Original Research Article

Overview of Flight Planning Optimization Research

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Abstract: From the analysis of different time stages of flight planning optimization, flight planning optimization can be divided into three aspects: static flight planning optimization, flight planning dynamic feedback optimization based on flight delay prediction, and flight planning dynamic adjustment based on airport collaborative decision -making (A-CDM). Then, it analyzes the static scheduling and optimization of flight plans from the preparation links of flight schedules, aircraft type assignments, and flight frequencies; then uses the optimization method of delay spread prediction and data mining prediction to analyze the correlation of flight plan dynamic feedback optimization based on flight delay prediction the study. Finally, according to the complexity analysis of flight plan optimization, the development trend and future research directions of flight plan optimization are given.

Keywords: Flight planning optimization, Delay prediction, Deep learning, Airport-collaborative decision-making, Supervised learning.

1. Introduction

Flight plans are the foundation and core of all production activities of airlines, and all other production plans revolve around flight plans. Therefore, timely and scientific arrangement of flight plans is of great significance to ensure flight safety, improve service work, increase aircraft utilization and carrying capacity, and increase economic benefits, and complete transportation production tasks[1]. In recent years, the aviation industry has developed rapidly. With the significant increase in flight volume, the problem of flight delays has become increasingly prominent[2]. Among the factors that affect flight delays, unreasonable flight planning is one of the important factors.

There was research on flight plan optimization in the 1970s, and foreign scholars such as Wegmann H M[3] and Dachkovsky V. Z[4] conducted earlier research. Subsequently, domestic researchers such as Zhu Jinfu[5] and Hu Minghua[6] conducted extensive research on flight schedules and route networks. After decades of development, research on flight plan optimization has become increasingly complex, no longer simply considering single factors and models. At present, research on flight plan optimization has begun to utilize theories such as deep learning, relying on the advantages of big data analysis to further improve the theory of flight plan optimization.

The article categorizes and summarizes the research results of flight plan optimization from different perspectives such as flight plan formulation and feedback adjustment. The research results are divided into three categories: the first category is the static arrangement optimization of flight plans, which involves research on flight frequency, flight schedule, etc; The second type is dynamic feedback optimization of flight plans, involving research on flight delay prediction; The third type is dynamic adjustment of flight plans, involving airport collaborative decision-making (A-CDM). From the perspective of airlines, static scheduling optimization of flight plans increases operational efficiency by optimizing flight schedules, aircraft types, crew, and other factors. However, if too much profit is pursued, the flight chain connection becomes too tight, and there is insufficient

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margin for stopover time. Once delays occur, delays are inevitable and losses will be greater. The research on flight planning based on delay prediction mainly uses relevant theories of machine learning to optimize and adjust flight plans while improving prediction accuracy. The research on dynamic adjustment and optimization of flight plans based on A-CDM aims to achieve temporary dynamic adjustment of flight plans under uncontrollable factors and reduce flight delays.

The specific chapter arrangement of the article is as follows: Firstly, in Section 1, relevant research on static optimization of flight planning is introduced, including the preparation of flight schedules, flight frequencies, and other aspects; Subsequently, in Section 2, the optimization of flight plans based on flight delay prediction was analyzed, which was further divided into two types of optimization directions: data mining prediction and delay ripple prediction; In Section 3, the dynamic adjustment of flight plans based on Airport Collaborative Decision Making (A-CDM) was discussed; Finally, in Section 4, a summary of the article's content is provided, and based on the current research status, three future research prospects are proposed from the perspective of the complexity of flight plan optimization research.

2. Optimization of Static Arrangement of Flight Plans

Airlines are the main body responsible for preparing flight plans, which are the central link in all production activities of airlines. The arrangement steps of flight plans are interrelated and closely linked, requiring continuous comprehensive consideration of the airline's existing production resources and in-depth analysis of market demand and revenue, which is a dynamic and changing process. However, the factors considered in flight plan arrangement are relatively static and have not fully considered factors such as weather and flow control. Therefore, flight plan optimization research from the perspective of airlines can be regarded as static optimization research of flight plan arrangement.

