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ASSESSING THE EFFECTIVENESS OF INTELLECTUAL TECHNOLOGIES FOR IDENTIFYING HAZARDOUS COMBINATIONS OF EVENTS IN CIVIL AVIATION FLIGHT SAFETY MANAGEMENT

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Abstract. This paper proposes an approach to assessing the effectiveness of intellectual technologies (artificial intelligence and machine learning) for identifying hazardous combinations of events in air transport systems. The influence of such technologies on flight safety and the aircraft's total cost of ownership is formalized. A simple model is developed to assess the effectiveness of implementing intellectual technologies when identifying a single hidden problem. This model is qualitatively analyzed to reveal the role of its parameters (the size and flight hours of the aircraft fleet, the duration and cost of systemic problem elimination, and damage from events of different severity). In addition, we model the identification and elimination of hazardous combinations of events during the life cycle of air transport systems considering the learning effect. According to this effect, the intensity of hidden systemic problems decreases over time with the accumulation of experience in the operation of an air transport system and the gradual elimination of such problems. The relative acceleration in the identification of hidden patterns is the main indicator that characterizes intellectual technologies for identifying such patterns in incidents. Both types of models can be used to estimate the dependence of expected losses on this indicator. It is also important to consider the dependences of model calculation results on other parameters of the models, including the duration and cost of eliminating the identified problems, damage from various events, and the size and flight hours of the aircraft fleet. As is demonstrated below, intellectual technologies are most effective in an air transport system with a small aircraft fleet and a low intensity of aircraft operation.

Keywords: flight safety, hidden hazards, intellectual technologies.

INTRODUCTION

The evolution of air flight safety management approaches, reflected in scientific papers and step-by-step corrections of ICAO regulations, gradually shifted the focus from increasing the reliability of aircraft (the 1950s–1960s) to reducing the influence of the human factor (the 1970s–1980s); see the figure below. In addition to the reliability of aircraft and the human factor, organizational factors and, in general, the complexity of large organizational and technical systems, have been considered nearly since the early 2010s [1, 2].

Several researchers actively studied the issues of improving flight safety by developing organizational aspects. For example, the papers [3, 4] were devoted to the application of the aviation event tree model for preventive risk management. In [5], this model was supplemented with a Bayesian approach to consider information from voluntary reports of employees on the specifics of a particular airline. Aviation accident forecasting systems were developed based on these methods; see [6].

The authors [7–9] proposed to treat accidents as the consequences of critical combinations of events due to aircraft failures, intentional violations of in-

