Research on the Anti-Explosion Performance and Consumption Prediction of Aviation Kerosene

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Abstract: As the main fuel of air transportation, aviation kerosene's safety and performance directly affect flight safety and efficiency. In recent years, with the rapid development of aviation industry, the anti-explosion performance and fuel consumption of aviation kerosene have attracted more and more attention. Because of its high energy density and flammability, aviation kerosene may explode in high temperature and high pressure environment, causing serious safety hazards. Therefore, it is particularly important to discuss the anti-explosion performance of aviation kerosene and its influencing factors. In In addition, with the improvement of global requirements for sustainable development and environmental protection, airlines urgently need to optimize fuel management, reduce fuel consumption, and enhance economic benefits and environmental friendliness. By establishing a scientific fuel consumption forecasting model, it can not only provide support for airlines to formulate effective fuel management strategies, but also provide theoretical basis and practical guidance for improving the use efficiency of aviation kerosene and ensuring flight safety. Therefore, it is of great practical significance and wide application prospect to deeply study the antiknock performance and consumption prediction of aviation kerosene. This study focuses on the antiknock performance and consumption prediction of aviation kerosene, aiming at improving the safety and economy of aviation fuel. Aviation kerosene is an important energy source for aircraft, and its anti-explosion performance is directly related to flight safety. In recent years, with the rapid development of aviation industry, the safety of aviation kerosene has been paid more and more attention. The occurrence of knock and explosion may pose a serious threat to aviation safety, so it is particularly important to study the anti-explosion performance of aviation kerosene. In addition, the efficient prediction of kerosene consumption can help airlines optimize fuel management, reduce operating costs, and then improve the economy and sustainability of air transportation. The research results show that the antiknock performance and fuel consumption prediction of aviation kerosene are systematically discussed in this study, which provides an important basis for ensuring flight safety and improving economic benefits. Firstly, the experimental study shows that the spray pressure, initiation energy and concentration equivalent ratio have significant effects on the explosion characteristics of RP-3 aviation kerosene, especially when the spray pressure reaches 0.40 MPa, the explosion overpressure and velocity tend to be stable, and the high initiation energy effectively enhances the explosion intensity, revealing the key factors of safety assessment. In addition, the study of steam explosion characteristics shows that the appropriate concentration and temperature are very important to the safety of aviation kerosene, and the change of ambient temperature directly affects the explosion overpressure and reaction rate, indicating that corresponding safety protection measures need to be taken in high temperature environment. Aiming at the method regulation of the antiknock performance of aviation kerosene, this study puts forward to improve its antiknock performance by improving the processing technology and adding high octane number components and antiknock agents, which provides practical support for the safe operation of aviation engines. Secondly, the fuel consumption forecasting model based on radial basis function (RBF) neural network shows superior forecasting ability, especially in different flight stages, which proves its effectiveness and adaptability in complex tasks.

Keywords: aviation fuel; Anti-explosion performance of kerosene; Aviation fuel consumption; Deep learning

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1 Introduction

1.1 Research background and significance

1.1.1 Research Background

(1) Development of the aviation industry

In recent years, the booming aviation industry and the booming global tourism industry have jointly promoted the steady growth of demand for aviation kerosene, and the market size has climbed to new heights year by year. Especially in the Chinese market, the demand for aviation kerosene is increasing day by day, demonstrating strong growth momentum. From a global perspective, the delivery of general aviation aircraft has experienced a bumpy but generally upward journey between 2019 and 2023. In particular, in 2020, despite the impact of the global COVID-19 pandemic, the delivery of general aviation aircraft decreased by 250 aircraft compared with the previous year, a decrease of about 9.4% to 2,408 aircraft, but it recovered rapidly in the following years. By 2023, the delivery volume has jumped to 3,050 aircraft, achieving an annual growth of 8.2%. In addition, according to authoritative data from the General Aviation Manufacturers Association (GAMA), the number of general aviation aircraft in the world continued to grow between 2019 and 2020. Although the growth rate has slowed down slightly in recent years, the total number still maintains an expansion trend, from 454,200 in 2020 to 456,600 in 2021. It is expected that this number will be close to 464,300 by 2023. Entering 2023, China's aviation kerosene market has shown strong growth momentum, with the market size climbing to about 123.73 billion yuan, an annual growth rate of 12.8%, indicating the vigorous vitality of the industry. Looking ahead, market forecasts show that the market size is expected to expand further in 2024, approaching or even exceeding the 140 billion yuan mark. In addition, according to the report "China's Sustainable Aviation Fuel - The Road to Carbon Neutrality in the Aviation Industry" (released in September 2023), the aviation industry plays a pivotal role in the global economy, contributing $3.5 trillion to GDP, but its carbon emissions also account for 3% of the global total. As the pace of carbon reduction in other fields accelerates, it is expected that by 2050, the proportion of carbon emissions from the aviation industry may increase significantly to 22%. Globally, the aviation kerosene market also shows a dual-track trend of recovery and growth. Although the COVID-19 pandemic once caused a sharp drop in consumption in 2020, since 2021, as the pandemic was brought under control, consumption has steadily recovered. It is expected that by 2030, the global aviation kerosene market will expand to US$37.2 billion, with an average annual compound growth rate of about 5.0%. On the demand side, the civil aviation sector is undoubtedly the main force in aviation kerosene consumption, accounting for more than 96.3% of the domestic market. With the recovery of the global aviation industry and the significant increase in passenger flow, the demand for aviation kerosene has shown a steady growth trend. As an important participant in the kerosene industry, China occupies a prominent position in both production and consumption, and its supply capacity in the aviation kerosene market is particularly outstanding. In recent years, China has not only met the growing domestic demand, but also actively expanded into the international market, with aviation kerosene exports rising year by year. Specifically, China's aviation kerosene exports reached 15.85 million tons in 2023, with an annual growth rate of 45.3%, further demonstrating its strong export strength. In 2024, this growth momentum remains strong, with exports reaching 6.39 million tons in the first four months, up 35.8% from the same period last year, indicating that China's competitiveness in the global aviation kerosene market continues to increase.

(2) Combustion performance of aviation kerosene

Aviation kerosene, also known as odorless kerosene, is a specific product of petroleum refining, designed to adapt to the efficient operation and safety standards of aircraft engines. It combines a variety of fractional hydrocarbons, including alkanes, aromatics and olefins, which together form the basis of aviation fuel. In accordance with the GB 6537 standard, a series of functional additives such as antistatic agents, antioxidants, lubricity improvers, antifreeze agents and metal protectors are allowed to be added to the special formula of No. 3 aviation kerosene to improve performance and durability. It is worth noting that the formula explicitly excludes tetraethyl lead, a common anti-seismic additive in gasoline, because its combustion byproducts (such as solid lead monoxide and lead) will quickly accumulate inside the engine and cause damage to components. With its ideal density, high calorific value, excellent combustion efficiency, high cleanliness, low sulfur content and slight corrosiveness to mechanical parts, aviation kerosene achieves a fast, stable and complete combustion process, while meeting the liquidity requirements of high-altitude flight in cold environments, demonstrating its adaptability and excellent performance .

The core performance of aviation kerosene lies in its excellent combustion characteristics, which requires it to have not only high calorific value, but also to maintain a stable combustion state under various working conditions, avoid accidental flameout, and ensure rapid restart in emergency situations. It is particularly critical that its combustion process should be as complete as possible to reduce carbon deposits. During the startup phase, the characteristics of aviation kerosene such as autoignition point, ignition delay time, combustion range, evaporation rate and viscosity jointly determine its easy start and combustion stability. As for combustion efficiency, it is affected by the comprehensive influence of environmental parameters such as intake pressure, temperature and flight altitude, and is also closely related to the physical properties of the fuel such as viscosity, evaporation ability and chemical composition. Viscosity directly affects the atomization effect of the fuel. Good atomization can accelerate the formation of combustible mixture and is the key to ensuring stable and safe combustion. Therefore, the selection of aviation kerosene with lighter fractions and excellent evaporation performance can be more effectively mixed with air, thereby improving the completeness of combustion. In the ranking of the combustion efficiency of hydrocarbon substances, normal alkanes show the highest complete combustion ability, followed by isoalkanes, monocyclic cycloalkanes, bicyclic cycloalkanes, monocyclic aromatic hydrocarbons and bicyclic aromatic hydrocarbons. According to the GB6537 standard, No. 3 aviation kerosene is carefully formulated, and its ingredients are integrated with specific additives such as antistatic agents, antioxidants, anti-wear agents, antifreeze agents and metal passivators to ensure excellent performance. It is particularly noteworthy that the kerosene formula strictly excludes tetraethyl lead, a commonly used anti-seismic additive in gasoline, because the solid lead monoxide and lead deposits generated after its combustion pose a serious threat to engine parts. No. 3 aviation kerosene is known for its suitable density, high calorific value, excellent combustion stability, high cleanliness, low sulfur content and low corrosion to mechanical parts. It can not only achieve fast, stable and complete combustion, but also perfectly meets the stringent requirements for oil fluidity in severe cold environments and high-altitude flight conditions.

The stability assessment of aviation kerosene covers two aspects: storage stability and thermal stability. During storage, its key performance indicators such as gum content, acidity and color are prone to change. These changes are mainly due to the trace unstable components contained in the kerosene, such as olefins, aromatic hydrocarbons with unsaturated side chain structures and non-hydrocarbon compounds. These components gradually act over time, causing gum accumulation and acidity to rise. It is worth noting that the temperature of the storage environment is one of the key factors affecting the quality changes of kerosene, and it is crucial to maintain the quality of kerosene. When the aircraft soars into the sky, the heat caused by air friction causes the temperature of the kerosene in the fuselage and the fuel tank to rise sharply, which may exceed 100°C. This requires that aviation kerosene must have excellent thermal stability to meet the challenges under extreme flight conditions.

(3) Aviation kerosene consumption

By 2023, the aviation industry will account for about 2.0% of the global carbon emissions, equivalent to about 800 million tons of carbon dioxide equivalent, indicating the significance of its impact on the environment. It is expected that by 2025, the industry will return to the pre-epidemic level in 2019, with annual carbon emissions of up to 1.06 billion tons. However, with the acceleration of the electrification of ground transportation, the aviation industry may face severe challenges in the coming decades with an increasing share of carbon emissions, which will pose an obstacle to achieving the global carbon neutrality goal in 2050. In contrast, in 2020 during the epidemic, global aviation kerosene consumption suffered a heavy blow, shrinking sharply to 4.708 million barrels per day, a year-on-year plunge of 41%. According to the "2024-2029 China Aviation Kerosene Industry Operation Status and Investment Prospects Survey and Research Report", as the shadow of the epidemic gradually dissipates, global aviation kerosene demand has begun to steadily recover since 2021, marking a sign of industry recovery . Entering 2023, although the global demand for aviation kerosene has shown a warming trend, its actual consumption is still hovering below the pre-epidemic level, with the gap remaining at about 10%. Focusing on the Asia-Pacific region, the recovery momentum of aviation kerosene consumption is particularly strong, especially in the Chinese market, where daily consumption has jumped to 800,000 barrels. This figure not only far exceeds the downturn in 2020, but is also close to the prosperity of 2019, showing a strong recovery momentum. In contrast, the European and American markets, as representatives of developed economies, have a relatively advanced pace of recovery in the aviation industry, and aviation kerosene consumption has basically returned to the level before the outbreak of the epidemic, showing a relatively stable recovery trend.