The process of preparing a comprehensive flight plan is completed from multiple aspects such as the selection of flight routes and segments, frequency and schedule, aircraft type assignment, flight number, flight schedule, etc. The study of frequency and schedule is also known as the study of flight frequency. When domestic and foreign scholars study flight plan optimization, they often focus on three aspects: flight frequency, aircraft type assignment, and flight schedule. The following will focus on introducing research on these three aspects.

2.1 Flight Frequency

The determination and optimization of flight frequency is a key link in flight planning, which involves factors such as capacity supply, available aircraft types, route demand, and competitor market share. The determination of flight frequency is also the basis for assigning flight schedules and aircraft types.

In the 1980s, Christopher C. Findlay[7] abroad used the standard optimization model to balance the relationship between the optimal ticket price and flight frequency. Then Du Scaron[8] used the absolute value of the difference between the actual departure time and the expected departure time to measure the economic effect of flight frequency. This method of considering single models and factors has been improved in recent years. Sze Wei Chang[9] developed the profit maximization model based on the lowest operating costs and passenger delay costs of airlines, but only targeted specific routes without considering flight frequency optimization under the route network. In China, Zhu Jinfu[10] was one of the earliest to establish a profit maximizing flight frequency optimization model; Zhu Xinghui[11] conducted research on flight frequency for air traffic volume prediction; Jiang Silu[12] established a flight frequency optimization model based on passenger planned delays, taking into account the impact of the competitive environment of multiple aircraft types and routes on flight frequency. However, taking a fixed value of flight frequency will cause difficulties in further obtaining feasible solutions, and the constraint conditions can be further increased. The mathematical expression formula of the model established is as follows:

$$\min C = \sum_l C_{SD} R_l MS_l \frac{T}{4\sum_k F_{lk}} + \sum_k F_{lk} C_l \quad \text{(Eq.1)}$$

Eq.1 is the objective function for minimizing the total cost. Among them, C is the total cost, which consists of two parts: passenger planned delay cost and operating cost; L is the set of flight routes, $l \in L$; K is the aircraft type combination, $k \in K$; C_{SD} is the unit cost of passenger delay; C_l is the operating cost of the flight; T is the flight planning cycle; MS_l is the market share of a certain airline on route l; R_l is the passenger occupancy rate of route l within a certain flight cycle; F_{lk} is the frequency of flight type K on route l.

The single flight frequency optimization model is gradually being replaced by multi constraint models, with constraints increasing costs such as delay from profit and operating costs. Integrating flight frequency with aircraft type assignment, route network, etc. to establish an integrated comprehensive optimization model is also the next research focus.

2.2 Model Assignment

Aircraft type assignment refers to the allocation of aircraft with different cabin capacities to corresponding routes based on the specific cabin capacity, revenue status, operating costs, and availability of the aircraft, in order to determine the optimal aircraft type for the flight and complete the flight plan[13]. It is also the core link of flight planning and the foundation for issues such as crew scheduling. The quality of aircraft type assignment directly affects the operational revenue of airlines, as well as issues such as crew configuration, maintenance, parking allocation, and subsequent flight connections.

The developed air transportation industry abroad has led to early research on aircraft type assignment issues. Most of the early studies focused on hub route networks and daily flight plans, with relatively average optimization effects. In 2006, Barry C. Smith[14] proposed a robust aircraft type assignment model from the perspective of airport purity, which required that the airports involved in a certain aircraft type be concentrated as much as possible. Oussama Aoun[15] used a hidden Markov model to estimate the most likely state to achieve the optimal allocation of crew members, which is an optimization of the subsequent problem of aircraft type assignment. Domestically, Zhu Xinghui[16] drew on Barry C. Smith's theory and established a robust aircraft type assignment model based on flight purity. In addition, Jiang Silu[17] established a comprehensive optimization model for flight frequency and aircraft type assignment based on the study of passenger plan delay calculation, and pointed out the possibility of comprehensive modeling of flight frequency, aircraft type assignment, and flight schedule.

