Big Data Analytics and an Intelligent Aviation Information Management System

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Abstract
The aviation industry is grappling with two big issues: safety and performance enhancement. In the sense of big data, they would be expected to be resolved. The influence of big data on the aviation industry, as well as the creation of an aviation big data platform and information systems, are the subject of this paper. To begin, the paper investigates the relationship between big data and the growth of the smart aviation industry. The paper then discusses the fundamental concepts and context for the creation of an aviation big data platform and information system. Finally, the paper proposes a multi-layer network correlation analysis approach and uses it to investigate the range and degree of coupling in an aviation big data information system. The study concludes that aviation big data plays a critical role in the growth of the smart aviation industry, and that the creation of an aviation big data information platform and information system, as well as the use of multilayer network correlation analysis methods, will significantly improve aircraft safety and efficiency. This paper offers suggestions and countermeasures for the preparation and implementation of a national aviation big data platform and information system, as well as the development of a global aviation big data collaboration process and aviation big data technology.

Keywords: big data, smart aviation industries, aviation safety, aviation performance, aviation big data platform, information system multilayer, network correlation, analysis spectrum and coupling degree analysis

1. Introduction

The modern aviation industry is confronted with two major challenges: increased safety and improved efficiency. One of the main practical issues that the aviation industry has been trying to address is how to improve the safety of the industry. In contrast to other modes of transportation, aviation incidents result in substantial loss of staff and property. Air traffic control, in particular, is influenced not only by its own technological and operational capabilities, but also by the external environment, especially harsh weather conditions. According to the investigation of aircraft crashes, bad weather conditions were responsible for about 45 percent of the accidents. As a result, the factors influencing the aviation industry's safety are extremely complex (Oster et al., 2015).

The technological performance of aerospace products, the meteorological environment, and aviation management all contribute to aviation safety. The technical performance of aircraft covers a wide range of

topics, including aircraft design, manufacture, service, and maintenance, and it is the foundation for ensuring aviation safety. The efficiency of aircraft has steadily improved since the invention of the first, significantly enhancing aviation safety. However, some aircraft safety accidents do occur at this time, mostly due to aircraft mechanical failure. As a result, one of the most critical technological problems to be solved in the future aviation industry is how to develop and enhance the technical efficiency of aircraft.
Another critical element in assessing aviation safety is aviation management. The wide variety of business areas and divisions involved in air traffic has increased the scope and challenge of aviation management. The aviation industry in various countries around the world has grown rapidly in recent years, and the challenge in effectively managing the industry has also increased. Aviation control mistakes are to blame for a certain percentage of aircraft safety incidents. As a result, a practical issue that must be addressed in the future growth of the aviation industry is how to dramatically increase the management level.

Another big issue confronting the aviation industry is how to boost its efficiency. To begin with, high costs have always been a major impediment to the growth of the aviation industry. Simultaneously, there is significant potential for growth in all areas, including aircraft service and management. Second, the aviation industry is competing with other modes of transportation. High-speed rail, for example, is putting competitive pressure on China's civil aviation industry, and that pressure is growing as the speed of high-speed rail increases. As a result, the aviation industry's operational and management efficiency must be strengthened in order to increase its competitiveness (Cui & Li, 2015; Yin, 2014).

High risks, high costs, and management complexity are all characteristics of the aviation industry, and they all influence and decide the industry's success. The aviation industry's high risks manifest themselves in disastrous results in the event of a crash. Airlines will suffer significant economic and property losses as a result of this. To improve the performance of the aviation industry, it is important to begin by reducing flight accidents (especially major flight accidents).

The aviation business is a high-priced one. Aside from the enormous expense of the aircraft itself, the costs of fuel and maintenance are also very high. Excessive fuel and repair costs have forced several airlines to declare bankruptcy. As a result, how to reduce aircraft fuel and maintenance costs is directly related to the airline's operating efficiency.

Since aircraft flights, airports, air traffic, the natural environment, and customer service are all part of the aviation industry's operations, the whole coordination and management process is complicated. If not properly handled, it will not only dramatically raise the aviation industry's operating costs, but will also result in severe aviation accidents. As a result, one of the major issues that airlines have been attempting to resolve is how to boost the management efficiency of the aviation industry.