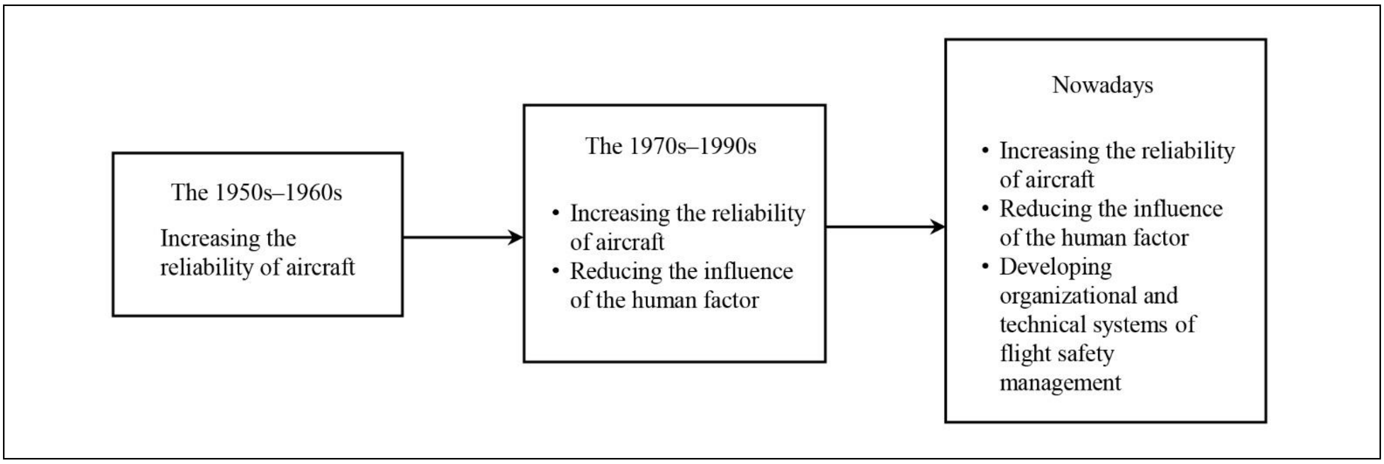

Fig. The evolution of flight safety management approaches in civil aviation.

structions by personnel, and external impacts. Such events may be of no hazard separately, but their combination may become critical. The minimal cut sets of event tree models are the models of critical combinations of events, and the probabilities of such combinations are determined. Approaches to ensuring flight safety in air transport systems (ATSs) operate the probabilities of critical combinations of events [10]. According to the analysis results presented in [11], the causes of aviation accidents due to personnel errors and equipment failures have a systemic rather than random nature. The extended use of the audio channel for inputting and outputting information, including aircraft navigation, control, and state monitoring systems, was investigated in [12].

However, an ATS includes such interacting elements as aircraft, civil aviation infrastructure facilities, and aviation personnel, therefore being a large-scale, complex, and multi-connection system. Therefore, it cannot be accurately modeled and optimally designed in terms of the criteria of flight safety and target efficiency. Any real ATS has systemic problems in ensuring the safety of aviation activities, to a greater or lesser extent, including the following:

• the design and production drawbacks of aircraft and infrastructure facilities;

• systemic drawbacks in training and maintaining the qualifications of aviation personnel (i.e., analogs of the design and production drawbacks in this area);

• systemic drawbacks in organizing the operation of aircraft and infrastructure facilities as well as in organizing the work of aviation personnel.

Potentially, they can cause incidents of different severity and aviation accidents. At the same time, these problems are systemic in nature and far from always obvious. At first, they are hidden because initially, when creating the elements of ATSs, the requirements of safety are taken into account. Apparently, ineffective constructive, technological, and organizational decisions would simply not have been made. Unobvious problems and contradictions in terms of flight safety are revealed during the operation of ATSs, aircraft, etc. According to the global experience of aviation development and aircraft building and the real-work experience of aviation safety improvement, this improvement is achieved to a large extent due to the gradual identification and elimination of hidden problems. Ideally, this identification should take place not in response to factual hazards with severe consequences (the reactive principle of safety management) but, on the contrary, based on the preventive analysis of preconditions for such hazardous situations (the proactive principle). Note that proactive safety management is more effective from the point of view of preserving human life and health, as well as from the economic point of view.

In the 2000s, there was a rapid development of intellectual technologies for improving flight safety. This was due to the accelerating evolution of intellectual data analysis methods and the tendency to increase the required level of flight safety. Nowadays, the topical tasks of flight safety improvement that can be solved using intellectual technologies are as follows:

– recognizing the elements of runways and taxiways;

– recognizing objects in the air;

– detecting air traffic conflicts;

– displaying the off-the-cab environment in the cab without glazing;

– monitoring of the pilot's state and actions;

– data processing for the predictive diagnosis of aircraft state;

– virtual assistant pilots, virtual co-pilots, and virtual pilots;

– control tasks.

Intellectual analysis of large data arrays on the state of ATS elements (aircraft, infrastructure objects, and aviation personnel) allows revealing hidden patterns of state changes, including those causing hazards. Experts in the field of flight safety management and aviation activity in general place their main hopes on the introduction of such technologies.

For example, we mention an intellectual system for collecting and analyzing flight data of aircraft engines that includes *Analitik*, a software package for operational analysis of post-flight parameters of the engine and its systems [13]. As was indicated in this paper, aircraft technical diagnosis requires analyzing a large database and, therefore, a considerable time for data processing. The software package significantly reduces the time of flight data analysis due to the formalized query tool.

