and E_θ is the energy of θ wave. Since the subjects did not sleep during the experiment, δ waves were not considered in the formula.

During data processing, Biotrace+ software performs Fourier transform and filtering on the EEG rhythm, eliminating outliers greater than 50 μV in the data. The average power spectrum is used instead of the EEG energy value to calculate the F value, which is the EEG fatigue value (Chen,2017), as shown in formula (2).

$$F = \frac{P_\theta}{P_\alpha + P_\beta} \tag{2}$$

In the formula, F is the fatigue value, P_α is the power of α wave, P_β is the power of β wave, and P_θ is the power of θ wave.

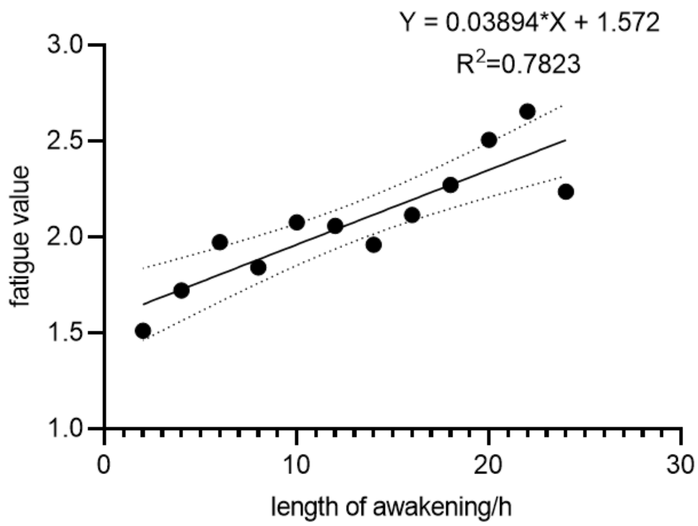
To verify the consistency of the fatigue value change curve with awakening time across subjects, correlation analysis was performed between the brain electrical fatigue data and the awakening duration of 12 subjects. Results revealed a significant correlation ($p<0.05$) between the EEG fatigue value and awakening time for most subjects. Table 2 below displays the correlation coefficients between the fatigue value and awakening duration, with letters representing the subject's fatigue value data number and awakening duration measured in hours.

Table 2
Results of Correlation Analysis between Fatigue Value and Awakening Time

Index		Subject A	Subject B	Subject C	Subject D	Subject E	Subject F
Wake time and EGG fatigue value	Pearson correlation	0.928**	0.694*	0.636*	0.748**	0.745**	0.736**
	Double tail sig. (p)	0.000	0.012	0.026	0.005	0.005	0.006
Index		Subject H	Subject I	Subject J	Subject K	Subject L	Subject M
Wake time and EGG fatigue value	Pearson correlation	0.686*	0.675*	0.738*	0.815**	0.740	0.791*
	Double tail sig. (p)	0.020	0.032	0.037	0.002	0.057	0.019

The table results demonstrate consistent changes in subjects' fatigue values with awakening time. Consequently, the average brain electrical fatigue value of all 12 subjects serves as a representative characteristic value to correlate with awakening time. Prior to computing the average, outliers are excluded at each time point to enhance the generalizability of the results. The fitting results are provided in Figure 2.

Figure 2
Fatigue Data Fitting Curve



The figure shows that the average EEG fatigue value of the subjects fluctuated and increased with the prolongation of awakening time. However, the fluctuation amplitude was small, and the overall correlation was strong. (R^2=0.7823). According to the trend line formula, the fatigue value prediction formula under the influence of biological rhythm can be obtained as Equation (3).

$$Y = 0.03894t + 1.572 \tag{3}$$

In the formula, Y represents the predicted value of fatigue changing with awakening time, and t represents the awakening duration, the difference between the current moment and the awakening moment of the day.

Model building

This article establishes a quantitative fatigue prediction model for air traffic controllers throughout the day. According to the regulations of the Civil Aviation Administration of China, radar controllers shall not be on duty continuously for more than 2 hours. They shall not have less than 0.5 hours off during work (MOT, 2017). On this basis, different control units have different requirements, and the general modes include 2 hours off for the upper 2 hours, 1 hour off for the upper 2 hours, 1 hour off for the upper 1 hour, and 0.5 hours off for the upper 1 hour. Controllers usually work from different positions at different times. Therefore, when considering the dynamic quantitative evaluation model of fatigue, the daily time is divided into different periods according to the work and rest patterns of the controller, and the fatigue values of the first and last nodes of each period are calculated.