The optimization problem of aircraft type assignment has made significant progress in recent years, with a focus on establishing comprehensive optimization models. With the in-depth research of market demand analysis and prediction, as well as the development of machine learning related theoretical methods, the research on aircraft type assignment problems will also be further developed.

2.3 Flight Schedule

In the past few decades, numerous time slot allocation optimization models have been proposed, ranging from single airport flight schedule optimization models to range network-based flight schedule optimization models. Flight schedules have always been the main focus of flight plan optimization research.

In traditional flight schedule resource management, the first factor to consider is passenger demand, namely departure and transfer; Secondly, consider the needs of the airline, namely the corresponding flight plan; Finally, consider the operational requirements of the airport, including supporting facilities and airspace capacity limitations. The flow management problem in China is unique, influenced by multiple factors such as terminal areas, route planning, and airspace limitations. When considering time optimization, it is necessary to consider the optimal utilization of airspace capacity. As early as 2003, Hu Minghua[18] proposed a multi-dimensional restricted flight schedule optimization model based on the multi-dimensional restricted ground waiting strategy, and solved it using an improved heuristic algorithm, considering pushing flights forward or backward to time periods to efficiently utilize airport and airspace capacity. However, the continuous growth of air traffic flow, the increasing impact of airspace capacity restrictions, and the limited possibility of airport expansion have led to an imbalance in the air traffic demand capacity of large airports and delays in inbound and outbound flights.

Large European airports have implemented strategic flight schedules to address the issue of air traffic capacity imbalance. Miguel Lambelho et al[19]. evaluated strategic flight schedules related to potential flight delays and cancellations using machine learning based methods, exploring potential performance bottlenecks at airports, and their model is universal. This is also the first time that machine learning methods have been combined with strategic flight schedule evaluation, and there is still significant room for improvement in the model's functional set. YuFeng Tu[20] studied the distribution of flight departure delays required for estimating air traffic congestion prediction models and developed a strategic level departure delay prediction model, providing a probability model foundation for subsequent flight schedule optimization. There is relatively little research on flight planning at the strategic level, and there is no systematic optimization method. The research results provide a theoretical basis for subsequent research.

In 2005, Loo Hay Lee[21] discussed the robustness of flight schedules based on potential violations, treating the elimination of potential violations such as equipment failures as a multi-objective optimization problem, providing ideas for subsequent flight schedule optimization. Subsequently, Ahmed Abdelghany[22] considered a competition based flight schedule optimization model, clearly considering the passenger demand transfer caused by route network competition between airlines. He integrated heuristic search algorithms, network competition analysis models, and resource (such as crew and aircraft) tracking models. Xi Geng[23] proposes an improved simulated annealing optimization model for multi airport systems (MAS) to optimize flight schedules, reducing the average displacement and delay of MAS. It can be seen that under the condition of multiple airports and a complete route network, flight schedule optimization will be more effective, and research on strategic optimization will be more powerful.

Flight schedules have always been a key focus of flight plan optimization, and optimization strategies have continuously developed from tactical to strategic levels, providing a rich theoretical basis for flight plan optimization. Reasonably allocating flight time slots will bring huge operational benefits to airlines and also improve passenger travel convenience.

3. Dynamic Feedback Optimization of Flight Plans Based on Delay Prediction

The problem of flight delay prediction has been a research hotspot in recent years, and research on flight delay prediction can be roughly divided into two categories: flight delay prediction based on data mining and flight delay prediction based on the impact of flight delay. Studying flight delay prediction is of great significance for airport flight schedule redistribution and ground resource support. In 2019, Fu Zhenyu[24], Liu Bo[25], and others reviewed research on flight delay prediction methods, providing a systematic theoretical introduction to flight delay prediction research.