The emphasis of this paper is on two topics. The first is to look at how big data affects the aviation industry. Big data has a wide range of implications for the aviation industry. It is primarily divided into two categories: technology and management. From a technological standpoint, big data would have a significant impact on aircraft design and performance, as well as aircraft activity tracking, preventive malfunction detection, and maintenance. The management of the aviation industry has a direct impact on the industry's operational efficiency. Big data, on the other hand, can be used in a variety of areas, including route planning and air traffic control, flight environment and safety management, flight management, and aviation business management. As a result, the emphasis of this paper will be on the potential effect of big data on aviation technology and management.
Another topic that needs to be discussed is the big data platform and its aviation information system. Because of the industry's size, the aerospace big data platform and its information systems are fraught with technological and application issues. This paper would first look at the concepts, basic structure, and main content of establishing an aviation big data platform and information system, as well as make policy recommendations.

The main goal of this paper is to present the key concepts and structure for the creation of an aviation big data platform and information system, as well as to suggest key solutions and policy recommendations. The position of big data is important in the aviation industry because the determinants of safety and performance improvement are complex. Big data is expected to revolutionize the aviation industry's technology and management model.

According to the findings, big data in aviation plays a critical role in the growth of the smart aviation industry. The safety and efficiency of aircraft can be greatly enhanced by constructing an aviation big data information platform and information system, as well as employing multilayer network correlation analysis methods.

This paper offers suggestions and countermeasures for the preparation and implementation of a national aviation big data platform and information system, as well as the development of a global aviation big data collaboration process and aviation big data technology. The benefit of this paper is that it proposes a multilayer network correlation analysis approach as well as an idea for aviation big data spectrum and coupling analysis. As a result, the analysis presented in this paper is both theoretical and realistic.

2. Methodology and results

2.1. Aviation big data and smart aviation industry development

Industry 4.0 has become a major target for the global growth of the manufacturing industry, with the goal of achieving intelligent development and operation of industry based on big data (Costa et al., 2017). Big data, as well as its closely related Internet of Things and artificial intelligence, will organically integrate all ties of the aviation industry's activity (including front-end, middle-end, and back-end) as well as the entire aviation industrial value chain, thereby promoting the industry's growth.

Second, it will assist aviation business decision-makers in better identifying problems and gaining access to more information. Inadequate and asymmetric knowledge has always been the key impediment to the current aviation industry's growth. Only big data and its closely related Internet of Things and artificial intelligence can provide ideal solutions because modern aviation industrial development has shifted to a global supply chain pattern, and the essence of realizing and generating global value is how to realize the organic convergence of customer-centered logistics/service flows, value flows, and knowledge flows.

Third, accurate prediction is the premise of rationalization of customer-centered planning and decision-making, but accurate prediction requires detailed and adequate information. Big data, along with the Internet of Things and artificial intelligence, can not only provide detailed and sufficient knowledge, but also intelligently process it and provide alternative solutions in a timely manner. Traditional manual decision-making cannot do this. With the continued maturation and convergence of big data, Internet of Things, artificial intelligence, and 3D printing technologies, it is expected that the future aviation industrial growth mode will experience revolutionary changes.

Finally, big data, as well as the closely associated Internet of Things and artificial intelligence, are beneficial to the overall growth of the aviation industry. Any national economic system contains numerous industrial departments of various levels, sizes, and structures, but effective communication and cooperation among these departments is impossible without complete information exchange and communication. This problem will be solved when big data and its closely related Internet of Things and artificial intelligence enter maximum growth. Any aviation industry sector would achieve optimal and sustainable growth at that time.

2.2. General method of aviation big data analysis: multilayer network correlation analysis

The same layer correlation analysis, adjacent layer correlation analysis, and interlayer correlation analysis are the three main components of the multilayer network correlation analysis process. The same layer correlation analysis examines the correlation between real-time and dynamic information between parallel nodes at the same stage, revealing each functional component node's cooperative activity status. The application of same layer correlation analysis to complex system construction, such as aircraft, is conducive to improving its protection and operation efficiency.