Establish a segmented function based on the controller's scheduling schedule to predict dynamic fatigue. Propose a fatigue dynamic quantitative evaluation model, as shown in equation (4).

$$P(n) = Q + k(t_n - t_0) + \sum_{i=1}^{n} (C_{i-1}W_{i-1} - R_{i-1})(t_i - t_{i-1}) \tag{4}$$

In the formula, the independent variable n represents the number of time required, P(t) is the fatigue prediction value at time t ; $i \in \{1,2,\dots,n\}$ is the time node number; t_i represents the time value of each time node during the duty process, such as t_0 represents the end of sleep and awakening time, t_1 represents the time when the first duty ends and the rest begins; t_m represents the moment requested; Q represents the initial fatigue value after sufficient rest; k represents the fatigue accumulation coefficient based on biological rhythm; C_i represents the fatigue value accumulation coefficient of the position that starts working at the i moment. If the rest starts at the i moment, C_i is 0; W_i represents the fatigue accumulation coefficient of the period when the work starts at the i moment. If the break starts at the i moment, W_i is 0; R_i represents the recovery coefficient of the period when the rest starts at the i moment. If the work starts at the i moment, R_i is 0. The parameter k in the formula has a value of 0.03894, and Q has a value of 1.572.

Case analysis

The authors conducted research at the regional control room of a specific Air Traffic Control Center, selecting several controllers as examples. The authors then calculated the fatigue quantification prediction values based on their scheduling information for a particular day, and the result of the model was verified and analyzed by the controller supervising the fatigue scale. In this control room, controller positions are categorized into director, coordinator, and supervisory roles. Controllers typically rotate between these positions according to a scheduling rule of 1.5 hours on duty followed by a half-hour rest period in the middle. The scheduling information of some controllers in the morning and evening shifts is shown in Table 3 and Table 4. The tables demonstrate the duty and corresponding duty positions of controllers at different times. The letter C stands for Coordinator, D stands for Director, and R stands for Rest.

Table 3
Schedule Information Sheet for Some Controllers (Morning Shift)

Controller number	0800-0830	0830-0900	0900-0930	0930-1000	1000-1030	1030-1100	1100-1130	1130-1200
A1	C	C	C	R	D	D	D	R
A2	D	D	D	R	C	C	C	R
B1	C	C	C	R	D	D	D	R
B2	D	D	D	R	C	C	C	R
C1	R	C	C	C	R	D	D	D
C2	R	D	D	D	R	C	C	C

Table 4
Schedule Information Sheet for Some Controllers (Night Shift)

Controller number	1800-1830	1830-1900	1900-1930	1930-2000	2000-2030	2030-2100	2100-2130	2130-2200
A1	C	C	C	R	D	D	D	R
A2	D	D	D	R	C	C	C	R
B1	C	C	R	Rt	D	D	D	R
B2	D	D	R	R	C	C	C	R
C1	C	R	D	D	D	R	C	C
C2	D	R	C	C	C	R	D	D

The six controllers are on duty during the morning and evening shifts, with morning shifts from 8:00 to 12:00, evening shifts from 18:00 to 22:00, and free breaks from 12:00 to 18:00 in the middle.

According to the questionnaire survey of the control room controllers and the surveyed scores, the specific position allocation of the unit and the load coefficient of each position is determined (Refer to Table 5, assuming that everyone in the same position has the same workload coefficient).

Table 5
Workload Coefficient of Each Position of An Approach Control Unit

Position Name	Director	Coordinator	Supervisory
Fatigue accumulation coefficient per hour	0.7	0.6	0.5

According to the change rule of actual flight flow, combined with the results of the questionnaire survey and expert scores, the duty-hours of controllers during the day shift were divided into four periods according to the degree of business, and the workload coefficients of each period were shown in Table 6.

Table 6
Working Load Coefficient of Each Period

Period	0800-1200	1200-1800	1800-2200	2200-2400
Fatigue accumulation coefficient per hour	2.0	1.5	2.0	1.4

The value of the controller's subjective fatigue degree was collected at the time node before the controller's middle rest and returned to work, that is, the value of the fatigue scale filled by the controller according to the current fatigue degree. The fatigue scale adopts the Stanford Sleepiness Scale, as shown in Table 7. The controller selects the most suitable state level according to the state description of the scale and records the current fatigue level value of the controller. The post-work fatigue scale value of controllers is correlated with the output value of the fatigue prediction model to verify the reliability of its application.

