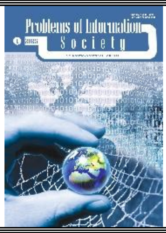

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Methods for modeling the mental load of a pilot as part of an aviation-technological complex

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ABSTRACT

The safety of civil aviation is the main goal of the International Civil Aviation Organization. It has long been known that most aviation accidents and incidents are due to suboptimal human performance. The negative influence of the human factor usually manifests itself when the crew approaches the limit of psychophysiological capabilities in the decision-making process. Therefore, any advance in the field of human factors research, including modeling of pilot performance under various modeling approaches, can have a significant impact on improving flight safety. With the advancement of aircraft automation and information technology, pilots must process more and more information during flight. They often have to process information on multiple tasks at once, and in such cases, mental workload tends to become an issue. Mental workload typically arises from tasks that require less physical effort but greater demands on the operator's cognition, thinking, and judgment. The simultaneous occurrence of information on several tasks leads to high mental load. Therefore, assessing pilots' mental workload during multitasking is of theoretical and practical importance. Based on the above, in the article, based on review studies using various methods for constructing a theoretical model of a pilot's mental load, methods and approaches for constructing a model of a pilot's mental load are reviewed and analyzed. The principles of constructing models using theories of information, automatic control and queuing are given.

1. Introduction

Dangerous deviations in the crew's actions to control the aircraft and its systems create a direct threat to flight safety (Collection of materials ICAO, 2003). In the process of flight control, it is necessary to take into account that the crew does not strive to create or complicate special situations. They arise as a result of errors in procedural, sensory-motor activity, when making decisions, as well as when the psychophysiological capabilities of the "operator-pilot" are exhausted in specific flight conditions. The reasons for such errors may be insufficient preparedness of the crew for flight operations, limited capabilities in choosing and implementing the best control technology for a specific aircraft in specific conditions, lack of attentiveness and other personal factors. Therefore, flight control should be based on compliance with the regulatory and technical documentation of the crew's actions, taking into account its psychophysiological capabilities and the ability to use them to the fullest.

Mental workload is an abstract attribute of human-machine interaction that cannot be observed directly (Hsu et al., 2015) The assessment of mental workload is usually carried out through various methods, such as subjective reports, performance ratings, and physiological measurements (Sperling, 1986). Performance assessments can be divided into performance assessments of primary and secondary tasks. A primary task is a task that has processing priority when an operator needs to perform multiple tasks simultaneously. In the case of priority completion of the primary task, the operator uses his residual capabilities to complete another task, the secondary task (Liu, 1994) Physiological measurement techniques for assessing mental workload include electroencephalogram (EEG), electrocardiogram (ECG), eye movement, and functional near-infrared spectroscopy (fNIRS). Mental workload cannot be accurately assessed using a single index or method, as individual and environmental factors will influence the mental effort expended to perform a given task (Gentil et al., 2014). Therefore, a comprehensive assessment method is needed.

Mental workload (MWL) is a key issue for all safety-critical industries, as elevated levels of MWL can impair human performance, potentially leading to fatal accidents. Conversely, extremely low MWL due to low arousal levels can cause boredom and lack of attention, and compromise job security. Aircraft piloting operations are typically complex sociotechnical systems that require the processing of a variety of information from a variety of sources, including visual and auditory signals, as well as environmental inputs both inside and outside the aircraft (Weelden et al., 2022).

This multifaceted problem demonstrates the critical importance of ongoing research and technological developments for the effective measurement and management of pilot MWL. Aviation safety statistics indicate that human error, which is primarily associated with abnormal MWL levels, is responsible for approximately 70% of aviation accidents (Kharufa et al., 2018). Despite the intuitive appeal of the MWL concept in many fields, the lack of standardized terminology remains a persistent problem in the literature (Fallahi. et al., 2016; Ellison e. al., 2008; Gabriel et al, 2016) is widely accepted that MWL is a multidimensional construct. There is a pressing need to differentiate between workload and MWL. The main difference between these two closely related terms is that MWL is further mediated by a number of additional factors, including past experiences, individual personality traits, and environmental context (Veltman et al., 1996; Yang et al. 2020).