Table 1 Flight Delay Prediction Related Processes.

Flight delay prediction	
Method/Model	Decision trees, random forests, linear regression, support vector machines, neural networks, Bayesian networks, etc
Required data	Arrival and departure flight data, airport data, delay data, meteorological data, transit time data, etc
Evaluation object	Flight delay, delay level, delay time, delay reason, delayed flights, etc.
evaluating indicator	Prediction accuracy, mean square error, ROC, mean absolute error, root mean square error, confusion matrix, etc.

3.1 Flight Delay Prediction Based on Data Mining

The flight delay prediction based on data mining mainly uses classic machine learning methods such as decision trees, random forests, support vector machines, Bayesian network models, and deep learning methods such as deep neural networks and convolutional neural networks. The classic Bayesian network model is widely used in flight delay prediction based on flight delay propagation. It consists of two parts: one is the set of nodes in a directed acyclic graph $G=(V,E), V=\{V_1,V_2,\cdots,V_n\}$, where $E=\{e_1,e_2,\cdots,e_m\}$ is the set of directed edges, V_i is the variable to be solved, and e_j is the relationship between nodes; The other part is the probability distribution table, where the root node represents the edge distribution $P(V_{root})$ and the non root node represents the conditional probability distribution. According to conditional independence, the joint probability distribution of node V is:

$$P(V_1,V_2,\cdots,V_n)=\prod_{i=1}^{n} P\left[V_i \middle| parent(V_i)\right] \tag{Eq.2}$$

In flight delay prediction, the theory of delay prediction has gradually enriched from considering single factor modeling that affects flight delays to multi factor analysis. Wang Nan[26] quantified the degree to which adverse weather at the airport affects the normal departure of flights, established a database of meteorological factors that affect flight delays, and analyzed the contribution of different seasons, meteorological factors, and other factors to flight delays in the form of decision trees. Severe weather is one of the important factors affecting flight delays, and the quantitative analysis of meteorological factors is of great significance for the role of flight delays, providing a theoretical basis for subsequent flight plan optimization. Sun Choi[27] also studied the impact of severe weather on flight delays and compared the accuracy of supervised machine learning methods such as random forests, decision trees, ensemble learning methods, and K-nearest neighbor (KNN) classification algorithms in predicting flight delays considering weather effects. The study used flight data between Denver International Airport (DEN) and Charlotte Douglas International Airport (CLT), The analysis of the results shows that although weather is an important factor affecting flights, it is not a unique element, and other factors should also be considered when studying flight delay prediction. When using supervised machine learning methods in flight delay prediction, when the selected data volume is required to be large and the relationships between various related factors are very complex or highly nonlinear, good prediction results can be achieved. When establishing a predictive model, supervised machine learning can compare the predicted results with the actual results (training validation data) and continuously adjust the predictive model, forming a learning process that continuously learns to achieve the expected results. The training process is shown in Figure 1.

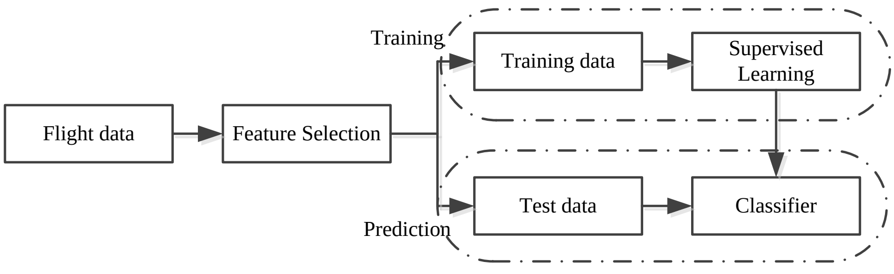

Figure 1 Supervised learning model training process.