National Aeronautics and Space Administration (NASA) has been practicing the developed technologies on Southwest airline data [14]. For example, they were used to find text descriptions of landings in voluntary reports without a direct indication of an unstable approach but with its high probability. The result of the study helped to improve the quality of approaches.

Smiths Aerospace, supported by the Federal Aviation Administration (FAA), developed a technology based on data mining algorithms and demonstrated its application on British Airways incident data and Flight Data Monitoring (FDM) data [15]. The technology revealed certain patterns in dates, takeoffs, landings, crews, and so on.

Studies on forecasting flight delays of US airlines by data mining methods were carried out in 2017 and 2019; see the papers [16] and [17], respectively.

Researchers also addressed the problem of increasing crew awareness through the audio channel of impact by creating audio interfaces [18].

The creation and implementation of such technologies can be very costly; when non-optimally applied, they may not yield the expected safety improvement. Therefore, objective assessments are needed for the impact of new intellectual technologies on flight safety and the target and economic efficiency of their use in aviation.

1. INTELLECTUAL TECHNOLOGIES FOR IDENTIFYING HAZARDOUS COMBINATIONS OF EVENTS IN ATSS: FORMALIZATION OF APPLICATION

From a formal point of view, the intellectual technologies described herein allow revealing hidden systemic problems of flight and aviation safety at early stages. In practice, this is achieved through the rapid automated processing of large datasets containing the "extended vectors" of object state indicators and the comparison of different component combinations of these vectors that have not been analyzed before. The analysis is performed almost in real time, i.e., based on flight data from aircraft recorders or portable devices, or even written and oral reports of aviation personnel about various events coming to a centralized information system (if possible, covering the entire ATS), at least at the end of each flight. Similar combinations and patterns can be identified in the extended state indicator vectors of ATS elements to reveal the common circumstances of the registered events (mainly the preconditions for events with more severe consequences). The results are the basis for further in-depth analysis of safety problems, which often cannot be automated.

It is essential that the earlier identification of hidden systemic safety issues is provided using incident information, i.e., events with low-severity consequences. Such events have no direct damage in terms of safety, but may cause economic losses due to a change in the flight plan. We denote these losses by c_{inc}, in monetary units per one incident on average. Let λ_{inc} be the intensity of incidents per one flight hour. Also, we denote by η the average flight hours of aircraft per year. Assume that the fleet consists of N aircraft. Thus, if the systemic problem is not identified and eliminated, the system will on average have

$$Q(T) = N\,\eta\,T\,\lambda_{\text{inc}}.$$

such incidents for a period of T years.

At the same time, low-severity incidents, being external manifestations of hidden systemic problems, can be preconditions for events with more severe consequences, up to aviation accidents. For the purposes of approximate modeling, the ratio of the probabilities of an aviation accident and an incident $(p_{\text{AA}}/p_{\text{inc}})$ can be assumed to be constant. Aviation accidents cause some damage in terms of flight safety (a value d_{AA} per one aviation accident on average, in certain units), up to human deaths, as well as very significant economic losses $c_{\text{AA}} \gg c_{\text{inc}}$, in monetary units per one incident on average.

In the past, the general circumstances of various ATS events were thoroughly analyzed, in the best-case scenario, only after a series of severe aviation accidents: often the participants in accident and incident investigations were limited in the detail of available information and in the coverage of ATSs, even on the scale of a single country. Nowadays, modern information technologies automatically analyze the extended indicator vectors with a reasonable consumption of time and other resources. Favorable opportunities for proactive safety management are offered by the fact that the dataset on aviation incidents is much more extensive than the dataset on aviation accidents, which are classified as rare events in modern aviation because $(p_{\mathrm{AA}}/p_{\mathrm{inc}}) \ll 1$. Considering the current development of Russian civil aviation and aircraft industry, such an expansion of the available empirical base for analysis seems very important. With relatively small aircraft fleets, compared to the world's largest aviation countries, accelerating the identification of hidden problems becomes a crucial factor in Russian aviation and aircraft industry (which is inevitable in their autonomous and autarkic development). In this context, we emphasize the following: the acceleration initially refers not so much to calendar time as to the total flight hours of the aircraft fleet or, even more precisely, to the accumulated number of preconditions for aviation accidents, upon reaching which, on average, systemic problems will be identified.