That is influenced by task demands, individual characteristics, and the environment. To summarize, while it may be reasonable in some contexts to use "taskload" as a proxy for MWL, it is important to recognize that these are fundamentally different, not interchangeable, terms and cannot be equally defined.

2. Related works

There are numerous methods for measuring MWL in human factors and ergonomics research. Typically, there are three groups of indicators: subjective, results-based and physiological (Alaimo et al., 2020) Subjective measures are based on self-reports and are widely used in practice due to their cost-effectiveness, ease of implementation and widespread acceptance among users (Grassmann et al., 2017; Wickens, 2017). However, subjective measurements have a number of disadvantages. For example, some participants may have difficulty distinguishing between task demands and mental effort, which may lead to underreporting.

A high level of mental workload for pilots during aircraft flight is associated with an increased risk of flight operation and the likelihood of making errors. According to studies, aviation accidents, especially fatal ones, can be explained by pilot fatigue due to high levels of mental overload (Wickens, 2017; Reimer, 2011; Wei et al., 2014) This necessitates the assessment and prediction of pilot mental workload, which has led to increased attention from human factors researchers in the last decade. Another key aspect of pilot MWL measurements is the creation of MWL prediction models. Accurate MWL prediction is critical due to its role in developing real-time MWL monitoring systems capable of anticipating abnormal mental states of pilots and thus reducing the risk of accidents due to human error. Traditional statistical methods prove insufficient to reveal the complex and nonlinear relationship between MWL and heart rate variability (HRV) signals. In contrast, machine learning-based algorithms have shown promising performance in detecting different levels of MWL based on HRV characteristics. Despite these advances, there is still no systematic review covering the application of machine learning methods to pilot MWL forecasting. In order to fill the aforementioned research gaps, the primary objective of this work is to comprehensively synthesize the current literature related to the evaluation of pilot MWL using HRV

Three modern methodologies for measuring cognitive load are presented in the literature: subjective, behavioral and physiological (Vidulich & Tsang, 2015). Specifically, the subjective assessments consist of questions asked to the pilots at the end of the performance. Behavioral measures are based on monitoring the pilot's actions during a flight mission and checking the compliance of the actions performed with those previously planned. Finally, physiological measurements involve monitoring the operator's physiological signals to determine the state of his cognitive load. While subjective ratings and behavioral measures are methods that have been studied and accepted for several years, physiological assessment of MWL has been increasingly used in recent years due to improvements in sensor technologies, resulting in unobtrusive measurements that provide object. (Hsu et al., 2015).

Pilots often have to process large amounts of information in a relatively short time and make quick decisions to respond to possible airspace emergencies (Reimer, 2011) Morey et al. suggest that rational optimization of operator mental workload distribution can effectively reduce human errors and improve system reliability and operator comfort (Wei et al, 1014; Vidulich & Tsang 2015). Therefore, studying the prediction of pilots' mental workload can maximize the prevention of flight accidents by effectively adjusting the flight task and pilots' mental state over time (Young et al. 2015; Rusnock & Borghetti, 2018).

Currently, quantitative modeling of mental workload research is still in its infancy (Longo. 2015, Hsu et al., 2015). First, most models are descriptive (Wanyan et al., 2015; Roy et al., 2016). Modeling of mental workload is mainly based on post-mortem mental workload measurement (Longo, 2015; Vera et al., 2017). Second, there are still many shortcomings in quantitatively predicting mental workload. Bean and Salvendy (Liang et al., 2014; Bi and Salvendy, 1994) propose a dynamic temporal conceptual model to predict mental workload, including instantaneous mental workload (IMW), average mental workload (AMW), cumulative mental workload (CMW), maximum mental workload, and total mental workload (TMW), regardless of the specific mission area scenario. Laughery et al. (Laughery et al., 2012; Klemmer and Muller, 1969) conduct a task analysis method to calculate mental workload by decomposing complex tasks into several simple behavioral elements and connecting the elements hierarchically and logically. However, the massive problem is difficult to analyze in detail. According to the single-channel theory, Siegel and Wolf (Modeling pilot, 2019) present a time-line analysis and prediction (TLAP) method in which the time load equaled the time required/available (TR/TA). However, these models do not account for the factors that influence mental workload in aviation and do not account for the impact of different types of tasks on mental workload. Xiao et al. comprehensively adopt factors such as information volume, time pressure, visual encoding, and attentional resource allocation to establish a multifactorial mental workload prediction model. However, the model does not take into account conflicts within task types and the dynamic effect of time.