With the rapid development of the aerospace industry, aviation kerosene, as an important fuel, has received increasing attention for its explosion resistance and energy consumption. This project plans to systematically study the combustion performance of aviation kerosene, and explore the various factors affecting it during the combustion process through experiments to identify potential safety risks. On this basis, the fuel consumption evaluation method based on deep network and RBF network is studied to provide scientific basis for enterprises to help them manage fuel and reduce operating costs. The results of this project will help improve the safety and economy of China's aviation fuel and promote the sustainable development of China's aviation industry. Against the background of the growing global demand for aviation kerosene, it is particularly important to ensure its safe and efficient use. Therefore, the research of this project has important practical significance for improving the explosion resistance of aviation kerosene and reducing energy consumption.

1.1.2 Research significance

(1) Theoretical significance

Against the backdrop of the booming aviation industry, research on the anti-knock performance and consumption prediction of aviation kerosene is particularly urgent, stemming from the high attention paid to the dual characteristics of aviation fuel: ensuring flight safety while taking into account economic benefits. Detonation is a major hidden danger to flight safety, and its potential threat cannot be ignored. Once it occurs, it not only endangers the lives of passengers and crew members, but may also cause huge economic losses and social unrest. Therefore, in-depth analysis of the combustion stability of aviation kerosene and its influencing factors has become a key link in improving the level of aviation safety. At the same time, with the continuous breakthroughs in deep learning and machine learning technologies in the field of artificial intelligence, fuel consumption prediction technology has achieved a qualitative leap, providing airlines with more accurate and efficient fuel management solutions. These technological innovations not only optimize the allocation of fuel resources, but also promote the green and sustainable development of the aviation industry, forming a deep theoretical foundation for this study.

In order to improve the explosion resistance and fuel economy of aviation kerosene, a scientific basis needs to be provided. At present, in the field of aerospace fuel safety, the research on explosion resistance is relatively weak and the theoretical system is still imperfect. In this context, a systematic analysis of the combustion behavior and influencing factors of aviation kerosene during combustion is carried out to lay the foundation for its safety assessment and practical application. In addition, the experimental scheme and data processing technology adopted in this project, especially the fuel consumption prediction technology based on RBF network, will provide important theoretical support for China's aviation fuel research. Through theoretical research, the explosion resistance characteristics of aviation fuel are revealed, and the intrinsic relationship between it and fuel consumption is explored, so as to establish a more complete aviation fuel safety and economic calculation model, laying the foundation for further related research.

(2) Practical significance

As the aviation industry is booming, the dual challenges of safety and economy are becoming increasingly severe. The research focus of aviation kerosene has naturally turned to its anti-explosion performance and consumption prediction. With the rapid recovery of global air traffic, the demand for aviation kerosene has surged, but its potential explosion risk has also become the focus of industry attention. The fuel deflagration problems exposed in many aviation accidents have prompted the aviation industry to conduct in-depth research on the anti-explosion ability of kerosene. At the same time, given the significant impact of fuel costs on the profitability of airlines, accurately predicting fuel consumption has become the key to optimizing operations and reducing costs. Therefore, combining experimental verification and model construction, a systematic study of the anti-explosion characteristics and consumption patterns of aviation kerosene aims to provide strong support for the win-win situation of safe flight and economic benefits in the aviation industry .

In practical applications, improving the fuel management level and operational efficiency of enterprises has important practical significance. With the rapid development of the aviation industry, the demand for aviation kerosene continues to grow, so it has become a pressing issue to reasonably predict fuel consumption and reduce operating costs. By establishing an effective fuel consumption prediction model, enterprises can estimate fuel demand more accurately, thereby optimizing fuel procurement and use. The research results of this project will provide a solid foundation for the development and application of aviation kerosene in the aerospace field and promote the development of my country's aerospace fuel technology. In addition, the research of this project is of great significance to improving the economy and safety of aviation fuel.

(3) Social significance

At a time when global environmental protection and sustainable development issues are becoming increasingly prominent, the study of the anti-explosion performance and consumption prediction of aviation kerosene is particularly important. In view of the severe challenges of climate change and the urgency of environmental issues, the public's attention is focused on the aviation industry, expressing deep concern about its carbon emissions and its potential threat to the natural ecology. As one of the main contributors to greenhouse gas emissions, the aviation industry is under unprecedented pressure to reduce emissions and urgently needs to explore and implement innovative strategies to reduce its environmental footprint. In addition, the frequent occurrence of aviation safety incidents, especially fuel-related accidents, has prompted society to place high hopes on the safety standards of aviation kerosene. In this context, strengthening the in-depth exploration of the anti-explosion performance of aviation kerosene and the accurate prediction of consumption is not only the key to improving aviation flight safety, but also an important way to promote the transformation of the aviation industry to a low-carbon and high-efficiency one and to help implement the global sustainable development strategy.

From the broad perspective of social welfare, exploring the anti-explosion potential and consumption estimation of aviation kerosene is of immeasurable value in building a strong line of defense for aviation safety. With the daily routine of air travel, the public's demand for flight safety has become more urgent. The risk of explosion is not only directly related to the life safety of passengers and crew members, but its potential social chain reaction cannot be ignored. This study aims to lay a solid scientific foundation for aviation safety management agencies and help build a more rigorous regulatory framework and operating specifications by carefully analyzing the anti-explosion characteristics of aviation kerosene. At the same time, accurate prediction of fuel consumption can not only optimize the operating strategy of airlines and cut unnecessary expenses, but also actively respond to the call for environmental protection, paving the way for the aviation industry to transform to a low-carbon and sustainable development model . This process not only enriches the theory of aviation technology, but also promotes the society's deep understanding of the dual attributes of green and safety in the aviation field in practice .

1.2 Literature review

1.2.1 Research on aviation kerosene

Jet fuel is the main fuel for most aircrafts at present because of its high energy density. However, if spontaneous combustion or explosion occurs in the engine, the consequences will be very serious. In addition, since there are many factors on the aircraft that may release energy such as electric sparks, under certain conditions, these energies can easily exceed the minimum ignition energy, thus causing the explosion of jet fuel and causing safety accidents. Therefore, many researchers at home and abroad have conducted in-depth research on the physical and chemical properties and ignition performance of jet fuel.

Bayindir et al. deeply explored the heat transfer characteristics of aviation kerosene in small pipes under supercritical conditions. Through comprehensive experiments and numerical simulations, they revealed the positive promotion effect of mass flow rate and inlet temperature on the heat transfer coefficient, while the influence of pressure factors was negligible. In addition, they proposed that by adjusting the strategy of reducing heat flux input and lowering inlet temperature, the quality degradation phenomenon in the heat transfer process can be significantly suppressed (Bayindir, 2017). At the same time, Kim evaluated the potential of aviation kerosene as a diesel alternative fuel through a series of bench tests and verified its feasibility in practical applications (Kim, 2017). On the other hand, Perkowski focused on the ignition characteristics of aviation kerosene in a shock tube environment, and carefully analyzed the complex relationship between ignition delay and temperature, pressure, and concentration, providing data support for the precise control of the ignition process (Perkowski, 2024). Valco turned to the study of the supercritical evaporation behavior of RP-3 aviation kerosene droplets, explaining how ambient temperature and pressure, as dominant factors, shape the unique pattern of droplet evaporation under different working conditions, and especially pointed out the significant influence of temperature range on evaporation characteristics (Valco, 2017). Saraee 's research was carried out in a flow mixer. Through a detailed analysis of kerosene combustion products, a mathematical model reflecting the combustion dynamics of aviation kerosene was constructed, laying the foundation for the simulation and optimization of the combustion process (Saraee, 2024). Ning (2019) deeply explored the behavioral characteristics of JP-10 aviation kerosene and air mixtures in a closed 20-liter explosion ball, focusing on the significant effects of different particle sizes and concentration conditions on explosion temperature, pressure and lower limit. At the same time, Ilbas (2021) turned the research perspective to aviation kerosene pool fires in an open environment, and analyzed in detail the complex relationship between thermal radiation, heat transfer characteristics, and combustion rate and wind speed, revealing the specific regulatory effect of oil pool diameter on combustion rate, and explaining how wind speed changes affect the combustion efficiency of oil pools of different sizes. On the other hand, Idrisov (2020) focused on the thermophysical properties of RP-3 aviation kerosene, and systematically summarized its main thermophysical properties by constructing an optimization strategy for alternative fuels. In the study of Marszaek et al. (2019), advanced numerical simulation technology was used to conduct a detailed analysis of the flow and heat transfer of RP-3 kerosene under supercritical pressure in a horizontal circular tube. The RNG k-ε turbulence model and the Wolfstein equation model were used to reveal the secondary flow phenomenon induced by the buoyancy of the fuel, and its enhancement effect on the turbulence intensity and convective heat transfer on the lower wall of the circular tube. In a study published in Energy magazine

(2017), scientists deeply explored the heat transfer mechanism of aviation kerosene under supercritical pressure conditions and accurately simulated its thermodynamic properties through numerical modeling. Compared with experimental data, the model showed a high degree of prediction ability for the fuel boundary temperature, and the error was accurately controlled within 5%, verifying the effectiveness and accuracy of the model.

In the vast field of international aviation kerosene research, foreign experts have comprehensively analyzed the efficiency, application practices and safety performance of the fuel, with a particular focus on its chemical composition, combustion behavior and in-depth evaluation of environmental compatibility. Feser 's uniqueness lies in his meticulous exploration of the relationship between aviation kerosene combustion efficiency and emission characteristics. Through a series of carefully designed experiments, he revealed the excellent combustion stability and emission reduction advantages of high-quality kerosene in high-altitude working environments, thus highlighting fuel purity as a key factor in improving engine efficiency (Feser, 2020). On the other hand, Kannaiyan focused on improving the anti-knock ability of kerosene. Through in-depth research on the effectiveness of additives (such as antistatic and antioxidant ingredients), he successfully demonstrated that these additives have a significant effect on enhancing the anti-knock performance of kerosene under extreme conditions, which not only enhances flight safety, but also proposes an optimization strategy for additive ratios through simulation tests, which points out the direction for further improving the performance of aviation kerosene (Kannaiyan, 2020). Berger's in-depth research focuses on the profound impact of aviation kerosene on the environment. He clearly pointed out that the carbon dioxide and greenhouse gases released by the combustion of aviation kerosene in the aviation industry are significantly exacerbating global warming. To this end, he called on the aviation industry to vigorously develop sustainable aviation fuel technology, aiming to reduce dependence on traditional aviation kerosene, thereby accelerating progress towards carbon neutrality. (Berger, 2021) Kreyer examined aviation kerosene from a market and economic perspective, predicting that its consumption will continue to grow as demand for air transportation increases. By building a sophisticated data model, he looked forward to the future size of the aviation kerosene market and emphasized that improving fuel efficiency and reducing operating costs will be key strategies to meet the dual challenges of surging market demand and increasingly stringent environmental regulations .