Su Aijing[28] initially established a flight operation simulation model for the airport, using the output delay time and aircraft utilization rate as evaluation indicators to identify bottleneck factors affecting flight operation and predict the probability of abnormal flights. This model can incorporate relevant data such as flow control and weather to establish a preliminary comprehensive model for predicting flight delays, which can analyze the propagation of flight delays and the robustness of flight planning systems. Establishing a comprehensive predictive model to analyze the factors that affect the normal operation of flights and the controllability and recovery of abnormal flights is currently a key research direction.

3.2 Flight Delay Prediction Based on Ripple Delay

Most studies on flight delays consider the concept of flight chains. Flight string refers to the arrangement of airlines to operate multiple consecutive flights on the same aircraft in a day on an economic basis, as shown in Figure 2. When a flight in the flight string is delayed, it may cause delays in subsequent flights, which is known as delay ripple.

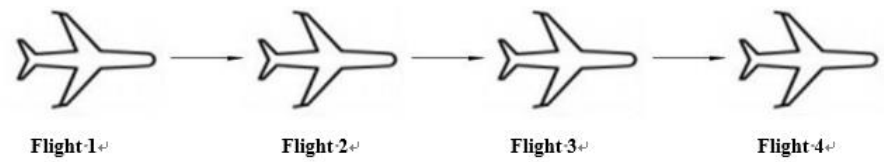

Figure 2 Flight Chain.

The prediction of affected delays requires consideration of factors such as multiple airports and routes. Dun bar and Michelle[29] calculate the minimum delay affected cost by comprehensively considering aircraft routes and crew pairing. CAO W D and HE G G. et al[30]. applied Bayesian networks to analyze the delay propagation between consecutive flights. The above study analyzed the delay propagation in the flight loop, but did not investigate the impact of airports on the delay propagation in the flight chain. However, Weiwei Wu[31] in China analyzed that flight arrival time is influenced by the previous departure flight, including the phenomenon of delay propagation and other factors that affect delay propagation in the network. Wu Weiwei[32] analyzed the impact of flight delays using a Bayesian network model based on flight strings, and predicted the overall delay status of the airport using a weighted Markov chain model. The prediction results were more reliable, and flight plans were adjusted, greatly improving the reliability of flight plan operation. Of course, Bayesian network models also have limitations in predicting delays. Delay prediction is not timely, and delays can only be predicted after obtaining a clear planned departure time. They only provide data support for flight plan changes. Gao Qiang[33] considers the problem of reallocating the slack time of flight layovers under the impact of delays, which is also a readjustment of controllable time gaps under the impact of delays. However, such research must ensure that flights have a reasonable margin of layover time. Zhang Haifeng[34] established a short-term flight plan scheduling model based on delay control. Compared with traditional flight plan scheduling optimization, flight plan scheduling considering delay analysis is more likely to reduce delay occurrence.

The above delay predictions are based on the impact of flight delays on subsequent flight plan changes, while Zhou Qin[35] focused on studying independent delays unrelated to flight plan changes and the role of flight path optimization models in improving the robustness of flight plans in advance. In summary, machine learning theory has a deeper application in the field of flight delay prediction, with higher accuracy in flight delay prediction, which has great reference value for optimizing flight plans. The optimization theory of flight plans based on delay prediction is constantly enriching, and subsequent research will also focus on big data and comprehensive directions.

4. Dynamic Adjustment of Flight Plans Based on Airport Collaborative Decision-Making

Adverse factors such as adverse weather conditions, flow control, and military activities can affect the normal entry and exit of flights. In addition, there are communication and coordination barriers between various organizations, which can cause large-scale airport delays and a large number of people to be stranded during a certain period of time. Therefore, an efficient decision-making system is needed to achieve dynamic adjustment of flight plans under adverse conditions, in order to reduce flight delays and delay losses.