Predicting pilot mental workload can provide cockpit designers with useful information to improve cockpit design and thereby reduce the likelihood of pilot error, the cost of pilot training, improve the safety and performance of control systems and thereby better meet the needs of pilots in decision making.

Complex, algorithmic, continuous in time and short-term human activity, solving, for example, problems of monitoring and managing an object in limited areas of operating time, may require the use of methods from the theories of dynamic programming, graphs, automatic control and information. If human activity is complex in nature, continuous in time, or has a significant duration, and its individual acts are repeated many times, then it is advisable to use methods similar to the methods used in the theory of queuing.

3. Materials and methods

The corresponding growth in human-machine interaction (HMI) systems in recent years has created a need to constantly be aware of the level of operator cognitive load, especially in a safety-critical context such as aviation. The concept of mental workload (MWL) has been studied for decades in several influential texts and chapters in the field of human factors and ergonomics (HFE). However, due to its complex and interdisciplinary nature, a unique and generally accepted definition is still missing.

Excessive or limited mental workload can lead to dangerous situations, especially when operating complex systems such as airplanes, cars or an airport control tower, leading to errors and accidents. Thus, the need to control the operator's mental load during its execution is obvious.

Based on a review of studies using methods for constructing a theoretical model of a pilot's mental load, it was revealed that all researchers used different methods (Markov chains, dynamic programming method, graph theory, etc.) when constructing the model. The main goal in constructing a theoretical model of a pilot's mental workload is to find, on the basis of these studies, a method or approach that would make it possible to predict (create a model) the pilot's mental workload based on the complexity of the task he is solving, his visual performance and experience.

In addition, when constructing a model, it is necessary to take into account that the predicted values of the proposed mental load model must be adequate with the actual estimates of mental load based on the results of experiments. It should also be effective in predicting pilots' mental workload over time.

3.1. Pilot mental load simulation using information theory

Based on the above, a theoretical model of pilot mental workload based on information theory is proposed, based on survey research, task complexity, pilot visual performance, and pilot experience.

When developing this model, it is necessary to take into account that the predicted values of the proposed mental load model must be correlated with the actual estimates of mental load from the results of experiments. In addition, the workload model must be effective in predicting pilots' mental workload over time.

Higher mental load is associated with a greater amount of information processed per unit of time (Klemmer & Muller, 1969). Therefore, the processing speed (CV) during a task can be used to assess the mental workload of pilots. The MWA-IT model (Zhang et al., 2019) is based on information theory and was designed to provide speed of information processing for pilots to complete specific flight tasks. The basic paradigm of information theory is stated by Shannon's law:

$$C = W \log_2 \frac{S+N}{N} \qquad (1)$$

where C is the information capacity (i.e., the maximum speed of information transmission in noise), W is the bandwidth (i.e., the amount of information transmitted per second), N is the noise power (i.e., the level of noise interference), and S - signal power. This law basically describes the possibility of transmitting information using noise interference.

In the MWA-IT model (Fig. 1), in order to correspond to the signal strength (S) in equation (1), the task complexity indicator (ST) was taken into account and used

In information theory, S represents the information itself, which is independent of the medium in which it is transmitted. S can be quantified by task difficulty (ST), since ST indicates an internal characteristic of S and is not influenced by the person performing the tasks. This parameter (S) is also capable of reflecting the task of the information process. More complex tasks require more information to be retrieved and are encoded. Ultimately, the pilot's xperience can affect mission performance. Experts quite logically prefer experienced pilots over beginners. Thus, the proposed model uses pilot experience (NE) to represent noise interference (N) in equation (1).