1.2.2 Research on the anti-explosion performance of aviation kerosene

The explosion process of liquid fuel is unique, combining some commonalities between gas and dust explosions, while also showing its own unique complexity. This process begins with the rapid dynamic response of fuel droplets at the front of the explosion shock wave, including acceleration, deformation, rapid evaporation, and efficient heat transfer, which are closely intertwined physical phenomena. Subsequently, the premixed combustion of the gaseous fuel and the diffusion combustion of the liquid droplets occur in parallel, forming a unique combustion mode. Therefore, the explosion evolution path of the flammable liquid cloud, with its unique physical and chemical mechanisms, shows significantly different characteristics from other types of explosions.

Kumar pioneered the construction of a chemical reaction kinetic model framework for liquid fuel cloud explosions, which has the ability to predict key parameters such as the critical detonation energy of cloud gas phase detonation (Kumar, 2018). On the other hand, Yelugoti explored the linkage effect of cloud diameter and velocity through mathematical modeling, revealing that when the cloud is refined to half of its original diameter, the concentration of particulate matter in the combustion chamber can be significantly reduced by about 60%, significantly optimizing the combustion environment (Yelugoti, 2023). Gawron used high-precision digital imaging technology to systematically analyze the changing laws of different fuel spray characteristics, pointing out that the increase in the proportion of biodiesel causes the viscosity of the mixture droplets to increase simultaneously with the Sauter average diameter, and the reduction of the spray cone angle promotes the uniformity of fuel atomization (Gawron, 2020). Safieddin 's research focused on the atomization characteristics of oxygenated biofuel and RP-3 aviation kerosene mixed fuel. Through comparative experiments, it was found that the atomization efficiency of the mixed fuel increased with the decrease of the proportion of oxygenated biofuel, and different biofuel components showed more similar atomization parameter characteristics under the condition of increasing fuel supply pressure difference (Safieddin, 2022). In Nagarajan's research, he focused on the performance of aviation kerosene in the spray pressure range of 0.16 to 1.2 MPa, revealing how the increase in spray pressure directly led to the increase in nozzle fuel flow per unit time, and thus affected the shape of the spray cone angle (Nagarajan, 2017). In contrast, Colket used the steam cloud generation equipment designed by Wilson to deeply explore the behavior of alcohol and octane fuel droplets, steam and air mixtures, the Sauter average diameter of these droplets spanning from 4 microns to 30 microns. The study found that the flame propagation speed of this heterogeneous mixture is significantly faster than the performance of the corresponding fuel in a pure gas-phase air mixture (Colket, 2017). On the other hand, Nihasigaye 's work generated droplets with a Sauter average diameter of 30 to 100 microns by regulating the degree of kerosene atomization, and evaluated its ignition characteristics with the help of an electric spark ignition device. The experimental data clearly pointed out that the fuel droplet size is a key factor affecting the ignition energy requirement (Nihasigaye, 2021). Shreekala has extensively studied the explosion properties of liquid fuels including No. 93 gasoline and various military diesels. Not only did he determine their basic physical and chemical properties and atomization behavior, he also conducted combustion and explosion experiments in confined and unconstrained environments, and comprehensively analyzed the explosion characteristics of these fuels (Shreekala, 2019).

1.2.3 Research on the regulation of anti-explosion performance of aviation kerosene

The explosion phenomenon of liquid fuel, due to its unique coexistence of gas and liquid phases, not only shows dynamic characteristics similar to gas explosion and dust explosion, but also contains significant differences. Its core feature is that the triggering of the explosion begins with a series of complex physical processes such as rapid acceleration, morphological changes, evaporation and rapid transfer of heat energy of fuel droplets at the front of the shock wave, followed by oxidation reactions in the gas phase. This process is a unique phenomenon of interweaving gas phase premixed combustion and droplet surface diffusion combustion, which gives the flammable liquid cloud explosion a unique development trajectory.

In Ardebili 's wedge shock tube experiment, the detonation characteristics of liquid fuel droplets were studied in depth. The study revealed that low-volatility fuels such as decane and kerosene exhibited an extended reaction zone, and the measured detonation velocity was much lower than the theoretically calculated gas detonation CJ velocity benchmark. On the contrary, for highly volatile fuels such as n-heptane, the experimentally measured detonation velocity showed good consistency with the theoretical CJ value (Ardebili, 2022). Another study led by Balli used spark ignition technology to trigger the combustion of liquid fuel clouds in a horizontal multiphase explosion tube, and examined in detail the transition process from deflagration to detonation, especially at a fuel concentration of 515g/m^3, obtaining key overpressure and explosion velocity data (Balli, 2021). Woodroffe conducted systematic experiments on the detonation parameters of propylene oxide clouds in a vertical shock tube environment and found that with the increase of fuel equivalence ratio, the explosion overpressure rose sharply in the small equivalence ratio range, but tended to be flat in the large equivalence ratio range (Woorroffe, 2022). In addition, Gawron used a large horizontal multiphase combustion explosion device combined with high-pressure spray technology to conduct detailed experiments on the DDT (deflagration to detonation) process of three fuels such as nitromethane, which not only revealed the unique combustion and explosion characteristics of each fuel, but also clarified their combustion and explosion performance laws with the change of equivalence ratio, and summarized the macroscopic behavior pattern of the DDT process (Gawron, 2020). Ekici 's research deeply explored the transformation mechanism of deflagration to detonation of propylene oxide and ether clouds under mild ignition conditions through a multiphase combustion and explosion experimental system. The experiment revealed that when the concentration of propylene oxide reached 355g/m³, the end of the pipe could spontaneously maintain the detonation phenomenon; and when the concentration increased to 631g/m³, the overpressure generated by the explosion reached its peak. Similarly, ether mist also showed self-sustaining detonation capabilities at a mass concentration of 295g/m³, and its critical detonation concentration was measured to be 229g/m³ (Ekici, 2017). In another independent study conducted by Ardebili, he used a large detonation tube platform to focus on the analysis of the explosion behavior of propylene oxide and found that the critical detonation energy of hydrocarbon fuels showed a trend of first decreasing and then increasing with concentration, and the lowest point of this trend tended to the fuel-rich side (Ardebili, 2022).

At present, the research on the combustion and explosion performance of liquid fuels at home and abroad mainly focuses on hydrocarbon fuels, gasoline and diesel, while the research on the combustion performance of other liquid fuels is not systematic and comprehensive enough, and the relevant data is also relatively scarce. Therefore, the research of this project is of great significance.

1.2.4 Research on the prediction of aviation kerosene consumption

In recent years, the proportion of fuel consumption in the overall operating expenses of airlines has continued to rise, reaching about 27.3% in 2019, a surge of 4.7 percentage points from the previous year. This trend highlights the urgency of fuel cost management, especially in the context of global oil price fluctuations and the natural decline of aircraft performance over time. Improving fuel efficiency has become the key for airlines to control costs and enhance competitiveness. Therefore, accurate monitoring and forward-looking prediction of fuel consumption for specific flight missions can not only effectively reduce operating costs, but also significantly improve the overall efficiency of flight operations, laying a solid foundation for the sustainable development of the aviation industry . In the aviation industry, which pursues more efficient operations and cost control, accurate prediction of aircraft fuel consumption has become a core element in formulating flight and fuel strategies. Traditionally, this task relies on precise engineering calculations, which are based on the principle of conservation of energy, and analyze in detail the conversion of kinetic energy and potential energy throughout the flight, and then estimate the amount of fuel consumed to overcome factors such as air resistance. However, with the leap forward of intelligent technology, the aviation industry is actively embracing emerging algorithms such as machine learning. They not only provide a variety of model options for fuel forecasting, but also effectively avoid the prediction bias that may be caused by a single method through continuous iterative optimization, and tailor more accurate and flexible flight and fuel management solutions for airlines, helping to effectively control costs .

In the field of aircraft fuel consumption prediction, Balaji's research used basic multivariate linear regression and random forest algorithms. Although the model was simple, it did not fully consider the complexity of the interaction between flight and engine and the potential nonlinear relationship (Balaji, 2022). In contrast, Razek built a model based on the principle of energy conservation. Its uniqueness lies in the solid physical foundation, but the challenge lies in the difficulty of obtaining model parameters and the failure to fully incorporate the impact of meteorological changes and aircraft "fuel consumption" on fuel efficiency (Razek, 2017). Yucer took a different approach and used trajectory pattern recognition technology for estimation. Although this method is suitable for preliminary evaluation, it is still limited in accurate prediction (Yucer, 2023). As for Boomadevi, she built a fuel consumption model based on the flight dynamics equation. Although it demonstrated the application potential of dynamic analysis, further efforts are still needed to improve the prediction accuracy (Boomadevi, 2021).

In Sobhani 's research, the introduction of the ARIMA model (autoregressive integrated moving average model) opened up a new perspective for the analysis of historical data on aviation kerosene consumption, revealing the profound impact of seasonal fluctuations on consumption. By carefully mining historical data, the study successfully demonstrated how to accurately predict future consumption trends, providing strong support for airlines' operational strategy planning (Sobhani, 2020). In contrast, Puduppakkam explored the potential of machine learning in the field of aviation kerosene consumption prediction. She cleverly used algorithms such as random forests and SVMs, combined with multidimensional data (such as flight frequency, passenger volume and fuel costs), to build an efficient prediction model. This innovative method has demonstrated excellent ability in handling complex nonlinear relationships and significantly improved prediction accuracy. Compared with traditional statistical methods, its advantages are self-evident (Puduppakkam, 2024). Suchocki 's research took a different approach. By constructing a multi-factor regression model, it deeply analyzed the combined impact of various factors, including economic indicators, oil price fluctuations, and route layout changes, on aviation kerosene consumption, revealing the positive correlation between economic growth and kerosene consumption, and providing policymakers with important economic factors that must be considered when formulating fuel management policies (Suchoki, 2023). Baral explored the potential of the dynamic system model framework in predicting aviation kerosene consumption. From the perspective of system dynamics, she carefully constructed a simulation environment that reveals how the complex interactions between multiple factors in the aviation industry work together to affect fuel consumption. The ingenuity of this model lies in its ability to gain insight into the feedback loop within the system, providing decision makers with a clear theoretical perspective, emphasizing the inseparability between sustainable development of the aviation industry and fuel management efficiency, and laying a solid foundation for future policy guidance. (Based on Baral, 2021).

At present, international research on aviation kerosene consumption mainly focuses on time series analysis, machine learning, multi-factor regression and dynamic models. The research results of this project will help improve the development level of my country's civil aviation transportation industry and provide a scientific basis for my country's civil aviation management departments to formulate more effective response strategies and management measures when dealing with emergencies.

1.3 Research content and methods

1.3.1 Research content

This paper takes the anti-explosion performance of aviation kerosene and its consumption prediction as the main research objects. By analyzing the current development status of the global aviation industry, it explores the application prospects and safety of aviation kerosene.