Airport collaborative decision-making was first proposed by the European Organization for Navigation Safety[36], developed from the earliest collaborative decision-making platform CDM, and applied earlier in Zurich

Airport, Switzerland, with significant results. The Civil Aviation Administration of China attaches great importance to the promotion of A-CDM. As of the end of 2019, 37 airports have completed A-CDM construction. The draft technical specifications for airport collaborative decision-making released by the Civil Aviation Administration of China (CAAC) state that through multi-party information sharing, communication barriers between departments and units can be broken down, flight waiting delays can be reduced, emergency prediction and response capabilities can be improved, and dynamic adjustments to flight plans can be achieved. Building an A-CDM system requires barrier free information communication and ensuring the integrity of shared data. Data integrity is the soul of A-CDM[37], and all units ensure the sharing of complete data. In the face of adverse conditions such as severe weather and flow control, the A-CDM system can achieve prediction, analysis of the degree of delay impact and development trends. The complete data includes two types: (1) traditional AODB data, booking system, departure system, and aviation travel APP system; (2) Air traffic control system, freight system, security inspection system, ground settlement system.

If there is a large-scale flight delay warning information, the A-CDM system will generate an adjustment plan based on the corresponding operational restrictions and affected time periods, and send information such as the reduction ratio and the need to adjust flights to relevant airport units. Generate and publish the final flight adjustment plan based on the flight cancellation or change plan departure time information provided by the airline. The A-CDM system can automatically track the execution status, real-time status, pre order status, and coordination status of flights that need to be adjusted, and assist the airport operations management committee in supervising airlines to implement adjustment plans. The specific process is shown in Figure 3.

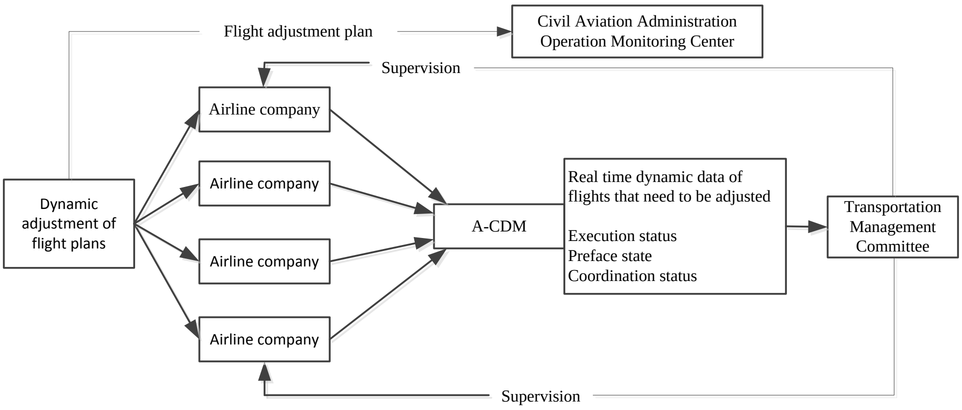

Figure 3 Dynamic schematic diagram of flight plan adjustment.

Beijing Capital Airport has developed a collaborative decision-making system CEP-CDM[39] based on complex event processing to address the shortcomings of A-CDM, which can only monitor and warn of milestone events. Compared to A-CDM, this system has the ability to actively perceive, analyze, and provide feedback to airports. Its advantage lies in learning flight support standards from historical flight operation data, verifying and managing current data, and achieving better dynamic adjustment of flight plans. But the construction of CEP-CDM requires reasonable planning in the medium to long term, even in the long term.

5. Summary and Outlook

The article provides an overview of research literature on flight plan optimization both domestically and internationally. From the perspective of flight plan preparation process and feedback optimization, it is divided into three categories: static preparation optimization, dynamic feedback optimization, and dynamic adjustment of flight plans. Based on the current research status of flight plan optimization, considering multiple environmental factors and multi-party collaboration, the problem of flight plan optimization is currently more complex. The following are three future research prospects. (1) Flight planning involves the revenue and operation of airlines, as well as the operation of relevant air traffic control and airport units. Simply looking at flight planning optimization from a certain perspective or factor has significant limitations and requires strategic coordination and analysis. (2) For short-term plans, it can be seen that airport collaborative decision-making A-CDM is the trend of airport future development. A complete A-CDM can dynamically adjust flight plans in real-time, predict and preprocess flight delays when facing flight delays. However, the long-term plan still requires comprehensive supervision and production based on the needs of all parties, and the A-CDM system still needs a long time to be improved and promoted. (3) In the face of the current increase in data volume, how to combine deep learning and other related theories with flight plan optimization research more reasonably and deeply is a future research hotspot.