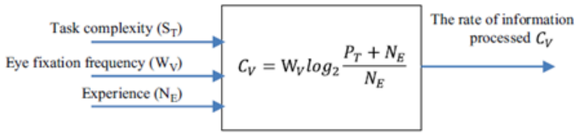

Fig. 1. Configuration of the MWA-IT model

It is known that 80% of the information acquired by a person is obtained through visual channels (Pulat, 1992) This means that analyzing an operator's eye fixation can indicate the amount of information required to complete a task. The fixation frequency (Wv), defined as the number of fixations per unit time, is given in equation (2):

$$W_V = \frac{n}{t} \qquad (2)$$

where n is the number of fixation samples, and t is the fixation time during the assessed task. The fixation frequency (Wv) can reflect the amount of information encoded by operators in a given period of time. Therefore, the fixation frequency (Wv) corresponding to the bandwidth (W) shown in equation (1) was included in the model. Therefore, the MWA-IT model can be represented as follows:

$$C_V = W_V log_2 \frac{S_T + N_E}{N_E} \qquad (3)$$

The inputs of the proposed model include task difficulty, eye fixation, frequency and experience (Fig. 1).

3.2. Building a pilot model using automatic control theory

An integrated approach to taking into account the influence of the human factor (HF) on flight safety is reflected in the international flight attendant optimization program (CRM), recommended by ICAO to all aviation companies (Guide, 2013).

All factors threatening flight safety can be divided into four independent groups: aircraft, crew, ground services, atmospheric conditions. In this case, the probability of an aviation event can be described by the following formula:

$$P_{op} = P_k^c + P_\kappa^{uc} + P_\kappa^a + P_\kappa^e + P^c q_1^e + P^{uc} q_2^e + P^a q_3^e +$$

$P^c P^{uc} q_4^e + P^c P^a q_5^e + P^{uc} P^a q_6^e + P^c P^{uc} P^a q_7^e$ (4)

Here: $P_{к}^{c}, P_{к}^{uc}, P_{к}^{a}, P_{к}^{e}$- the probability of occurrence of one of the dangerous (catastrophic) factors associated with the aircraft, ground services, atmospheric conditions and crew; P^c, P^{uc}, P^a, P^e - the probability of occurrence of one of the non-hazardous factors included in these groups; $q_1^э$ ... ... $q_7^э$ - probability of crew error in the event of one or more combinations of catastrophic factors.

From formula (1) it is clear that the probability of an accident can be reduced in two main ways: $P^c, P^{ис}, P^a, P^e$ - by reducing the probability of the occurrence of one of the non-catastrophic factors and - q_i^e by reducing the conditional probability of crew errors.

In relation to aircraft, the first way is to ensure high reliability of the design, engine, fault tolerance, and also implies improving flight control systems. The second way involves the development and use of information support tools for decision-making (including intelligent systems) by the crew when a combination of one or more non-catastrophic factors occurs, taking into account stress and lack of time when making decisions.

The structure of a control system with a human operator working in a closed control loop is shown in Fig. 2

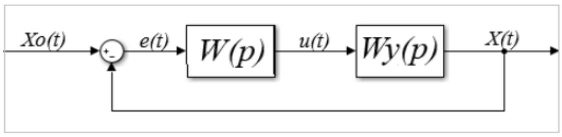

Fig.2. Structure of the control system with a human operator

Over the years, researchers have proposed many different important models of operator behavior (action) in an ergodic system (ES): both linear and nonlinear, both continuous and discrete, in order to assess the compatibility of the dynamics of the object and the operator (Ismayilov, 2022; Ismayilov, 2018) Various and the extent to which they approach actual activities. Among these models, one of the interesting ones was the Tasten model (Ozerkina et al., 2009). The operating principle of this model is based on harmonic analysis of the values of output quantities, when the input quantity is the sum of three sine waves. The transfer function of the model is determined by the following formula:

$$W(p)_{\text{h-o}} = k\left(\frac{k_1}{p} + k_2\right)e^{-\tau p} \quad (5)$$

where: p – complex value; τ - time delay (neuromuscular delay);

k=1.2, k_1=0.28, k_2=1.5 – parameters that depend on the choice of dynamic characteristics of the control object, since human-controlled objects can be of various types (including aircraft) and k is selected depending on their characteristics, k, k_1, k_2 parameters (according to the theory of automatic control). In this article, the above parameter values are randomly selected for conducting experiments. For different objects, these values may change and, accordingly, the transient characteristics.