Assume that a "critical mass" of homogeneous low-severity incidents is required to identify a hidden problem. We denote this minimum number of incidents by $Q_{\mathrm{inc}}^{\min}$. (Of course, it should be understood as an average value.) The intellectual technologies studied here allow reducing this threshold several-fold to some level $Q_{\mathrm{inc}}^{\min\,\mathrm{AI}} < Q_{\mathrm{inc}}^{\min}$. There are detailed mathematical models for identifying hidden patterns in large datasets considering the dimension of the state indicator vectors. We mean not particular identification methods (different multivariate statistical analysis methods) but the models connecting the number of analyzed events, the accuracy and reliability of statistical conclusions, the impact of the dimension of the state indicator vector on them, and so on.

After the hidden patterns are identified, the revealed systemic problems are studied in detail, and appropriate decisions are elaborated and implemented to reduce either the probability of hazardous combinations of events or the severity of their manifestations. (Note that the decisions are also systemic, e.g., changes in the design of aircraft, the principles and programs of aviation personnel training, as well as aircraft operation and personnel work organization). This process can be very long and costly, including scientific research, design and development work, a set of practical measures in the sphere of production and operation of aircraft, etc. A set of measures to eliminate or minimize the impact of the revealed systemic problems has some cost C_{elim} and duration T_{elim} (in calendar years, not in flight hours). During the identification and elimination of a hidden problem, a certain number of incidents may occur, entailing economic losses only. Moreover, these incidents may escalate into real aviation accidents with economic losses and even with human injuries and deaths.

2. THE PRINCIPLES OF ASSESSING THE EFFECTIVENESS OF INTELLECTUAL TECHNOLOGIES FOR IDENTIFYING HAZARDOUS COMBINATIONS OF EVENTS IN ATSS

Thus, to assess the effectiveness of intellectual technologies for identifying systemic safety problems based on the analysis of large datasets, it is necessary to compare the following indicators for the original "critical mass" of low-severity events and for its new value reduced using the intellectual analysis of large datasets on the state of ATS objects:

- the expected economic costs and losses due to the occurrence of different-severity incidents (until the systemic problem is identified and eliminated);
- the expected human injuries and deaths over this period.

The expected economic and non-economic losses over the modeling horizon can be expressed by

$$C(T) = C_{\mathrm{elim}} + \left(N\,\eta\,\lambda_{\mathrm{inc}}\,T_{\mathrm{elim}} + Q_{\mathrm{inc}}^{\min}\right) \times \left(c_{\mathrm{inc}} + \frac{p_{\mathrm{AA}}}{p_{\mathrm{inc}}}\,c_{\mathrm{AA}}\right),$$

$$D(T) = \left(N\,\eta\,\lambda_{\mathrm{inc}}\,T_{\mathrm{elim}} + Q_{\mathrm{inc}}^{\min}\right)\frac{p_{\mathrm{AA}}}{p_{\mathrm{inc}}}\,d_{\mathrm{AA}},$$

where T is the modeling horizon (in years) satisfying the condition $T \ge T_{\mathrm{elim}} + \dfrac{Q_{\mathrm{inc}}^{\min}}{N\,\eta\,\lambda_{\mathrm{inc}}}$. (The modeling horizon significantly exceeds the expected duration of identification and elimination of the systemic problem.) For the sake of simplicity, a systemic problem is supposed to be completely eliminated.