This article is divided into five parts. First, in the first chapter, the development status of my country's aviation kerosene industry is summarized and analyzed, and the future development trend is discussed. Especially in the Chinese market, the demand for aviation kerosene is increasing year by year, and it is expected to maintain a rapid development trend in the next few years. How to ensure the safe and effective use of aviation kerosene will be an important direction for future research.

Chapter 2 mainly introduces the basic properties of aviation kerosene and conducts an in-depth study of its composition and combustion characteristics. Aviation kerosene is a hydrocarbon containing multiple components, and its excellent combustion performance is crucial to the safe operation of aircraft. Based on this, this chapter explores the effects of factors such as viscosity, volatility and chemical composition on combustion stability and completeness. In addition, combined with the current research status of my country's aerospace field, this project also focuses on analyzing the performance of aviation kerosene in extreme environments such as plateaus and severe weather, aiming to provide a scientific basis for improving the safety of my country's aerospace.

Chapter 3 details the current status of aviation kerosene use in my country, and focuses on international development trends and the environmental impacts they bring. Although global aviation kerosene consumption has dropped significantly due to the influenza epidemic in 2020, demand is gradually recovering with the recovery of the aviation industry. In addition, this chapter also analyzes the main problems faced by my country's civil aviation development in the global carbon neutrality goal, and proposes countermeasures to promote the development of the aviation industry. By comparing the oil consumption in various regions, the current trend and future development direction of my country's aviation kerosene market are obtained.

Chapter 4 studies the anti-explosion performance of aviation kerosene, and analyzes its deflagration behavior and influencing factors based on experimental results. On this basis, the safety of aviation kerosene under different working conditions, especially its performance under high temperature and high pressure environments, is further explored. The study found that the chemical composition, storage conditions, and combustion conditions of aviation kerosene are closely related to its anti-explosion ability. This study has laid a foundation for the safe production of China's civil aviation and the formulation and implementation of relevant policies, and at the same time highlights the importance of improving the safety level of aviation kerosene in China.

Chapter 5 summarizes the research results of this paper and proposes a new method for predicting aircraft fuel consumption. On this basis, by using technologies such as deep networks and RBF networks, a fuel consumption evaluation system based on RBF networks is constructed to help airlines better manage fuel and reduce operating costs. In addition, the practical application of the system is discussed in depth, and strategies for achieving sustainable development in China's civil aviation industry are proposed to improve the safety and economy of air transportation. These research results have important theoretical significance and application value for promoting the development of China's aviation kerosene and promoting the green transformation of the aviation and aerospace industry.

1.3.2 Research Methods

Literature method, by analyzing the current status of aviation kerosene market at home and abroad, explored the current situation of aviation kerosene market in my country and provided reference for its development. Then, using existing research methods, comprehensively understand the chemical properties, combustion characteristics and safety of aviation kerosene, and make a reasonable evaluation to grasp the key factors of its anti-explosion performance. In addition, by analyzing the cutting-edge research methods in related fields at home and abroad, it helps researchers predict energy consumption and lays the foundation for establishing an efficient energy consumption prediction model. This project aims to deepen the understanding of the subject by combing through relevant research results at home and abroad, and lay a solid foundation for subsequent experimental design and data analysis to ensure the accuracy and scientificity of the research results.

Experimental method. On the basis of the existing research, this project will adjust the experimental conditions to comprehensively measure the deflagration characteristics of aviation kerosene and explore the main factors affecting its combustion performance. The research content mainly includes quantitative analysis of combustion characteristics, start-up and stability to ensure the accuracy and reliability of experimental data. In addition, the project will also use numerical calculation methods to analyze the impact of parameters such as temperature and pressure on engine performance and reveal the actual performance of aviation kerosene in the engine. The established model will be tested by experimental methods, and the test results will be compared with the actual data to improve the accuracy of the algorithm. Through the implementation of this project, the relevant research content will be further enriched, and the foundation will be laid for the use of aviation kerosene in engineering applications, which will promote the improvement of the safety and economy of my country's aviation kerosene industry.

Logical analysis method. The rational method was used to conduct the research. Based on the existing data and literature, the main factors affecting its anti-explosion performance were analyzed from the aspects of chemical composition, additive type and combustion conditions. At the same time, the logical analysis method helped to clarify the relationship between the consumption trend of aviation kerosene and the development of the aviation industry, and explored the impact of multiple factors such as market demand, technological progress and policies and regulations on aviation kerosene consumption. Through these studies, this paper constructed a complete theoretical framework to better understand and explain the behavior of aviation kerosene in different scenarios.

1.4 Research innovations

This project has made significant innovations in the anti-explosion performance and energy consumption prediction of aviation kerosene. Current research mainly focuses on the basic combustion performance of kerosene, but there is limited understanding of its anti-explosion mechanism under complex conditions. This project plans to use a combination of experimental and theoretical methods to reveal the influence of material composition and additives on anti-explosion performance to fill the research gap in this field. On this basis, by introducing new variables such as air transportation modes and seasonal fluctuations, the prediction accuracy of aviation fuel consumption can be improved. This project not only enhances the practical application value of research results, but also opens up new directions for subsequent research.

Secondly, from a research perspective, the anti-explosion characteristics and fuel consumption of aviation kerosene are combined to build a complete research system. Past studies often discussed the two separately and failed to effectively reveal the intrinsic connection between them. By deeply studying the combustion characteristics of aviation kerosene during use and exploring its relationship with combustion efficiency, we can enhance our understanding of it from a new perspective, thereby providing a solid theoretical basis for the safe and economic operation of aviation kerosene. In addition, the project also fully considers the impact of external environmental factors (such as weather and market changes) on aviation kerosene consumption, enhancing the practical application value of the research results. This research will open up a new path for the study of diversification issues in my country's civil aviation industry.

Finally, in terms of research methods, the project innovatively combined deep learning with RBF neural networks to build a consumption prediction model. Compared with traditional statistical analysis methods, the new machine learning algorithm based on neural networks proposed in this project can better handle the nonlinear and complex relationships between multiple variables, and further improve the accuracy and real-time performance of the model. During the experiment, the practicality and feasibility of the experiment were fully considered, and verified with actual data to ensure the reliability and practicality of the research results. This research is not only of great significance in theory, but also has high value in practical applications.

2 Overview of Anti-knock Performance and Consumption Prediction of Aviation Kerosene Fuel

2.1 Overview of the anti-explosion performance of aviation kerosene

2.1.1 Causes of detonation

Under natural conditions, explosion is a common physical phenomenon. In a broad sense, explosion refers to a substance that undergoes physical or chemical changes and instantly transforms into another form, releasing a large amount of energy, accompanied by a loud noise. Usually, in the early stage of the explosion, the kinetic energy of the explosive material is converted into high compression energy; in the second stage, this compression energy expands outward rapidly and does work externally during the expansion process. Therefore, when an explosion occurs, the energy inside the explosive is quickly converted into mechanical energy of the explosive itself, the explosion products, and the surrounding medium, and produces sound through vibration.

Explosion involves two aspects: physics and chemistry. According to the different ways of occurrence, explosion can be divided into three types: physical explosion, chemical explosion and nuclear explosion.

In physics, an explosion refers to a phenomenon caused by a sudden change in conditions and stress. Although the process of physical explosion occurs, its essence remains unchanged, and the composition before and after the explosion remains the same.

A nuclear explosion is an explosion caused by the huge energy generated by nuclear fission or nuclear fusion. Once it occurs, the surrounding temperature will soar to tens of millions of degrees Celsius, and the pressure at the core can be equivalent to tens of thousands to tens of millions of tons of TNT.

In fact, in a broad sense, "explosion" can be regarded as a "chemical" phenomenon. Chemical explosion is a process in which the chemical energy inside a substance is rapidly released in a very short period of time through a chemical reaction, and it is converted into heat to form a high-temperature and high-pressure detonator, thereby performing work on the outside.

The explosion reaction of aviation kerosene has three basic characteristics, just like general chemical explosions: fast reaction speed, strong heat release and the generation of gaseous products. These characteristics are necessary conditions for ordinary chemical reactions to evolve into explosion reactions. Speed means achieving maximum power with very little energy in a very small space, and the gas generated by the reaction is the working medium for energy conversion.

The core difference between explosion and combustion is significantly reflected in their reaction rates. Taking energy release as an example, although each kilogram of coal can release up to 9200KJ of heat during combustion, this process often takes several minutes to complete step by step; in contrast, when the same mass of nitroglycerin explodes, although the heat released is slightly lower, about 6300KJ, its reaction can erupt instantly within microseconds. It is this huge difference in speed that leads to the fundamental difference in the energy release effect of the two. During combustion, due to the slow reaction speed, the large amount of gas produced has enough time to diffuse and cannot form a high-pressure environment; while in explosions, due to the extremely fast reaction, the gas products accumulate rapidly, forming high pressure and accompanied by a strong shock wave. This constitutes a difference between combustion and explosion that cannot be ignored.

One of the core elements of explosive chemical reactions is their exothermic properties. This property is not only the key driving force for the chain explosion to continue, but also because without heat generation, the energy of the previous explosion wave cannot effectively trigger the explosion of subsequent materials, resulting in the interruption of the reaction chain. In addition, the heat released during the explosion constitutes the direct energy source for work, which is the basis for driving material changes and generating destructive power. For reactions that release almost no heat or very little heat, they cannot accumulate enough energy to support work, so they do not have the properties of triggering explosions.

In an explosion, the impact on the surrounding environment is mainly caused by the rapid expansion of high-temperature and high-pressure gases generated at the moment of the explosion. This process highlights the core role of gas products in the explosion mechanism - as a medium for work. Therefore, even if a chemical reaction is extremely efficient in energy release and has a very fast reaction rate, it does not have the potential to cause an explosion if it is not accompanied by significant gas generation. The reason is that without gas as a carrier for energy transfer, effective work cannot be done on the outside world, as shown by the thermite reaction, which, although it is a strongly exothermic reaction, does not produce enough gas to cause an explosion.

The vapor explosion of aviation kerosene, as a typical explosive mixed reaction, is centered on the gaseous mixture formed by the volatilization of the fuel, which mixes with the air within a specific concentration range and then explodes suddenly under the triggering of external energy. The kerosene cloud explosion is a more delicate drama, which shows that the fuel droplets are distributed in a specific form in space. These tiny droplets are instantly ignited under the action of external fire sources, triggering a chain reaction. The formation of kerosene cloud is a fragmentation process of liquid under the joint compression of internal and external forces, forming tiny particles suspended in the air. Compared with pure gas phase explosion, the explosion process of liquid fuel cloud is intertwined with complex physical transformations (such as dispersion, fragmentation, evaporation) and fierce chemical reactions (combustion and explosion). Its uniqueness lies in the tiny size of the cloud-like liquid phase, which gives it characteristics similar to gas phase explosion, so it is often regarded as a manifestation of gas phase explosion. From the perspective of chemical mechanism, whether it is liquid fuel or gas mixture, the deep-seated cause of its explosion is based on the same chemical kinetic principle.