Taking into account these values and parameters (k = 1.2, k1 = 0.28, k2 = 1.5 and p = 1), as well as by writing and executing the Payton code that calculates formula (5), the result is the graph shown in Fig. 3.

```
import numpy as np
import matplotlib.pyplot as plt

k = 1.2
k1 = 0.28
k2 = 1.5
p = 1
def wp_func(x_vals):
  i = np.linspace(0, 3.2, 1000)
  wp_vals = []
  for j in i:
    wp = k * ((k1/p) + k2) * np.exp(-j*p) * np.sin(j*x_vals)
    wp_vals.append(wp)
  return wp_vals
x_vals = np.linspace(0, 20, 1000)
wp_vals = wp_func(x_vals)
plt.plot(x_vals, wp_vals)
plt.xlabel('i')
plt.ylabel('wp')
plt.show()
```

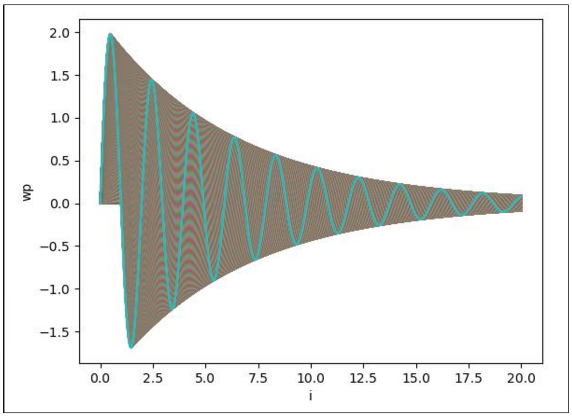

Fig. 3. Experimentally measured transient response of the system with the above model parameters

This code snippet allows you to perform math calculations and plotting using the numpy and matplotlib libraries. First, the variables are assigned the values: k=1.2, k1=0.28, k2=1.5 and p=1. These values are the parameters that will be used in the calculations. The wp_func function is defined, and this function takes the x_vals parameter. Inside the function, an array called i is created that contains 1000 equally spaced points from 0 to 3.2. An empty array called wp_vals is then created. Using a loop, wp is calculated for each i value and added to the wp_vals array one at a time. Next, the wp value is calculated using the formula:

$$k^*((k_1/p) + k_2)^*np.exp(-j^*p)^*np.sin(j^*x\_vals) \quad (6)$$

This formula is a mathematical expression. The wp_vals function returns the calculated array. Then, using the np.linspace x_vals function, an array of 1000 equally spaced points from 0 to 20 is created. The result is assigned to the wp_vals variable.

Finally, using the plt.plot function, a graph is built using the x_vals and wp_vals_ arrays. The plt.xlabel and plt.ylabel functions set the x and y axis labels. The plt.show function displays a graph on the screen. In short, this code allows you to perform mathematical calculations with given parameters and visualize the results.

As can be seen from the data presented, when developing models of a human operator, various methods are used, formed in the classical theory of automatic control. However, when examining the developed models, models are developed based on spectral analysis methods and parameter settings. Currently, adaptive methods and neural network models of human operator activity are becoming increasingly widespread.

3.3. Building a pilot model using queueing theory

At any given moment, a person can only perform one task since their higher nervous centers (central decision-making channel) operate in a time-sharing mode. This is confirmed by the results of aviation accident investigations, where emergency signals were ignored by the crew because the pilot, while processing other critical information, could not timely switch their attention to analyze dangerous deviations that arose at that moment. By the time the priority information is processed, the operator may forget some messages stored in the short-term memory block. In a tense environment with a high flow of incoming messages, situations may arise where the decision-making channel becomes overloaded, increasing the likelihood of crew errors (Braginsky et al., 2016; Gerasimov et al., 1993)

Considering the nature of the activity process and the typical conditions for problem analysis and synthesis, the most appropriate criteria should be the period of continuous engagement and the ability to perform this type of operation. The latter characterizes the quality of the process, while the former defines the conditions under which this quality is achieved. Optimizing processes based on these criteria allows us to determine the operator's workload level, their throughput for standard operations, issues related to labor stress tolerance, and the optimal workload level, which in turn defines the optimal degree of process automation.