Intellectual technologies for identifying systemic safety problems based on the analysis of large datasets allow reducing the value of the parameter $Q_{\mathrm{inc}}^{\min}$ to $Q_{\mathrm{inc}}^{\min\,\mathrm{AI}} < Q_{\mathrm{inc}}^{\min}$. (By assumption, the reduction of this critical mass of events is several-fold.) The dependence of economic and non-economic losses on this key parameter is linear, but not directly proportional: there are constant terms associated with the elimination of the systemic problem. From a qualitative point of view, an important role is played by the ratio of the two expected durations: the terms $Q_{\mathrm{inc}}^{\min}/N\,\eta\,\lambda_{\mathrm{inc}}$ (systemic problem identification) and T_{elim} (systemic problem elimination). If the first term prevails, the main contribution to the amount of damage will be made by the critical mass of incidents used to identify a systemic safety management problem.

With all other parameters being fixed, the fraction $Q_{\text{inc}}^{\min} / N \, \eta \, \lambda_{\text{inc}}$ will take higher values for smaller aircraft fleets, smaller average annual flight hours of the aircraft fleet, and lower intensities of manifesting preconditions for aviation accidents. In other words, under such conditions (characteristic of the autarkic scenario of development of Russian civil aviation and aircraft industry), intelligent technologies for identifying hidden patterns based on the analysis of large incident datasets will be most valuable and effective.

The absolute gain in expected costs and losses can be expressed as

$$\Delta C^{\text{AI}}(T) = C(T) - C^{\text{AI}}(T)$$
$$= \left(Q_{\text{inc}}^{\min} - Q_{\text{inc}}^{\min \text{AI}}\right)\left(c_{\text{inc}} + \frac{p_{\text{AA}}}{p_{\text{inc}}} c_{\text{AA}}\right),$$

where $C^{\text{AI}}(T)$ is the additional costs of implementing the technologies of intellectual analysis of large datasets discussed here. Strictly speaking, they are created and implemented to identify different systemic problems. The basis of the corresponding end-to-end intellectual technology is universal for all branches of the economy and all types of activity.

At first glance, the absolute gain is independent of most of the model parameters. However, its relative "weight" (with respect to the initial value) depends on the ratio of the expected duration of identifying and eliminating systemic problems before and after the implementation of these technologies; see below. In turn, this ratio depends on the average annual flight hours and size of the aircraft fleet, on the intensity of manifesting preconditions for aviation accidents, and on the duration of eliminating the systemic problem.

Within the concepts introduced here, such an external model for assessing the effectiveness of intellectual technologies for improving aviation safety can be built and studied via simple arithmetic formulas. This model is called external because it incorporates the parameters of the studied technologies as initial data. It operates the resulting parameter, i.e., the reduction of the critical mass of preconditions to aviation accidents achieved by intellectual technologies that suffices to identify the hidden problem. Nevertheless, even a qualitative analysis of such a simple model reveals the role of its various parameters, such as the size and flight hours of the aircraft fleet, the duration and cost of eliminating a systemic problem, and the damage from different-severity events.

Example. Let hazardous combinations of events turn into incidents with a probability of 0.1. Before the implementation of an intellectual technology, it was possible to identify a hazardous pattern after the occurrence of 100 incidents (i.e., 1,000 hazardous combinations). Then, an intelligent aviation technology for identifying hazardous combinations was implemented to analyze flight data rather than incidents. It became possible to identify hazardous combinations of events based on the analysis of a dataset, e.g., with 100 hazardous combinations. (This figure depends on the specific technology.) Thus, $Q_{\text{inc}}^{\min} = 1000$ and $Q_{\text{inc}}^{\min \text{AI}} = 100$.

Now we compare the efficiency of this technology by the indicator $\Delta C(T)/C(T)$ under two different values of the aircraft fleet size N and the average annual flight hours η; see the table below.

Comparing the effectiveness of the technology for different aircraft fleets and flight hours

Effectiveness indicator	Aircraft fleet size N and average annual flight hours η			
	N = 5000, η = 3000	N = 100, η = 3000	N = 5000, η = 1000	N = 100, η = 1000
$\Delta C(T)/C(T)$	19%	84%	40%	88%

Thus, the maximum reduction of flight safety improvement costs will be achieved for small aircraft fleets of a certain type (which is typical for Russia) with low flight hours.