References

1. Pan Weijun. Fundamentals of Air Traffic Management [M]. Second Edition. Chengdu: Southwest Jiaotong University Press, 2013:206-207.
2. Xu Haiwen. Research on the controllability of restoring abnormal flight plans [D]. Nanjing University of Aeronautics and Astronautics, 2018.
3. Wegmann H M, Hasenclever S, Michel C, et al. Models to predict operational loads of flight schedules. 1985, 56(1):27-32.
4. Dachkovsky V.Z., Pozdnyakov V.V., Yanbykh G.F.. The Decision -making Procedure in the Automated Process of Formulating a Flight Schedule. 1983, 16(20):465-470.
5. Jiang Tao, Zhu Jinfu. Research on the Benefit Analysis of Airline Network Configuration [J]. Industrial Technology and Economics, 2006 (11): 105-107.
6. Hu Minghua, Chen Aimin, Xu Xiaohao, Yuan Weidong. Research on Ground Waiting Strategy Problems with Multiple Constraints [J]. Journal of Nanjing University of Aeronautics and Astronautics, 1998 (01):3-5.
7. Christopher C. Findlay. Optimal Air Fares and Flight Frequency and Market Results. 1983, 17(1):49-66.
8. Du&scaron, an B. Teodorovi&cacute. Flight Frequency Determination. 1983, 109(5):747-757.
9. Sze -Wei Chang, Paul Schonfeld. Optimized Schedules for Airline Routes. 2004, 130(4):412-418.
10. Zhu Jinfu. Air Transport Planning [M]. Xi'an: Northwest Polytechnical University Press, 2010.
11. Zhu Xinghui. Research on Optimization Design of Airline Flight Plans [D]. Nanjing: Nanjing University of Aeronautics and Astronautics, 2007.
12. Jiang Silu, Zhu Jinfu, Kong Mingxing, Zhou Qinyan. Optimization of Flight Frequency Based on Passenger Plan Delays [J] Journal of Wuhan University of Technology (Transportation Science and Engineering Edition), 2019, 43 (01): 136-140.
13. Zhu Xinghui, Zhu Jinfu, Gong Zaiwu. Research on aircraft type assignment models and algorithms for Chinese airlines [J]. Industrial Technology and Economics, 2007 (04): 75-77.
14. Barry C. Smith, Ellis L. Johnson. Robust Airline Fleet Assignment: Imposing Station Purity Using Station Decomposition. 2006, 40(4).
15. Oussama Aoun, Malek Sarhani, Abdellatif El Afia. Investigation of hidden markov model for the tuning of metaheuristics in airline scheduling problems. 2016, 49(3):347-352.
16. Zhu Xinghui, Zhu Jinfu, Gao Qiang. Research on Robust Aircraft Type Assignment Problem Based on Flight Purity [J]. Prediction, 2011, 30 (01): 71-74.
17. Jiang Silu. Research on Comprehensive Optimization of Flight Frequency and Model Assignment [D]. Nanjing University of Aeronautics and Astronautics, 2019.
18. Hu Minghua, Zhu Jingbo, Tian Yong. Research on the Optimization Model and Method of Multivariate Constrained Flight Schedule [J]. Journal of Nanjing University of Aeronautics and Astronautics, 2003 (03): 326-332
19. Miguel Lambelho, Mihaela Mitici, Simon Pickup, et al. Assessing strategic flight schedules at an airport using machine learning-based flight delay and cancellation predictions. 2020, 82.
20. Yufeng Tu, Michael O Ball, Wolfgang S Jank, Estimating Flight Departure Delay Distributions—A

Statistical Approach With Long -Term Trend and Short -Term Pattern [J]. Journal of the American Statistical Association, 2008, 103.