Indeed, if the period of continuous engagement of a person starting at time ti is known, the ratio of this period to the time interval Top=ti+1 − ti will characterize the workload of the person on one hand and the intensity of their work on the other. The period of continuous engagement increases with the number of operations that need to be performed (assuming they overlap in time and the operations require "waiting" for completion).

Let us analyze the physical nature and quality of the values F(t) and B(t), taken as criteria, using the example of a person performing uniform operations with an exponential distribution for T_{op} and T_{fw} under stationary, regular, and straightforward conditions, given as follows.

$$\left.\begin{aligned} F(t) &= 1 - e^{-\lambda t} \\ B(t) &= 1 - e^{-\nu t} \end{aligned}\right\} \quad (7)$$

We define the degree of human workload as the ratio of the mathematical expectation of the continuous engagement period to the mathematical expectation of Top , i.e.,

$$Q = M[T_{\mathrm{dp}}]/M[T_{\mathrm{op}}] \quad (8)$$

and denote the probability of operation completion as P_{op}.

The conditions for process implementation, from the perspective of the discipline of operation execution during their overlap, can be defined for the following three characteristic cases:

1. With infinite "waiting" for operation execution.
2. With "loss" of subsequent or preceding operations during their overlap.
3. With "loss" of both subsequent and preceding operations during their overlap.

Let us find the distribution function of the continuous engagement period for the first case. Assume that at time t=0, the operator, previously idle, begins performing an operation and must complete it at u<t.

The engagement period may end there. However, it is also possible that within the time n, the necessity to perform n additional operations arises. To ensure consistency, let us assume that the last of the n operations is performed first (inverted order).

Let P(t) denote the distribution function of the employment period, and let $P_n(t) = \int_0^t P_{n-1}(t-1)\,dP(u)$ represent the distribution function of the sum of n random variables (n>1), each of which has the distribution function P(t). Assume and Π_1(t)=Π(t). At the beginning of employment, one operation is being performed. Suppose the time required to complete the operation is u≤t. During this time, n operations may be requested for execution with probability $[(\lambda u)^n/n]e^{-\lambda u}$. The remaining employment time is equal to the sum of the employment periods, but no more than (t–u).

For n=2, the engagement period equals the sum of two mutually independent random variables with distribution functions B(t), P_1(t) and P (t), or the sum of two random variables. If n=0, the engagement duration equals the time of the first operation. If n=1, the engagement period includes both the time of the first operation and the subsequent operation and equals the sum of two mutually independent random variables with distribution functions B(t) and P2(t).

$$P(t) = \int_0^t \sum_{n=0}^{\infty} \frac{(\lambda u)^n}{n!} e^{-\lambda u} P_n(t-u)\,dB(u) \qquad (9)$$

In the case of "loss" of subsequent or preceding operations, the continuous engagement period will clearly equal the operation execution time (Q=λ/ν), and the probability Pop can be determined using the well-known formula from queueing theory:

$$P_{op} = P_0/(1+\lambda/\nu) \qquad (10)$$

In the case of "loss" of both subsequent and preceding operations:

$$Q = \lambda/\nu \text{ and } P_{op} = P_0/(1-\lambda/\nu) = (1-\lambda/\nu)/(1+\lambda/\nu) \qquad (11)$$

As shown, aside from the first case (with infinite waiting for operations), there is a direct relationship between Q and Pam for the second case:

$$Q_{II} = 1/P_{op\,II} - 1 \qquad (12)$$

and for the third case:

$$Q_{III} = \left(1 - P_{op\,III}\right)/\left(1 + P_{opII}\right) \qquad (13)$$

Thus, in the second and third cases, the process can almost entirely be characterized by either Q or P_{op}. Depending on what is of primary interest, one can choose either the value of relative workload or the probability of operation execution

The real process, obviously, will not exactly correspond to the three cases and will be in some intermediate region. When solving problems of process analysis in any specific case, you can always clarify this area and indicate the proximity of the process to any of these cases.