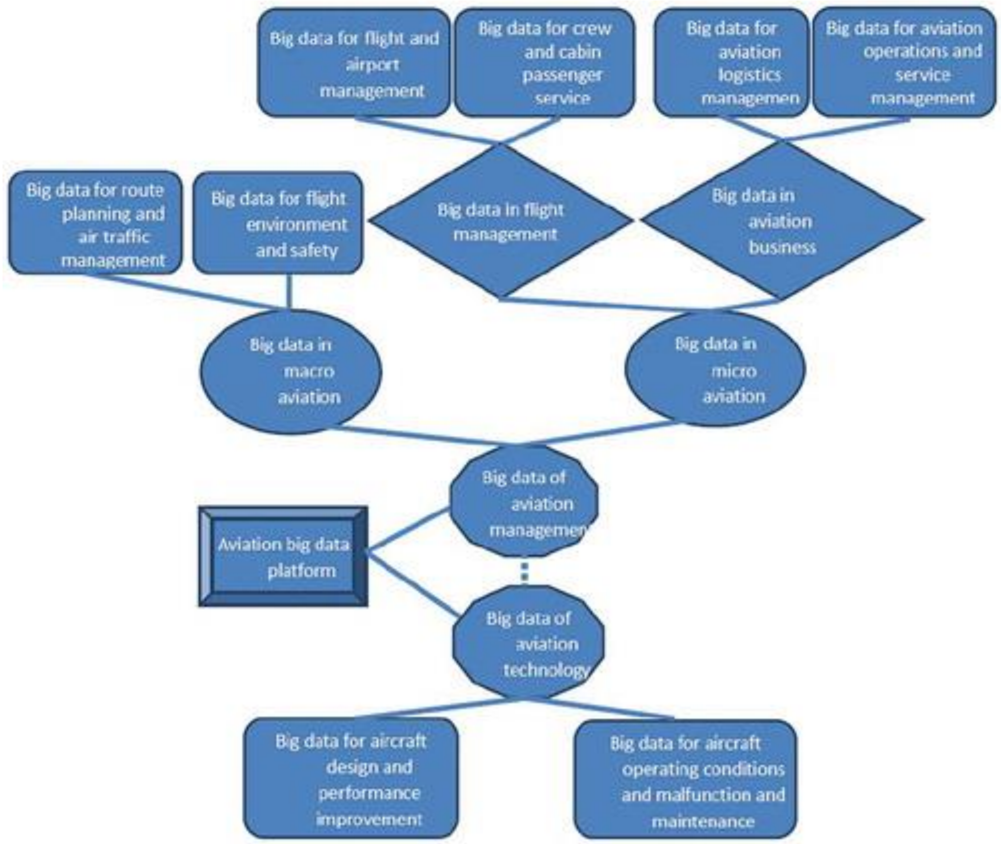
Adjacent layer correlation analysis examines the relationship between instant and dynamic data between cross-layer nodes at various levels, revealing the cooperative activity status of various functional component nodes in context. The vertical correlation analysis and the cross correlation analysis of adjacent layers are two aspects of adjacent layer correlation analysis. The analysis of direct vertical correlation is the focus of the vertical correlation analysis of adjacent layers, while the analysis of dislocation vertical correlation is the focus of the cross correlation analysis of adjacent layers.

The aim of interlayer correlation analysis is to look at the correlation of real-time and dynamic data between nodes that span one or more intermediate levels. In a dynamic functional chain, it shows the cooperative activity status of each functional component node. It involves vertical correlation analysis and cross correlation analysis of interlayers, much like the correlation analysis of neighboring layers.

By constructing different wavelet functions, the direct path, indirect path, and cross path can be filtered and denoised in the specific algorithm. To reduce the risk of intelligent misjudgment, a combination of intelligent automated analysis technology and manual analysis should be used, particularly for nonsupervised issues.