2.1.2 Explosion parameters

This article deeply explores the explosion characteristics of aviation kerosene mist (i.e. its vapor form) under specific conditions, focusing specifically on the explosion pressure and velocity, two key parameters that directly reflect the power of the explosion. In addition, the critical detonation energy and explosion limit are carefully analyzed. These two indicators play a vital role in assessing the triggering difficulty and safety threshold of the explosion. Through a comprehensive study of these parameters, the aim is to enhance the understanding and prevention and control capabilities of the potential explosion risks of aviation kerosene.

When aviation kerosene vapor is mixed with air, it will not directly cause an explosion in any proportion. Its characteristic is that there is a specific concentration range, which defines the minimum (i.e., lower explosion limit) and maximum (i.e., upper explosion limit) vapor concentrations where an explosion may occur. Only when the concentration of this mixture falls within this range and is excited by sufficient energy, will an explosion occur. This range is called the explosion limit. This limit is usually quantified as the volume ratio of vapor in air, and this limit value is measured under standard environmental conditions (such as normal temperature and pressure). However, it is worth noting that the actual range of the explosion limit can be adjusted with changes in the initial temperature of the environment, the pressure level, the oxygen content, the intervention of inert gas, the ignition energy, and the characteristics of the container [S1-52] . In fact, the cloud formed by kerosene and the corresponding vapor-air mixture show a high degree of similarity in terms of the lower explosion limit. However, it is worth noting that the lower explosion limit of flammable gas (or vapor) traditionally recognized is set above the flash point temperature, and this limit is crucial for safe operation. In contrast, the lower explosion limit of kerosene mist crosses this boundary and extends downward to the area below the flash point temperature. This characteristic needs special consideration when assessing its potential explosion risk. Table 2.1 lists the explosion limit ranges of many common flammable gases and liquids in detail, further revealing this difference .

Name of combustible material	Lower explosion limit/%	Upper explosion limit/%
Methane	4.6	14.3
Methanol	6.4	37.0
Anhydrous ethanol	3.5	15
93# Gasoline	1.3	7.1
diesel fuel	0.5	4.1

Table 2.1 Explosion limits of common flammable gases and flammable liquids

2.1.3 Liquid fuel explosion mechanism

Under certain conditions, aviation kerosene can respond to external energy stimulation and cause violent combustion and even explosion. During this process, the spread rate of the flame may increase sharply, realizing the transformation from stable combustion to explosive combustion, that is, the transition from deflagration to detonation. It is worth noting that the complexity of aviation kerosene explosions stems from the intricate physical and chemical processes behind them, which are driven by both thermal reactions and chain reaction mechanisms. These two mechanisms are intertwined and reinforce each other, jointly maintaining and promoting the continuation of the explosion reaction. Given that aviation kerosene is mainly composed of about 90% hydrocarbon compounds, the following will focus on the mechanism of action of hydrocarbon fuels in the explosion process as the key to understanding its overall behavior.

2.2 Overview of Jet Fuel Consumption Forecast

2.2.1 Factors affecting aviation kerosene consumption

With the booming global economy and the increasing frequency of human activities, greenhouse gas emissions have risen sharply, becoming the main driver of global warming. In view of this, China has set a clear goal to control greenhouse gas emissions to a peak level around 2030, and strive to achieve a grand blueprint of carbon neutrality by 2060. Looking at the data in 2019, the industrial sector, with a share of 51%, has become the primary source of carbon emissions in my country; followed by the transportation industry, accounting for 10%, of which road transportation has an absolute dominant position in this field, as high as 75%, and the aviation industry is closely behind with a share of 10%. The carbon footprint of the aviation industry mainly comes from the burning of aviation fuel during flight, which accounts for more than 95%. Specifically, the total amount of fuel consumed by airlines throughout the year is equivalent to 36.89 million tons, which in turn generates about 116 million tons of carbon emissions, accounting for almost 97% of the carbon emissions of the entire industry. In 2021, the EU released the "A ROUTE TO NET ZERO EUROPEAN AVIATION" aviation target 2050 plan, which drew a clear blueprint for the European aviation industry to move towards net zero emissions. The report not only deeply analyzed the emission reduction strategies of the three key links of airline operations, airspace and air traffic management, and airport ground operations, but also elaborated on the challenges and factors faced in air traffic control technology and aircraft operations, and planned multi-stage and multi-dimensional policies and action plans to ensure the steady achievement of emission reduction targets. In view of the global advocacy of green aviation and the strict requirements for environmentally friendly aviation in China, coupled with the fact that aircraft kerosene consumption occupies a pivotal position in the overall operating expenses of airlines, which is approximately equivalent to 30% of the main business cost, this naturally prompted the airlines to generate a strong motivation to promote fuel-saving measures. At present, the focus of airline research has shifted to how to accurately predict the kerosene consumption of aircraft, and to achieve this goal by building a more refined prediction model, and strive to achieve significant results in reducing kerosene consumption and reducing carbon emissions.

affecting aviation kerosene consumption from the composition and characteristics of aviation planning data. By studying the mechanism of action of these factors, the main influencing factors are determined, thus providing theoretical support for the prediction of aviation kerosene consumption.

This part selected 156 round-trip A330 flights between Beijing Capital Airport and Shanghai Hongqiao Airport, and extracted various indicators from their actual flight schedules, as shown in Table 2.2. At the same time, the actual fuel consumption data corresponding to these flights was also obtained.

Table 2.2 lists in detail the essential core elements of aviation flight, which are accurately recorded within a time frame of months. It not only captures meteorological dynamics such as flight duration, route wind speed, and temperature that directly affect fuel efficiency and safety, but also deeply analyzes the flight altitude layer and expected air distance, laying the foundation for accurate flight planning. In terms of fuel management, the table details the diversified needs from the basic fuel volume of the planned flight to the maneuvering fuel, unexpected fuel, alternate fuel, and standard waiting fuel to deal with various emergencies, ensuring that the aircraft can maintain sufficient fuel reserves in any situation. At the same time, the accurate calculation of takeoff fuel,

Table 2.2 Parameter extraction description table

serial number	parameter	illustrate	unit
1	month	1-12	--
2	Flight time	Estimated flight time	min
3	Wind speed on route	Estimated wind speed	k
4	En route temperature	Estimated temperature	℃
5	Level	Estimated flight level/	hft
6	Air distance	Estimated air distance	nm
7	model	Aircraft Model	
8	Engine Type	Aircraft engine model	
9	Flight fuel	Planned voyage fuel	kg
10	Motor oil	Planned fuel quantity	kg
11	Unexpected fuel	Plan for unexpected fuel quantities	kg
12	Alternate fuel	Planned fuel quantity for alternate landing	kg
13	Standard waiting oil	Planned standard waiting fuel volume	kg
14	Essential Oils	Plan required fuel quantity	kg
15	Extra Oil	Plan for extra fuel	kg
16	Take-off oil	Planned fuel level for takeoff	kg
17	Sliding oil	Planned taxi fuel quantity	kg
18	Total oil	Planned total fuel volume	kg
19	Takeoff weight	Planned takeoff weight	kg
20	Actual fuel consumption	Actual fuel consumption	kg

taxiing fuel, and total fuel has laid the foundation for fuel allocation that emphasizes both economy and safety at the beginning of the flight. Finally, the accumulation of actual fuel consumption data, like a mirror of flight performance, provides valuable data support for subsequent operational analysis and strategy optimization, and promotes the intelligent process of aviation operation decision-making.

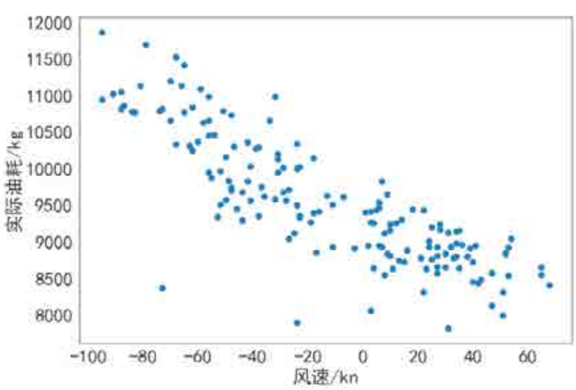


Figure 2.2 Relationship between wind speed and actual fuel consumption

According to the data in Figure 2.2, when the wind force increases, the fuel consumption will decrease with the increase of wind speed; conversely, when the wind speed decreases, the fuel consumption will increase. The same phenomenon also occurs under headwind conditions, which shows that wind speed has a significant negative correlation with aircraft fuel consumption. In addition, the relationship between factors such as air distance, flight time, takeoff fuel, flight fuel, required fuel, total fuel and takeoff weight and fuel consumption also shows a similar law.

The temperature data is compared and analyzed with the actual fuel consumption of the aircraft, as shown in Figure 2.3.

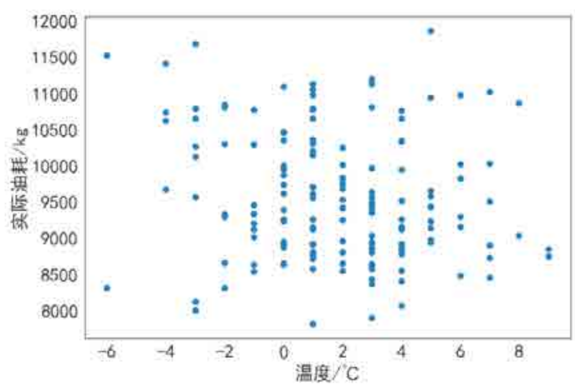


Figure 2.3 Relationship between temperature and actual fuel consumption

According to Figure 2.3, it can be seen that there is a weak linear relationship between temperature and actual fuel consumption of the aircraft, and this fitting effect is not good, which needs further study. In addition, the relationship between additional fuel and alternate fuel and actual fuel consumption also shows similar characteristics.

The aircraft altitude data is compared and analyzed with the actual fuel consumption, as shown in Figure 2.4.

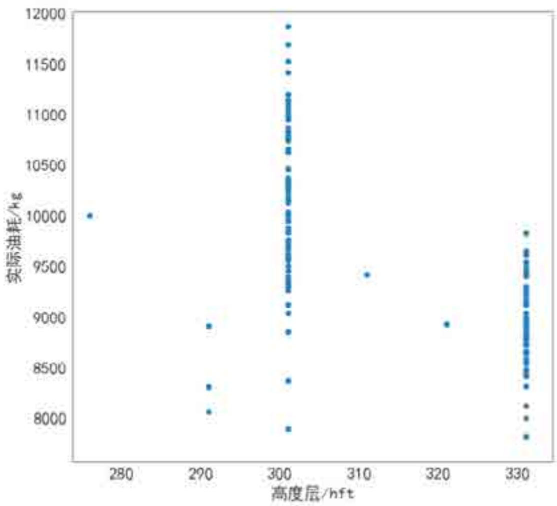


Figure 2.4 Relationship between altitude layer and actual fuel consumption

Due to the limitation of the data in this paper, the selected aircraft is only suitable for a single route. Therefore, when designing the aircraft, there are fewer optional altitude layers, mainly concentrated between 331 hft and 301 hft . In addition, since the model fails to fully reflect the actual flight status and the actual fuel consumption, it was not considered in subsequent studies. Similarly, the relationship between monthly lubricants and actual fuel consumption is similar.