21. Loo Hay Lee, Chul Ung Lee, Yen Ping Tan. A multi-objective genetic algorithm for robust flight scheduling using simulation. 2005, 177(3):1948-1968.
22. Ahmed Abdelghany, Khaled Abdelghany, Farshid Azadian. Airline flight schedule planning under competition. 2017, 87:20-39.
23. Xi Geng, Minghua Hu, Stefan Balint. Simulated Annealing Method -Based Flight Schedule Optimization in Multiairport Systems. 2020.
24. Fu Zhenyu, Xu Haiwen, Fu Qiang. Overview of Flight Delay Prediction Research [J]. Science and Innovation, 2020 (03): 1-4.
25. Liu Bo, Ye Bojia, Tian Yong, Yang Minhao. Research Review on Flight Delay Prediction Methods [J]. Aviation Computing Technology, 2019, 49 (06): 124-128.
26. Wang Nan, Yang Hongru, Zhou Jianjun, Cao Dunbo. Quantitative study on the impact of severe weather on flight delays at Urumqi Airport [J]. Drought Meteorology, 2018, 36 (04): 684-693.
27. Sun Choi,Young Jin Kim,Simon Briceno,Dimitri Mavris. Prediction of weather -induced airline delays based on machine learning algorithms [A].in:IEEE，.2016 IEEE/AIAA 35th Digital Avionics Systems Conference : [Volume 1 of 2] Pages 1-657.[C]. 2016: 1-6.
28. Su Aijing, Yang Wendong, Zhang Chong, Kong Mingxing. Simulation modeling analysis of flight operation system [J]. Journal of Harbin Institute of Technology, 2019, 51 (09): 49-55.
29. Dunbar, Michelle,Froyland, Gary,Wu, Cheng-Lung. Robust Airline Schedule Planning: Minimizing Propagated Delay in an Integrated Routing and Crewing Framework [J]. Transportation Science,2012,46(2).
30. CAO W D, HE G G. Bayesian networks analysis for sequence flight delay and propagation [J]. Journal of Computer Applications, 2009, 29(2): 606-610.
31. Weiwei Wu, Cheng-Lung Wu. Enhanced delay propagation tree model with Bayesian Network for modelling flight delay propagation. 2018, 41(3):319-335.
32. Wu Weiwei, Meng Tingting, Zhang Haoyu. Research on Flight Plan Optimization Based on Airport Delay Prediction [J]. Transportation System Engineering and Information, 2016, 16 (06): 189-195.
33. Gao qiang, Zhou Qin, Chen Xin. Redistribution of Relaxation Time for Flight Overrides Based on Affected Delays [J]. Journal of South China University of Technology, 2019, 10:151-156.
34. Zhang Haifeng, Hu Minghua. Short term flight plan scheduling model and algorithm for airlines [J]. Journal of Nanjing University of Aeronautics and Astronautics, 2015, 47 (04): 553-558.
35. Zhou Qin, Gao Qiang, Li Weiwen. Aircraft Path Stochastic Optimization Model Based on Impact Delay [J]. Traffic Information and Safety, 2017, 35 (03): 117-123.
36. Implementation Manual for Collaborative Decision Making at European Airports (Chinese Version) [S] Air Traffic Management Bureau of the Civil Aviation Administration of China, 2013.
37. Guo Yaxi. On the Development of Civil Aviation Collaborative Decision Making (CDM) System [J]. Chinese and Foreign Entrepreneurs, 2020 (04): 29-30.
38. Business - Airline and Airport Management; Data from Universidade da Beira Interior Broaden Understanding of Airline and Airport Management (The airport A-CDM operational implementation description and challenges). 2020.
39. Lu Min, Feng Xia, Xu Tao. A review of research on airport collaborative decision-making [J]. Intelligent Building, 2018 (08): 58-61.