2.3. Aviation big data platform and information system design

Figure 1 depicts the aviation big data platform and data management system. Aviation big data platform can be seen to include two fundamental facets of aviation technology and aviation management big data. To ensure flight safety and enhance aircraft performance, aviation technology big data is primarily used to document and represent the basic conditions of aircraft design and performance, operating states, malfunction diagnosis, and maintenance. Big data on aircraft design and performance enhancement, as well as big data on aircraft operating conditions, malfunction detection, and repair, are included in the scheme.
Figure 1. Aviation big data platform and information system



Big data in aviation management mainly tracks and represents the state of aeronautical operations and operational efficiency, which aids in the protection of aviation traffic and the optimization of aviation operations performance. Macro and micro aviation management big data are two aspects of big data in aviation management. Big data in macro aviation management primarily tracks and represents the fundamental states of route planning and air traffic management, as well as the flight environment and safety management. With the growing number of aerospace vehicles and limited air route capital, big data will play an increasingly important role in route planning and air traffic management.

Micro-aviation management big data, which includes flight management and aviation business management, primarily tracks and represents the fundamental states of flight and aviation business management. The regular flight and safety of flights are directly related to flight management, which includes flight and airport management as well as crew management. The position of big data is becoming increasingly important as the limitations of conventional manual management modes become more apparent.

Air logistics management, as well as airline operations and service management, are all aspects of aviation business management. With the growth of civil aviation, the aviation logistics industry is becoming more established. As a result, aviation companies must consider how to ensure their protection and increase their operational efficiency. Because of the high costs of air transportation and the complexities of operations and service procedures, aviation operations and service management involves more fundamental business concerns and directly determines the profitability of air transport companies. Intelligent management and operations focused on big data have major benefits in this field. As a result, the big data sub-platform for aviation business management is critical to the overall aviation big data platform.

2.4. Interpretation of different functional modules

2.4.1. Big data of aviation technology

2.4.1.1. Big data for aircraft design and performance improvement

Big data for aircraft design and performance management contains both data about the aircraft's internal health and performance as well as data about the outside environment and services. On the one hand, they serve as a foundation for improving aircraft design and efficiency. These big data, on the other hand, can be used to create models that improve the overall design of aircraft (Keshtegar et al., 2017; Marinus & Poppe, 2015; Wang et al., 2018).

Big data for aircraft design and performance enhancement provides historical, practical, and potentially predictable big data that serves as the foundation for digital aircraft design and application. Since big data comprehensively records and reflects the structure and function of aircraft, an overall analysis and optimization approach can be used to obtain an optimized design model, which is conducive to ongoing aircraft design improvement and optimization as well as substantial improvements in aircraft efficiency.

2.4.1.2. Big data for aircraft operating conditions and malfunction and maintenance

Data collection and analysis was part of the big data networks and information systems for aircraft operating conditions, failure, and repair. The processing of data is at the very top of the list. Highly sensitive and intelligent sensing instruments that collect data from all aspects of aircraft and their synchronized operational status in real time are extensively used in the collection of aircraft operating conditions, failure, and maintenance data. Data information is transmitted to the data processing department for real-time analysis and implementation through the transmission system.

An intelligent big data technology analysis system, which is an organic synthesis of big data and computer deep learning, is used to analyze the big data of aircraft operating conditions, malfunctions, and maintenance. Technically, the new statistical analysis theory and approach based on big data also needs to be developed. Data mining for nonsupervised problems, in particular, is still in its infancy. With the continuous improvement of intelligent big data analysis technology, big data of aircraft operating states, malfunctions, and maintenance will play a full role in ensuring flight safety and improving aircraft performance (Badea et al., 2018; Dinis et al., 2018; Hur et al., 2018; Yanto & Liem, 2018).

2.4.2. Big data in macro aviation management

2.4.2.1. Big data for route planning and air traffic management

Both the big data of available route status and the big data of real-time route use are included in the big data for route planning and air traffic management. The former keeps track of historical and real-time route knowledge and data, while the latter displays current route knowledge and data.

In the age of big data, big data of available route status may represent comprehensive and adequate available route knowledge and information, especially the real-time natural and man-made environmental states of route, as weather and climate change on some routes are impermanent, and some routes can pose a threat to aircraft safety due to war or other factors. The establishment of big data and its information system of historical and practical paths, as well as their environmental change, will provide timely information for aircraft flight, ensuring aircraft flight safety (Ho-Huu et al., 2018).

The real-time route utilization status big data offers real-time information for regular flight and air traffic route management. With the growing number of flights, air traffic safety is receiving more attention. It is important to provide globally centralized big data on air traffic states and information systems based on national and regional bases. It is one of the most critical essential facilities for ensuring air traffic control (Adacher et al., 2017; Gallegoa et al., 2018; Insua et al., 2018).