In summary, since the range of values of factors such as altitude layer, month and taxiing oil is relatively limited, it is difficult to fully reflect the complex changes in actual fuel consumption, so they are excluded from consideration in this analysis. Eleven variables, including route wind speed, route temperature, air flight distance, flight time, takeoff fuel, additional fuel, range fuel, required fuel, alternate fuel, total fuel and takeoff weight, are preliminarily determined to be related to the actual fuel consumption of the aircraft. However, the specific forms of these relationships still need to be accurately characterized through in-depth multi-dimensional analysis.

(1) Principal component analysis

means of dimensionality reduction, principal component analysis can integrate multiple complex variables into a few core components. The core advantage of this multivariate statistical method is that it can effectively eliminate redundant information between variables, that is, the correlation between them, making the analysis more concise and clear. However, this process also comes with a certain cost, that is, the specific meaning and detailed information of some original variables may be weakened or lost during the conversion process .

to reduce the dimension of the 11 factors affecting fuel consumption and arrange them according to their contribution. The results are shown in Table 2.3. As can be seen from the table, most of the influencing factors scored above 0.3, and the cumulative contribution rate of the first 9 influencing factors reached 99.99%.

Table 2.3 Principal component contribution table

Influencing factors	Score	Contribution rate/%	Cumulative contribution rate/%
Flight fuel	0.3691	65.4438	65.4438
Take-off oil	0.3648	18.6187	84.0625
Total oil	0.3637	8.3390	92.4015
Air distance	0.3633	4.6051	97.0066
Wind speed on route	-0.3615	2.6479	99.6545
Flight time	0.3584	0.1742	99.8287
Essential Oils	0.3384	0.1455	99.9742
Takeoff weight	0.2849	0.0242	99.9984
En route temperature	-0.0790	0.0015	99.9999
Extra Oil	0.0706	0.0001	100.0000

In the in-depth analysis of the complex factors of aviation fuel consumption, Table 2.3 uses principal component analysis technology to reveal the unique role of each factor in total fuel consumption. The most prominent one is the trip fuel, with a high score of 0.3691 and an excellent contribution rate of 65.44%, which directly pushes it to the first position affecting fuel consumption. Next, the takeoff fuel follows closely with a score of 0.3648 and a contribution rate of 18.62%, proving the critical importance of the takeoff stage in fuel management. In addition, the contribution rate of total fuel is 8.34% and the score is 0.3637, which once again emphasizes the impact of total fuel control on fuel efficiency. Although the contribution rates of air distance and route wind speed are relatively low (4.61% and 2.65% respectively), they are still factors that cannot be ignored . Although the flight time, required fuel and takeoff weight are slightly inferior in score, their impact on fuel consumption is still worthy of attention. As for route temperature, extra fuel and alternate fuel, their small contribution rates indicate that these factors may be in a relatively minor adjustment category when optimizing fuel consumption strategies. In summary, this table provides valuable data reference for airlines to formulate refined fuel management strategies, especially pointing out that trip fuel and takeoff fuel are the main focus of improving fuel efficiency.

(2) Grey correlation analysis

grey correlation analysis method is used to evaluate by comparing the geometric similarity of the change curves of the influencing factors. Since this method has a certain degree of subjectivity, this paper also uses two main factor analysis methods to study the model and conducts a preliminary discussion. The 11 main fuel consumption factors are ranked by grey correlation, and the results are shown in Table 2.4. It can be seen from the table that the grey correlation coefficients of most factors are between 0.7 and 0.9, and a few factors are lower than 0.7.

Table 2.4 Grey correlation table

Influencing factors	Relevance
Air distance	0.8314
Flight time	0.8237
Total oil	0.8196
Take-off oil	0.8176
Flight fuel	0.7971
Essential Oils	0.7661
Takeoff weight	0.7617
Alternate fuel	0.7222
En route temperature	0.6883
Extra Oil	0.6749
Wind speed on route	0.5976

Table 2.4 reveals in detail the core factors affecting aviation fuel efficiency and their grey correlation analysis, and deeply depicts the close relationship between each variable and fuel consumption. Among them, air distance ranks first with a correlation of up to 0.8314, highlighting the decisive role of route planning in controlling fuel costs. The flight time (0.8237) and total fuel reserve (0.8196) that follow closely are also not to be ignored. They emphasize the key impact of flight duration and initial fuel planning on fuel efficiency. The amount of fuel required for takeoff (0.8176) and fuel consumption during the flight (0.7971) also show a high correlation, further proving the importance of fuel management at the beginning and throughout the flight. In addition, the correlation between required fuel (0.7661) and takeoff weight (0.7617) is also quite significant, indicating the direct contribution of operational details to fuel efficiency. Although the impact of alternate landing fuel (0.7222) and route temperature (0.6883) is slightly smaller, they still provide valuable references for the formulation of fuel management strategies. As for the impact of extra fuel (0.6749) and en-route wind speed (0.5976), although relatively low, they also remind airlines of the aspects they need to consider when dealing with uncertainties. These analyses provide airlines with a multi-dimensional perspective to optimize fuel management strategies and improve operational efficiency.

2.2.2 Prediction method of aviation kerosene consumption

2.2.2.1 Neural Network Method

In the application of aviation fuel consumption management, the neural network method has shown its unique advantages. Its core is to take the historical data of aircraft fuel consumption as input. Through multiple iterations and self-adjustments within the network, that is, the "learning" process, the neural network can gradually build a deep understanding of fuel consumption characteristics. The network model generated by this process can accurately predict the fuel consumption performance of the aircraft after sufficient data "training", as shown in Figure 2.5. In order to further improve the generalization ability of the model, unknown data samples are then introduced for testing, and the prediction results are compared with actual flight data for verification. Although early studies such as Trani have attempted to predict fuel consumption through neural networks, they are limited by the data source that relies on the aircraft performance manual, which requires detailed aerodynamic parameters or a large operating database support, and the model needs to be frequently updated to adapt to different flight conditions, which limits its wide application and recognition. Zhang innovatively combines particle swarm optimization (PSO) and back propagation (BP) neural networks. By introducing the PSO algorithm to optimize the weights and biases of the BP network, this hybrid strategy not only innovates the training process of the neural network, but also significantly improves the accuracy of the fuel prediction model. Unlike the traditional BP algorithm that directly adjusts network parameters, this hybrid algorithm uses the global search capability of PSO to effectively avoid local optimal solutions, thereby achieving a leap in fuel prediction accuracy. On the other hand, Khan took a different approach and designed a convolutional neural network (CNN) based on self-organizing structure (although the original text is CNN here, it is understood as a neural network with a specific structure according to the context, not a convolutional neural network in the traditional sense). The network architecture adopts a hierarchical cascade design and determines the connection weights between neurons through dynamic analysis, providing a novel and efficient solution for flight fuel consumption prediction. Although neural networks have made significant progress in the field of fuel prediction, their complexity has also come with it, especially the hyperparameter settings such as learning rate, fine adjustment of connection weights, selection of the number of hidden layer units, and optimization of the gradient descent algorithm, which may become key factors affecting the convergence speed and performance of the model.

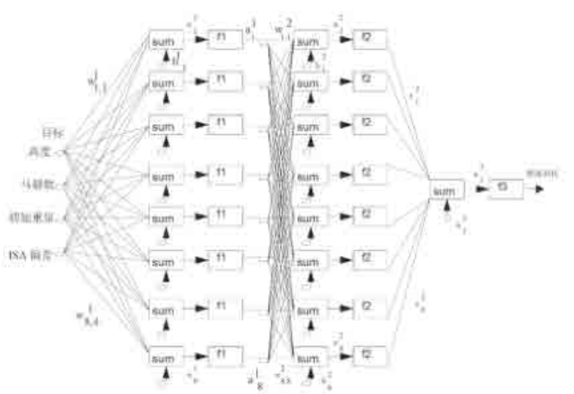


Figure 2.5 Schematic diagram of three-layer neural network predicting fuel consumption

2.2.2.2 Classification and regression tree method

The CART (Classification and Regression Tree) algorithm, carefully crafted by pioneers such as Leo Breiman, is a full-featured machine learning tool that excels at both classification tasks and regression analysis. This algorithm is known for its efficient automation, which reduces the need for human intervention, and as a non-parametric method, it does not require a preset basic function set, which enhances flexibility and adaptability. In the field of fuel prediction, CART has shown extraordinary stability, especially when dealing with complex flight data sets containing outliers and irrelevant data. In specific applications, this method achieves model construction and optimization by subdividing the data set of the aircraft flight process (such as ascent, cruise, and descent) into training sets, test sets, and validation sets. For each flight phase, a unique CART model is constructed for different aircraft models, and the input variables include key factors such as flight altitude, ground speed, lift rate, and takeoff weight. The output focuses on the standardized single-engine fuel flow in the ICAO database. Through multiple iterations and verifications, the optimal model is selected for accurate fuel consumption prediction.

The CART algorithm shows higher accuracy in predicting fuel consumption than the ICAO database and BADA method. However, its prediction performance is slightly insufficient during the descent and approach phase of the aircraft, which may be due to the more dynamically changing flight operations involved in this phase, which increases the difficulty of prediction. It is worth noting that the CART algorithm not only provides fuel consumption predictions, but also evaluates the uncertainty of fuel flow, effectively quantifies the inherent variability in actual flight operations and the impact of factors not included in the model, and provides a more comprehensive perspective for decision-making. Its calculation process is simple and efficient.

2.2.2.3 Genetic Algorithm

The genetic algorithm model shows remarkable reliability in predicting linear and nonlinear relationships. The core of this algorithm starts with the construction of a random initial population of appropriate size, which is composed of individuals composed of a series of input parameters. Its size is directly related to the quality of the algorithm output and the efficiency of solution. Each input parameter is encoded in binary form to form a unique genome, which has different lengths (i.e., the length of the sequence of 0 and 1), which is the basis for the algorithm to search for the optimal solution. By simulating the crossover (recombination) and mutation mechanisms in natural selection, the genetic algorithm continuously adjusts the composition of the genome in each iteration, aiming to find the coding combination that can produce the best output. Specifically, the crossover operation involves exchanging the binary bits of specific fragments between the selected genomes, while the mutation randomly changes the state of certain bits to increase the diversity of the population. Given the flexibility and optimization capabilities of the genetic algorithm, it can be widely used to optimize different aspects of aviation flight operations, such as fine-tuning the fuel consumption prediction model.

The genetic program architecture is carefully constructed from multiple modules. The first module focuses on defining its fundamental properties, covering the core elements of genetic algorithms such as population size, number of iterations, balance between crossover and mutation ratios, and accuracy standards. In addition, specific considerations are given to the needs of the aviation field, such as the consideration of the flight dimension D, the wide coverage of observation data, and the variable boundaries defined by flight parameters. Subsequently, the intermediate module takes on the responsibility of fine-tuning and screening gene sequences, and realizes cross-recombination and random mutation between genes through code to ensure the continuous evolution of genetic diversity. The final module focuses on the documentation of iterative results, not only recording the output, but also performing verification work.