Table 7
Stanford Sleepiness Scale (SSS)

Degree of Sleepiness	**Scale Rating**
Felling active; Vital alert or wide awake	1
Functioning at high level but not at peak; Able to concentrate	2
Awake but relaxed; Responsive but not fully alert	3
Somewhat foggy; Lie down	4
Foggy; Lossing interest in remaining awake; Slowing down	5
Sleepy; Woozy; Fighting sleep; Prefer to lie down	6
No longer fighting sleep; Sleep onset soon; Having dream-like thoughts	7
Asleep	x

According to formula (4) and Table 3 through Table 6, fatigue prediction values of six controllers in morning and evening shifts were calculated. According to the survey results of the scale, the fatigue values of the six controllers were generally the same before starting work at 8:00 in the morning shift. They were relatively excited, and the self-rated fatigue level was 2 or 3. Therefore, it is considered that the initial fatigue state of controllers is the same, and the same Q value is taken. Since 12:00 to 18:00, between the morning and evening shifts, was free rest time, the controllers got sufficient sleep supplements and were in a relatively complete state of spirit before the 18:00 shift. The self-rated fatigue value was the same, and the same Q value was used for calculation.

Taking the early shift of controller A1 as an example, the parameters in the model are calculated. The controller wakes up at 6:00 that day, t_0 is 6, the start time is 8:00, t_1 is 8, and so on. Based on the working load coefficient of each position in each period, the values of each parameter are shown in Table 8. In the definition, C_0W_0 is the fatigue accumulation coefficient of commuting and preparation work, and the value is 0.5. In addition to working hours, the rest coefficient R_i equals 0.05. Any parameter equal to 0 is omitted from the table.

Table 8
Parameter Value Table

Parameter name	Value	Parameter name	Value
t_0	6	C_1	0.6
t_1	8	C_3	0.7
t_2	9.5	W_1	2.0
t_3	10	W_3	2.0
t_4	11.5	$R_{2,4}$	0.05
t_5	12	C_0W_0	0.5

The above parameter values were substituted into formula (4) to calculate the cumulative fatigue value and cumulative rest recovery value at each moment and obtain the fatigue prediction evaluation value at each moment, as shown in Table 9.

Table 9
Calculation Results of Controller A1 Morning Shift Fatigue Model

Start time	End time	Duration/h	Work or activity type	Fatigue value	Rest value	The end-time fatigue evaluation value
0600	0800	2.0	Commute and shift preparation	2.650	0	2.650
0800	0930	1.5	Coordinator	1.858	0	4.508
0930	1000	0.5	Rest	0.019	-0.025	4.502
1000	1130	1.0	Director	2.158	0	6.660
1130	1200	0.5	Rest	0.019	-0.025	6.654

The same method was used to calculate the fatigue prediction value of each node of the evening shift of the A1 controller and the morning and evening shifts of the remaining controllers. The fatigue prediction trend of six controllers in the morning and evening shifts was obtained, as shown in Fig. 3 and Fig. 4. The solid line in the chart represents the controller's work process, and the dotted line represents the rest of the controller.