2.4.2.2. Big data for flight environment and safety

Internal and external big data are also included in the big data for flight environment and defense. Internal flight environment and safety big data also refers to data including cabin noise, speed, and fuel consumption that are directly linked to the aircraft itself. Others are closely linked to aircraft technology big data and its information system, while others are concerned with the external environment and how it reacts to the real flight phase. They are fundamental requirements for ensuring aircraft flight safety (Lali et al., 2018).

External flight environment and safety big data primarily capture and represent awareness and information about various external environmental states experienced during aircraft flight. National and international aviation organizations will develop specialized external flight environment information collection facilities and organizational structures in the era of big data to provide comprehensive and sufficient data for aviation flight and ground management (Walker, 2017; Wooder et al., 2017).

2.4.3. Big data in micro aviation management I: Big data in flight management

2.4.3.1. Big data for flight and airport management

Both national flight and airport management big data and global flight and airport management big data are included in the big data for flight and airport management. Unique big data on individual flight and airport management is what the term "specific big data on specific flight and airport management" refers to. Although a data information system has been developed in this field, its size and scope are still insufficient. It hasn't yet introduced intelligent management and data sharing, in particular.

Big data for global flight and airport management applies to big data and its information systems for national and global flight and airport management. The growing number of flights and airports in different countries, as well as the increasing number and range of flights around the world, necessitates the interconnection and sharing of flight and airport management data. It is a prerequisite for ensuring domestic and international flight safety (Hrastovec & Solina, 2016; Zhang et al., 2018).

2.4.3.2. Big data for crew and cabin passenger service management

The primary purpose of big data for crew and cabin passenger service management is to record and represent big data on flight and crew operations, as well as related areas. Its goal is to make crew and cabin passenger service management more intelligent and automated, lowering management costs and operational errors while improving management efficiency (Gupta et al., 2018; Yondo et al., 2018).

Big data can automate the processing of flight details such as aircraft take-off, arrival, delay, termination, return, and reserve in terms of flight status. It can not only provide timely information, but also make it easier for relevant operations and management staff as well as passengers to accept and inquire through various mobile terminals.

2.4.4. Big data in microaviation management II: Big data in aviation business management

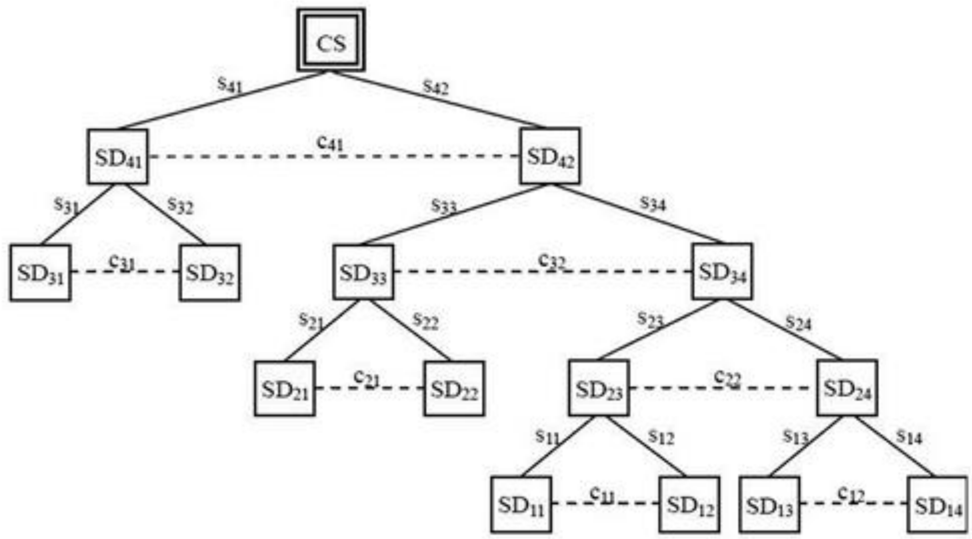
2.4.4.1. Big data for aviation logistics management

Big data for air logistics management is primarily used to record and reflect the supply and demand status of aviation logistics, which is beneficial to the intelligence and automation of the aviation logistics industry. With the growing size and complexity of the aviation logistics industry, big data in aviation logistics management will inevitably increase efficiency and minimize costs, dramatically improving the industry's competitiveness (Wang & Chen, 2018).