In the performance evaluation of civil airliners, the dynamic relationship between fuel flow and pressure altitude has become a strategy for accurately predicting fuel consumption. By integrating detailed information in the flight data recorder (FDR), such as fuel flow, flight speed, engine speed N1 and N2, and real-time altitude, subtle changes in the flight process can be captured. Genetic algorithms are cleverly used to analyze these data, especially in the descent phase, revealing the inverse correlation law that fuel flow increases as pressure altitude decreases. This method not only optimizes the efficiency and accuracy of problem solving, but also improves performance in duration and sensitivity. In addition, based on this discovery, the fuel flow-altitude relationship was further explored to support delay control strategies in advanced flight management systems.

Through the carefully constructed model, the close relationship between fuel flow and flight altitude was successfully revealed. Its predicted data graph (see Figure 2.6) is highly consistent with the actual observed data, verifying the accuracy of the model. Further analysis of the graph shows that when the aircraft performs a descent operation, if it can strategically maintain a higher flight altitude for as long as possible (i.e. reduce the frequency of low-altitude crossings), fuel efficiency will be significantly improved. This key discovery provides airlines with a new perspective and tool for optimizing fuel consumption strategies and formulating more economical and efficient flight plans.

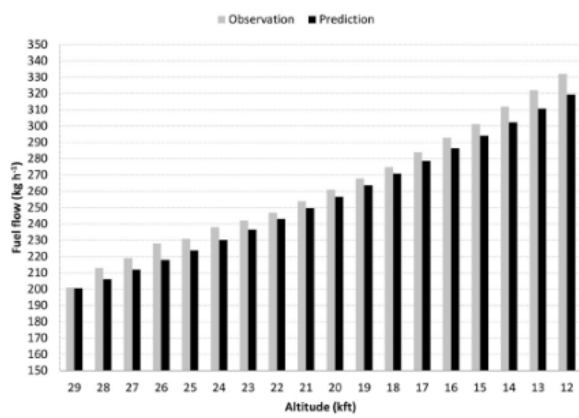


Figure 2.5 Schematic diagram of three-layer neural network predicting fuel consumption

2.3 Summary of this chapter

This chapter deeply analyzes the key attribute of aviation kerosene - anti-knock performance, and proactively explores its consumption prediction strategy.

First, focusing on anti-knock performance, the causes of detonation, key explosion indicators, and the unique explosion mechanism of liquid fuel are carefully analyzed, thus revealing the potential safety challenges of aviation kerosene under extreme operating conditions. This analysis not only deepens the understanding of the safety boundary of aviation kerosene, but also highlights the rigor that is indispensable to ensuring aviation flight safety. Subsequently, turning to the field of consumption prediction, a comprehensive review of the multi-dimensional factors that affect aviation kerosene consumption, such as flight range, air wind speed conditions, and aircraft models, is conducted, and current advanced prediction tools, such as statistical models based on big data and cutting-edge machine learning algorithms, are introduced. Through this comprehensive perspective, this chapter provides airlines with valuable insights into optimizing fuel efficiency and reducing operating costs, and opens up new paths for subsequent research on aviation kerosene performance optimization and cost control.

3 Analysis of Anti-explosion Performance of Aviation Kerosene

This chapter focuses on the study of the cloud explosion behavior of RP-3 aviation kerosene in a large vertical detonation tube, and uses high-intensity ignition methods to conduct experiments. The experiment deeply analyzes the kerosene spray characteristics, especially how the spray pressure and ignition delay time affect the key parameters of kerosene cloud explosion. By precisely controlling the spray pressure and adjusting the ignition delay, the specific effects of these variables on the kerosene explosion velocity and explosion pressure are quantified. In addition, by adjusting the charge of the detonator to change the initial energy input, the trend of the change of the aviation kerosene cloud explosion characteristics with the detonation energy is systematically explored. The experiment also covers kerosene clouds at different concentration equivalence ratios, and detailed measurements of multiple parameters including explosion velocity, pressure, and the minimum detonation energy (critical detonation energy) required to achieve explosion. This series of experiments not only reveals the basic laws of aviation kerosene cloud explosion, but also lays a solid experimental foundation for in-depth exploration of the field of aviation kerosene combustion and explosion safety research .

3.1 Air-kerosene cloud deflagration experiment

3.1.1 Experimental device and test system

The experimental equipment is a vertical shock tube, the main structure of which includes the shock tube body, spray system, ignition source and synchronous control system, and pressure measurement system.

3.1.1.1 Vertical shock tube

The core equipment studied in this chapter is a large vertical detonation tube independently designed and manufactured by the Safety Engineering Department of Nanjing University of Science and Technology. It is exquisitely divided into three functional areas: the detonation source section, the main experimental section, and the observation window section. The tube is 5.4 meters long, with an outer diameter of 240 mm and an inner diameter of 200 mm. During the experiment, the effective space capacity is close to 169 liters. The main material is a high-strength 20CrMo gun steel tube, which ensures the safety and stability of the experiment.

Along the two sides of the longitudinal axis of the detonation tube, 32 sets of symmetrically distributed injection systems are cleverly arranged, and the distance between each set of nozzles is carefully set to 350 mm. These systems can not only effectively spread solid powder evenly into the space inside the tube, but also refine liquid substances into tiny droplets, fully mix them with air, and form the cloud-like environment required for the experiment. In addition, multiple measurement interfaces are carefully arranged around the tube body, with a uniform spacing of 500 mm.

3.1.1.2 Injection device

In the experiment, a high-pressure gas-driven injection system was used to finely atomize the aviation

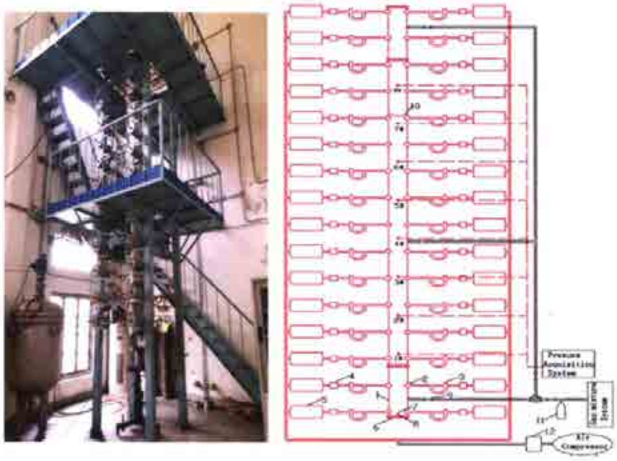


Figure 3.1 Physical picture (a) and schematic diagram (b) of vertical shock tube experimental system

kerosene and evenly distribute it in the internal space of the shock tube. The core of this system is to use the injection devices arranged on both sides, combined with high-pressure gas and specially designed nozzles, to efficiently convert the fuel into fine mist. Although the operation process is relatively complicated, it ensures the uniform distribution of droplets in the tube. This system consists of multiple components working together: the air compressor is responsible for pressurizing the air and storing it in a high-pressure air chamber with a volume of about 690 ml until it automatically stops after reaching the preset pressure threshold. At this time, the explosion-proof solenoid valve remains closed, waiting for instructions. Once the solenoid valve receives a signal to open, high-pressure gas instantly flows into the special "U"-shaped liquid storage tube, pushing the kerosene liquid to the hollow hemispherical nozzle with 119 tiny nozzle holes (aperture of about 1 mm). The kerosene is refined into countless tiny droplets at the moment of passing through these precise holes, thus forming a uniform cloud-like distribution in the shock tube.

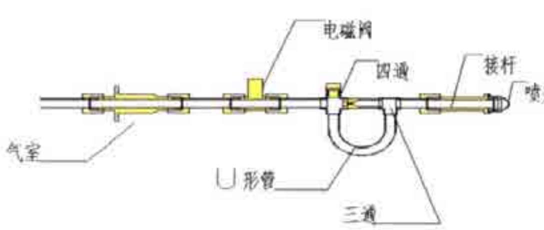


Figure 3.2 Schematic diagram of powder spraying device

3.1.1.3 Ignition source and synchronization control system

In the experiment, the core of the detonator is composed of an 8# industrial detonator and a variable amount of RDX plastic explosive. The energy required for detonation is finely controlled by adjusting the weight of the explosive. This energy regulation mechanism ensures the flexibility of the experimental conditions. The detonator assembly is precisely placed at the flange position at the bottom of the shock tube and is firmly connected to the detonator base with the help of a delayed igniter, aiming to guide the shock wave generated by the explosion to propagate vertically upward, thereby ensuring the accuracy of the experimental results. Based on the energy calculation formula in existing literature, the direct relationship between the energy output of the explosive in the experiment and the amount of medicine it contains can be clearly determined.

$E = 5945.3 + 5860 \times W$

Where: E is the initial energy, J; W is the weight of the explosive, g. The relationship between the amount of explosive and the detonation energy is shown in Table 3.1.

In the shock tube experimental environment, given the instantaneous release characteristics of the detonation energy, it is assumed to be uniformly distributed along the radial direction of the shock tube cross section. In order to quantify this energy distribution, the concept of plane detonation energy E1 is introduced, which represents the detonation energy E distributed per unit area, thus providing a more accurate way to measure energy density.

$$E_1 = E/(\pi \cdot r^2)$$

Where: r is the inner radius of the shock tube, m.

Table 3.1 Explosive quantity and detonation energy

Detonation source	Output energy/(KJ)	Plane detonation energy/(MJ/m 2)
1D	5.94	0.19
1D+1g RDX	11.78	0.37
1D+2gRDX	17.66	0.56
1D+3g RDX	23.53	0.75
1D+5g RDX	35.25	1.12
1D+8g RDX	52.82	1.68

independently developed by Nanjing University of Science and Technology has a unique design that realizes precise timing control of the solenoid valve and detonator in the injection system. The core of this device is to flexibly set the time interval between the opening of the solenoid valve and the triggering of the detonator, ensuring that after the material is smoothly sprayed into the shock tube, the solenoid valve is immediately closed to form a closed environment, and then the detonator is accurately detonated.

As shown in Figure 3.3, once the start button is triggered, the built-in solenoid valve control module and the ignition delay system are started in parallel, each operating independently according to the preset delay parameters, cleverly coordinating the sequence of fuel injection and ignition actions, demonstrating a high degree of time control accuracy.

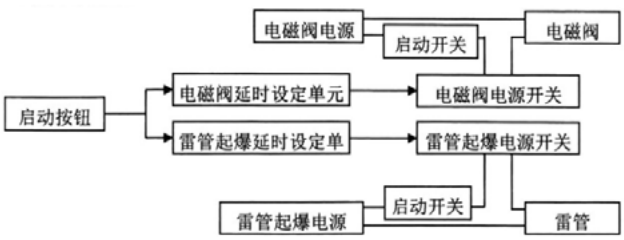


Figure 3.3 Working principle of DHY-6 ignition delay device

3.1.1.4 Stress test system

The pressure measurement system integrates multiple core components, including pressure sensors, charge conversion units, data capture devices, and back-end processing software. The operation process is briefly described as follows: When the experimental sample explodes in the shock tube, the shock wave released hits the pressure sensor, which responds and converts the sensed pressure fluctuations into signals in the form of electric charges. These charge signals are then directed to the charge amplifier for conversion into easy-to-process voltage signals. Then, the data acquisition system intervenes to capture and record these voltage signals. Finally, these data are processed by computer, and a dynamic curve graph of pressure changes over time is drawn using special software, which enables intuitive display and in-depth analysis of the experimental results.