Figure 3
The Trend of Fatigue Prediction of the Controller Early Shift

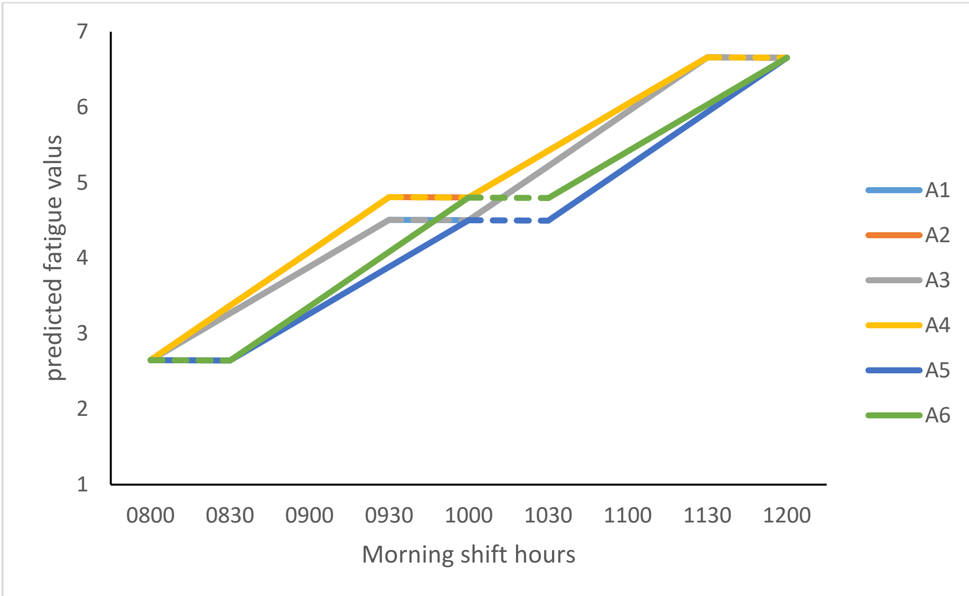
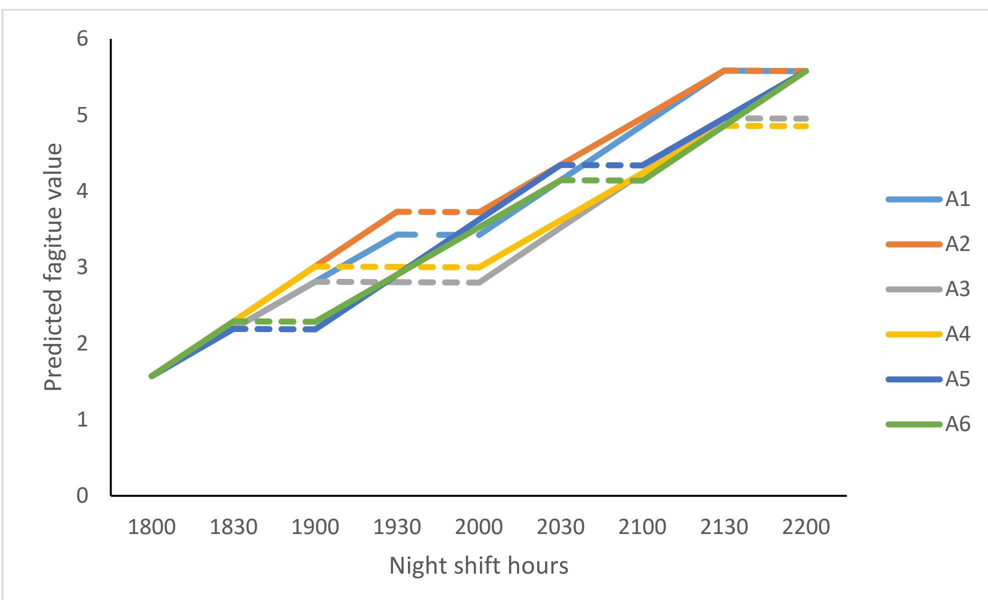


Figure 4
The Trend of Fatigue Prediction of the Controller Night Shift



Spearman correlation analysis was conducted between the predicted fatigue value of the controller at every moment, and the subjective fatigue scale value filled in, and the results are shown in Table 10. The results showed that the model output value strongly correlated with the subjective fatigue value, and the two results were consistent. This model can be used as a dynamic quantitative evaluation method for controller fatigue, providing a convenient and effective controller prediction.

Table 10
Correlation Analysis Result

		Model output value	Subjectivity fatigue value
Model output value	Correlation coefficient	1.000	0.681
	Sig. (double tail)		0.000

This paper introduces a biorhythm-based approach to predict the fatigue levels of controllers during duty. Through a carefully designed 24-hour sleep deprivation experiment, EEG fatigue changes of subjects were recorded continuously within the 24-hour period post-awakening. Data analysis and fitting techniques were then applied to derive a formula correlating EEG fatigue with wakefulness time. Subsequently, a dynamic quantitative evaluation model for fatigue was developed, integrating workload coefficients specific to each control position and working period. The reliability of the model for fatigue prediction was then confirmed through verification. The conclusions drawn are as follows:

1) The output value of the established fatigue quantitative evaluation model demonstrates a significant correlation with the subjective fatigue scale values reported by the subjects, indicating strong consistency. This model effectively predicts the fatigue experienced by controllers on duty, thereby providing a foundational framework for proposing optimal rest and scheduling strategies for personnel. Such measures are essential for mitigating safety risks associated with air traffic control operations.

2) The fatigue of controllers on duty was analyzed from two angles: biological rhythms and workload. We established a functional formula correlating fatigue with awakening time using objective EEG test data, and subjective workload coefficients were assigned for different positions and periods. By integrating these components, a comprehensive model was developed. This model allows for the quantitative evaluation of fatigue levels at any given moment of duty, with input derived from the controller scheduling table.

3) The participants in this experiment consisted of male control students with slight variations in age and health status, resulting in a limited sample size that may restrict the generalizability of the findings. To address this limitation, future experiments will involve in-service controllers of diverse genders and ages with an expanded sample size. These subsequent experiments aim to enhance the reliability and accuracy of the fatigue detection model by broadening the scope of experimental content.

Future Study

In the future, if the physiological data of controllers can be tracked for a long time, the physiological database of controllers can be established, and the fatigue prediction model of controllers can be established by using the method proposed in this paper.

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