2.4.4.2. Big data for aviation operations and service management

The primary purpose of big data in aviation operations and service management is to record and represent passenger information, booking information, customer service information, operational and financial conditions, and other related data. To support the best intelligent and automated services, a full big data business solution will effectively combine separated operational and service information. Integrating big data from aviation operations and service management with various mobile terminals, in particular, would result in a new mode of aviation activity and service management (Fasone et al., 2016; He et al., 2017).
2.5. Spectrum and coupling analysis of aviation big data information system

2.5.1. Frequency spectrum analysis
Frequency spectrum analysis includes single spectrum analysis and joint spectrum analysis. Single spectrum analysis focuses on analyzing spectrum change situation between two adjacent nodes (components), which reflects the functional status of front-end nodes (components). As shown in Figure **2**, spectrum function s_{ij} measures the spectrum variation of the corresponding front-end nodes (components) at different levels. Through the analysis of the change of spectrum function s_{ij}, we can know the running status of each functional component in time. In the specific analysis, we can use wavelet transform and Fourier transform to analyze time domain and frequency domain, so as to fully understand and master the functional status of the corresponding front-end nodes (components).
Joint frequency spectrum analysis focuses on the analysis of multistep joint spectrum function of interlayer nodes (components), which reflects joint function status between dynamic sequential nodes (components). For example, the joint spectrum function of spectrum functions s_{14}, s_{24}, s_{34}, and s_{42} in Figure **2** measures the joint cooperative function status of information path $SD_{14} \rightarrow SD_{24} \rightarrow SD_{34} \rightarrow SD_{42} \rightarrow CS$. Joint spectrum analysis has the characteristics of multilayer recursive analysis step by step. For example, in the information path analysis of "$SD_{14} \rightarrow SD_{24} \rightarrow SD_{34} \rightarrow SD_{42} \rightarrow CS$," there are four levels: "$SD_{14} \rightarrow SD_{24} \rightarrow SD_{34}$," "$SD_{14} \rightarrow SD_{24} \rightarrow SD_{34} \rightarrow SD_{42}$," and "$SD_{14} \rightarrow SD_{24} \rightarrow SD_{34} \rightarrow SD_{42} \rightarrow CS$" (see Figure **2**).
Figure 2. Spectrum and coupling analysis of aviation big data information syste



SD_{11}: Big data for flight and airport management; SD_{12}: Big data for crew and cabin passenger service
SD_{13}: Big data for aviation logistics management; SD_{14}: Big data for aviation operations and service management
SD_{21}: Big data for route planning and air traffic management; SD_{22}: Big data for flight environment and safety
SD_{23}: Big data in flight management; SD_{24}: Big data in aviation business
SD_{31}: Big data for aircraft design and performance improvement
SD_{32}: Big data for aircraft operating conditions and malfunction and maintenance
SD_{33}: Big data in macro aviation; SD_{34}: Big data in micro aviation
SD_{41}: Big data of aviation technology; SD_{42}: Big data of aviation management
CS: General control system; C_{ij}: Coupling degree; S_{ij}: Spectrum function

For some functional components, cross spectrum analysis is also needed. Cross spectrum research looks at the spectrum situation between a node (component) in one information direction and a node (component) in another. Cross-single spectrum analysis and cross-joint spectrum analysis are also included. For some flight control subsystems, cross spectrum analysis is needed. Of course, the cross-spectrum analysis algorithm is complicated and necessitates additional processing.

2.5.2. Coupling degree analysis

The emphasis of coupling degree analysis is on the joint and coordinated activity of different nodes (components). The same-layer coupling degree analysis and the cross-layer coupling degree analysis are two types of coupling degree analysis. The study of coupling degree on the same layer, on the other hand, is fundamental. The cij in Figure 2 tests the degree of coupling between adjacent nodes (components) on the same layer, for example.