For large aircraft fleets (on the global scale), probabilistic laws work well, and hazardous combinations of events will be identified earlier simply due to higher flight hours. For large aircraft fleets, intellectual technologies for identifying hazardous combinations of events will also have an effect, albeit smaller in relative terms.

3. IDENTIFYING AND ELIMINATING HAZARDOUS COMBINATIONS OF EVENTS DURING THE LIFE CYCLE OF ATSS: PROCESS MODELING

Besides identifying and eliminating a single systemic safety problem (or minimizing its impact to some achievable level), it is possible to consider these processes on a long-term basis for all such problems in general. This approach seems reasonable since the additional costs $C^{\text{AI}}(T)$ of implementing intellectual analysis technologies for large datasets, even in the case of aviation, are most likely not associated with identifying and eliminating a single safety problem.

When treating the identification and elimination of various systemic safety problems in an ATS as a single long-term process rather than a one-time act (see the elementary model above), we assume that the most significant problems (with the greatest threats to safety) are identified and eliminated first. Indeed, due to their high frequency of occurrence, such problems are likely to manifest themselves before others, and their elimination becomes a priority because of potentially the greatest damage. Therefore, the process of identifying and eliminating systemic problems can be considered on long-term intervals, i.e., during the life cycle of a given ATS. This process resembles learning-by-doing, widely known in the field of complex manufacturing. We introduce a learning rate γ, which shows the reduction in the probability of systemic problems (or the risk of their manifestation, i.e., the probability multiplied by the expected damage), e.g., when doubling the ATS operation experience. With the accumulated incident analysis experience of Q events, the current intensity of manifesting systemic problems in an ATS (per some unit, e.g., flight hour, passenger- or ton-kilometer) can be expressed by the logarithmic formula

$$\lambda_{\text{inc}}(Q) = \lambda_{\text{inc}}^{\infty} + \left(\lambda_{\text{inc}}^{0} - \lambda_{\text{inc}}^{\infty}\right)(1-\gamma)^{\log_2 \frac{Q}{Q_{\text{inc}}^{\min}}}.$$

Here, λ_{inc}^{0} denotes the intensity of incidents under zero ATS operation experience. The logarithmic model of learning and experience accumulation shows that the process of eliminating systemic problems, starting with the identification and elimination of the most significant and weighty problems, gradually slows down. In addition, the "irreducible value" $\lambda_{\text{inc}}^{\infty}$ in this model reflects natural safety improvement limits due to the laws of nature and the capabilities of intellectual technologies. The process of learning, i.e., identifying and eliminating systemic problems, allows approaching the limit.

Within this model, the impact of intellectual technologies for identifying hidden patterns can be represented as an equivalent "acceleration" rate of learning, i.e., the accumulated experience multiplied by some constant factor corresponding to a relative reduction in the number of incidents $Q_{\text{inc}}^{\min} / Q_{\text{inc}}^{\min\,\text{AI}}$ required to identify a hidden problem.

By analogy with the elementary model for a single systemic problem, it is possible to consider the delay in eliminating systemic safety problems, i.e., a lag of T_{elim} years (or other calendar periods) between the accumulation of incident analysis experience and the implementation of the resulting decisions in ATSs.

For both models (identifying and eliminating a single systemic problem or all systemic problems during the life cycle of an ATS), it is required to assess the dependence of expected (economic and non-economic) losses on the main general indicator that characterizes intellectual technologies for identifying hidden patterns in preconditions for flight accidents, i.e., the relative acceleration of their identification. Of course, it is also important to assess the dependence of calculation results on other model parameters, including the duration and cost of eliminating the identified problems, damage from various events, and the size and flight hours of the fleet.

CONCLUSIONS

According to the results presented in this paper, intellectual technologies for identifying systemic safety problems based on the analysis of large datasets will yield the greatest effect (the highest relative reduction of economic and non-economic damage) for relatively small aircraft fleets with low-intensity operation and small-scale ATSs.

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