Fig. 4 shows the dependence of the degree of load and the probability of performing operations on the value λ/ν in the simplest cases, and Fig. 5 shows the dependence characterizing the relationship between the degree of load and the probability of performing operations in typical simple cases.

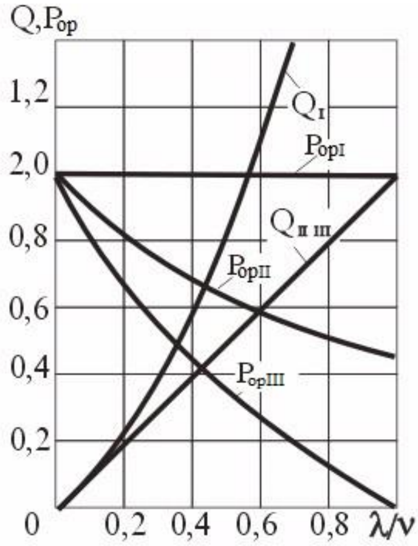

Fig.4. Dependence of load degree and probability of execution operations on the value λ/ν in the simplest cases

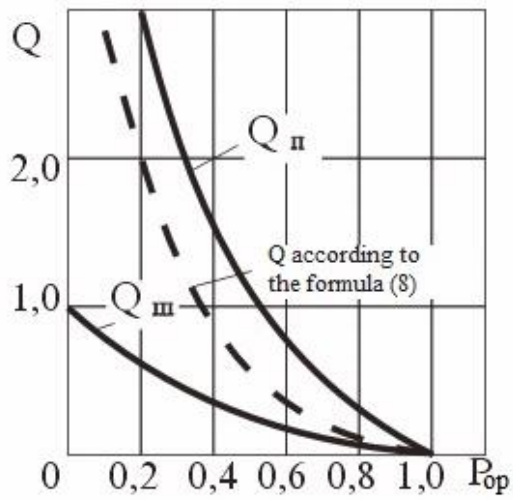

Fig.5. Dependencies characterizing the relationship between the degree of load and the probability of performing operations in typical simple cases

Thus, the proposed methodological principles for the mathematical description of the process and the selected criteria make it possible to assess the quality of the process in terms of human workload and the probability of performing operations of a given type.

4. Discussion

It should be noted that the methods and models for studying operator activity in ergodic systems discussed in the article differ from real activity. The application of each model depends on the complexity of the research object, the flow of information being processed, external conditions, situational awareness, etc. So, for example, in modern airliners such as Boeing and Airobus, in which pilots must process several streams of information simultaneously and mental load is one of the main problems in the interactive man-machine mode when working with several tasks, it is advisable to use a pilot mental load model with using information theory. To assess the compliance of the dynamics of an object with an operator, both in linear and nonlinear, continuous, and discrete ergodic systems, as well as in control systems with a human operator working in a closed control loop, you can apply a pilot model using automatic control theory. If human activity is complex in nature, discontinuous in time, has a significant extent and its individual acts are repeated many times, it is advisable to use methods similar to the methods used in the theory of queuing.

5. Conclusion

Based on review studies using methods for constructing a theoretical model of a pilot's mental load, various methods and approaches to constructing a model of a pilot's mental load are reviewed and analyzed. As a result of the research, three methods (approaches) were proposed for constructing a theoretical model of a pilot's mental load:

- modeling the pilot's mental load using information theory,
- building a pilot model using automatic control theory
- building a pilot model using queuing theory.

In the first model, when determining the speed of information transfer, the main attention was paid to the speed of information processing, taking into account the frequency of fixations, the complexity of the task and the experience of the pilot. It is taken into account that the predicted values of the proposed mental load model must be correlated with actual estimates of mental load based on the results of experiments.

In the second model, in accordance with the theory of automatic control, the transient response of the model was determined experimentally using the Payton environment.

The third model proposes methodological principles for the mathematical description of the process and selected criteria that allow assessing the quality of the process in terms of human workload and the likelihood of performing operations of a given type.

Thus, the article proposes principles for constructing analytical and simulation models of a human operator (pilot), which would take into account the functioning of a person both at the physical and psychophysiological level, and at the level of logical inference for solving control problems.

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