In general, the degree of coupling between the same layer nodes (components) in different information paths is measured by the study of coupling degree on the same layer. For example, c11 in the first layer measures the degree of coupling between SD11 and SD12 of the same layer, c22 in the second layer measures the degree of coupling between SD23 and SD24 of the same layer, and so on (see Figure 2). Clearly, this step-by-step calculation and analysis of coupling degree at the same stage improves the accuracy of analysis results. Coupling degree analysis can, of course, be used to determine the degree of coupling between adjacent nodes (components) on the same information path. It's close to spectrum analysis in this case.

Furthermore, cross-layer cross-coupling analysis is a successful form of analysis. However, the related algorithm's complexity would be significantly increased. As a result, Figure 2 does not depict this scenario.

2.5.3. Multilayer network feedback control system

Sensor data and related guidance and control systems are used in both spectrum and coupling analysis. It is important to build a multilayer network feedback control system for a complex functional large-scale system such as an airplane in order to improve the system's reliability. It includes the required hardware and software components. The crux of the issue is figuring out how to organically incorporate the hardware and software systems.

The measuring component, signal processing component, amplifying component, and executing component are all part of the flight control system. A multilayer network feedback control system based on different functional units and subsystems can be built against the backdrop of big data, taking into account the large scale, multidimension, and real-time characteristics of big data.

3. Discussion and implications

3.1. Planning and construction of national aviation big data platform

Since the planning and construction of a big data platform entails a number of issues such as rules, standards, and knowledge sharing, macro planning and construction at the national level is needed. The first is the creation and advancement of aviation big data and related laws and regulations. Since big data is a relatively new phenomenon, its laws and regulations have yet to be fully developed, and laws and regulations in aviation big data and related fields are in a state of flux. As a result, it is critical to move quickly with the regulation of aviation big data and related fields.

Another critical concern is the establishment and implementation of specifications for the aviation data platform and its information systems. Currently, various airlines have set up aviation service data and information systems, but they are still in the early stages of development and fragmentation. To respond to the demands of big data and intelligent growth, national standards must be standardized in order to establish the conditions for big data and knowledge sharing. On the other hand, it also serves as a foundation for national aviation administrations to effectively control the aviation industry (Insua et al., 2018).

3.2. The construction of the cooperation mechanism of global aviation big data

The aviation industry is one of the most globalized, with a growing number of international flights. To enhance international flight safety, a globally shared aeronautical big data network and its information system must be built to provide basic information for country flight control and efficient management and monitoring of all flights within their airspace.

One of the most pressing issues confronting the international aviation industry today is determining how to track and control the status of aircraft in real time. At this stage, black boxes are mostly used to record aircraft operations, but they can only provide flight data for post-mortem examination. Big data can offer a new way to track and control the status of planes in real time. To provide basic protection for global aviation safety, all national aviation organizations must work together to create a global aviation big data cooperation system.

4. Conclusions

The growth of the aviation industry will be revolutionized by big data. It will have a significant impact on aircraft design and performance, aircraft operation and maintenance, route planning and air traffic control, flight environment and safety, flight and airport management, crew management, air logistics management, aviation operations, and service management.

The study of the aviation big data system must use a multilayer network correlation analysis approach due to the complexities of the aviation system and big data. Same layer correlation analysis, adjacent layer correlation analysis, and interlayer correlation analysis are at the heart of it.

The establishment and implementation of an aviation big data platform and its information management system are at the heart of aviation big data growth. Aeronautical science big data and aviation management big data are two of the most important aspects. Big data in aviation is primarily used to document and represent the fundamental conditions of aircraft design and performance, as well as operating conditions,

malfunction diagnosis, and maintenance. The primary purpose of big data in aviation management is to record and reflect the status of aeronautical operations and operational efficiency. They work together to evaluate the aviation industry's safety results. As a result, certain steps must be taken to accelerate the development of the aviation infrastructure and technical advancement based on big data.
The study's drawback is that no particular quantitative analysis model has been established, and no calculations or simulation analyses involving actual aircraft complex systems have been performed. Furthermore, machine learning and deep learning technology are used in the smart aviation knowledge management system. This paper does not explain these issues since it only looks at them from the viewpoint of management. In the future, these issues will need more debate and study.

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