(1) Pressure sensor

The core of this experiment is to use the piezoelectric properties of quartz crystals to build a pressure sensor system. This property is manifested in that when external force acts on the crystal, its internal structure produces polarization, which causes the separation of positive and negative charges on the surface of the crystal, forming a potential difference. This conversion mechanism ensures that pressure changes can be accurately and directly converted into electrical signal output. Five such sensors were deployed in the experiment, which were arranged in a straight line with an interval of 0.5 meters and an increasing distance from the detonation point, ranging from 1.4 meters to 3.9 meters. These sensors are carefully built by Yangzhou Radio Factory No. 2 and feature excellent piezoelectric quartz technology. Their highlights include: -10PC electrical signal change can be output for every 10Pa pressure change, showing extremely high sensitivity; linearity error is less than 1% of the full scale, ensuring the precise linear relationship of the measurement results; insulation impedance of up to 2103Ω, enhancing the reliability of signal transmission; a wide measurement range covering 0 to 60atm, suitable for a variety of environments; stable operation within the operating temperature range of -40℃ to 150℃, showing excellent temperature adaptability; and 150% overload capacity, ensuring the safety performance of the equipment under extreme conditions. In addition, the sampling frequency of 1MHz ensures rapid capture and processing of data. Combined with its long life, low temperature coefficient and wide frequency response range, this sensor system is undoubtedly an ideal choice for high-precision pressure measurement.

(2) Charge amplifier

As a key component of signal conversion, the core function of the charge amplifier is to effectively reduce the impedance of the sensor output signal, achieve a transition from high to low, and cleverly convert the charge signal transmitted by the sensor into a voltage signal output. The strength of this voltage signal is directly positively correlated to the increase in the amount of input charge, which effectively amplifies the weak signal from the sensor. In the experimental configuration, this amplifier provides six independent channels, each of which has seven adjustment options from basic to thousand-fold amplification, which can flexibly meet different experimental needs. In addition, the filter integrated in each channel has five settings (1 to 100) to ensure the accuracy and purity of signal processing and adapt to diverse experimental filtering requirements. It is particularly worth mentioning that the amplifier has automatically completed data calibration at the time of output, and the user does not need to calibrate it again in the subsequent software processing. The calibration value is intuitively displayed on the control panel, which greatly improves the efficiency and convenience of the experiment. In this experiment, the YE5853A charge amplifier of Jiangsu Lianneng Electronic Technology Co., Ltd. was used.

(3) Data acquisition device and supporting software

The data acquisition system is composed of the PCI-1112 data acquisition card carefully built by Chengdu Micro Test Technology Co., Ltd. and its supporting advanced software, forming a set of efficient data processing solutions. The data acquisition card stands out for its excellent performance. It has four independent acquisition channels, each channel supports a sampling frequency of up to 60MHz/s, ensuring the high-speed data capture capability. Its 14-bit A/D conversion accuracy provides a solid guarantee for data quality. In terms of storage, the card provides flexible storage configuration options, with a storage capacity starting from 2kB and a maximum expandable to 1MB, and supports 2kB units. The system has functions such as data acquisition, storage, processing and calculation. The supporting data acquisition software can control various instrument parameters, set sampling, perform data acquisition and transmission reading and writing, and also supports screen display, value comparison, integration, storage, waveform spectrum analysis, and Fourier analysis.

3.1.2 Experimental aviation kerosene fuel

Aviation kerosene, as a product of deep processing of petroleum, is transparent in texture. Its refining process integrates a variety of technologies such as straight distillation, hydrocracking and hydrofining. One of its core varieties, RP-3 aviation kerosene, or No. 3 jet fuel, is carefully blended from hydrocarbons from multiple distillation sections and incorporates key ingredients such as tetraethyl lead, antistatic additives, antioxidants and corrosion inhibitors to ensure its excellent performance. The domestically produced RP-3 kerosene used in the experiment is a heavyweight kerosene fuel with a complex chemical composition that covers hundreds of different substances, which can be roughly divided into 92.1% saturated hydrocarbons and about 7.9% aromatic hydrocarbons. The specific proportions are shown in Table 3.2.

Table 3.2 RP.3 aviation kerosene components

	Cycloalkanes							total
	Single Ring		Three Rings					
52.2	33.8	6.0	0.1	5.1	1.3	0.6	0.9	100

3.1.2.1 Main physical and chemical properties

Table 3.3 lists its main physical and chemical properties. Among them, density, viscosity, calorific value and distillation range are the key factors that determine its combustion and explosion performance.

Table 3.3 Main physical and chemical properties of RP-3 aviation kerosene

Physical and chemical properties	value	Physical and chemical properties	value
Molecular formula	C7-C16	Smoke point (mm)	24.6
Molecular weight	148.83	Latent heat of vaporization (kg/ kj)	345
20℃ density/(g/ cm ^{3})	0.79	Low calorific value (kj / m^3)	43200
Boiling point(℃)	185	Theoretical air-fuel ratio	16
Condensation point (℃)	-60	Cetane number	43

From the data shown in Table 3.3, we can fully understand the key physical and chemical characteristics of RP-3 aviation kerosene, which together constitute the cornerstone of its high-efficiency aviation fuel. Its chemical structure is complex, consisting of hydrocarbon compounds from C7 to C16, with an average molecular weight of 148.83, showing rich chemical diversity. In terms of density, RP-3 is precisely positioned with a density of 0.79 g/cm³, which perfectly meets the weight and volume requirements of aviation applications. In terms of temperature tolerance, its excellent boiling point (185℃) and extremely low freezing point (-60℃) ensure stable operation under various extreme climatic conditions. In terms of combustion quality, the combination of low smoke point (24.6 mm) and high latent heat of vaporization (345 kg/kJ) promotes clean and efficient combustion. At the same time, its low calorific value is as high as 43200 kJ/m³, combined with the theoretical air-fuel ratio of 16, further improving the efficiency of energy conversion. Furthermore, the excellent performance of cetane number of 43 verifies the high quality and applicability of RP-3 in the field of aviation fuel. These detailed and in-depth physical and chemical property analyses not only lay a solid foundation for the widespread application of RP-3, but also provide valuable reference for the innovation and safety assessment of future aviation fuels.

3.1.2.2 Kerosene substitute model selection

Given the extreme complexity of kerosene, which combines hundreds of different alkanes, cycloalkanes and aromatic compounds, this characteristic makes it a major challenge to accurately analyze its detailed composition under current technology. In addition, the composition of kerosene will vary depending on the origin, manufacturer and even the year of production, further increasing the difficulty of analysis. In order to improve the universal applicability of scientific research and the repeatability of experimental results, researchers have introduced the concept of hydrocarbon fuel substitutes, that is, a mixture of a few pure hydrocarbons in a specific proportion to accurately simulate the performance of real kerosene in thermophysical properties and a series of other physical and chemical properties. In the experimental design for aviation kerosene cloud explosion, the specific chemical formula of the fuel will directly affect the calculation result of its stoichiometric ratio φ. Therefore, it is crucial to select a suitable substitute model and determine its molecular formula before the experiment. This experiment adopted the substitution model constructed by Yu Weiming, which carefully proportioned chain alkanes (49%), cycloalkanes (44%) and aromatic hydrocarbons (7%). The average molecular formula was determined to be C10.57H21.99, the molecular weight was 148.83, and the theoretical air-fuel ratio was set to 16.

3.1.3 Experimental methods

3.1.3.1 Air tightness inspection

Before conducting an overpressure measurement experiment of a fuel cloud explosion in a shock tube, it is crucial to ensure the airtightness of the shock tube to prevent leakage from affecting the accuracy of the pressure value. To this end, a series of pre-detection measures were taken. First, after sealing the shock tube, the internal air pressure was reduced to 0.04MPa using a vacuum pump and observed for one hour. During this period, the pressure was recorded to rise to 0.049MPa, revealing an average pressure drop of 0.15kPa per minute, equivalent to 0.25% gas leakage per minute. Subsequently, the reverse operation was performed, the high-pressure air chamber was inflated by an air compressor, and the gas was precisely controlled to be injected into the shock tube using a solenoid valve to bring the internal pressure to 0.25MPa. After the same one-hour test, the pressure dropped to 0.23MPa, indicating that the leakage rate was about 0.13% per minute at a higher pressure. This series of airtightness test results show that the overall sealing performance of the shock tube meets the experimental requirements.

3.1.3.2 Experimental procedures

In the standard experimental process, the first step is to implement the alternating injection of liquid fuel, which is carefully distributed to both sides of the respective "U"-shaped tubes. At the same time, the air compressor starts working, pressing the dehumidified dry air into the air tank to ensure that the preset pressure standard is reached.

Subsequently, the detonator is safely placed in the lower flange position, and the experimental environment is prepared by tightly closing the upper and lower flanges. Once ready, the air compressor is started and the pressure monitoring system is configured synchronously. At this time, the DHY-6 delay controller plays a key role, accurately controlling the activation of the solenoid valve and the detonator in sequence, thereby triggering the explosion of the detonation source and recording the pressure data in real time. After each test cycle, the tube body will be thoroughly cleaned with fresh compressed air for multiple rounds to ensure the purity of subsequent experiments. In order to verify the stability and accuracy of the experimental data, the entire experimental process will be repeated twice .

3.1.3.3 Method for determining critical detonation energy

In the experiment, determining the critical detonation energy of the fuel relies on the carefully designed rise-and-fall method and the fold test method. The core of these two methods is to locate the energy threshold by step-by-step approximation, that is, first define an energy point that is sufficient to trigger the fuel cloud explosion and an energy point that is insufficient to stimulate the reaction. Then, the average of these two energy values is selected as the starting point for subsequent tests. If the test results show that the fuel is successfully ignited and the flame spreads to the top of the shock tube, the energy range is further narrowed to the median of the current successful detonation energy and the last failed attempt energy; conversely, if no detonation phenomenon is observed, it is adjusted to the median of the current failed energy and the last successful detonation energy. This process is repeated until the measured detonation energy stabilizes at the preset 0.02MJ/m².

3.1.4 Calculation of concentration equivalence ratio

When discussing the RP-3 aviation kerosene hydrocarbon fuel substitute model proposed by Weiming, the concentration equivalence ratio in the experiment was accurately set based on its molecular weight of 148.83. This equivalence ratio qφ is essentially the mass ratio between the theoretical amount of air required for complete combustion of the fuel and the actual amount of air supplied. When the φ value reaches the ideal state of 1, it means that the fuel and oxygen react completely to produce pure carbon dioxide and water. In order to determine the corresponding fuel volume v when φ=1, the Clapeyron equation is used to estimate the number of moles of air in the tube n, and then the volume v of the required fuel is inferred through a specific calculation formula under the condition that the concentration equivalence ratio p is exactly 1.

$$n = \frac{PV}{RT}$$

(3.1)

$$v = \frac{21\% \cdot n \cdot M}{a \cdot \rho}$$

(3.2)

Where (3.1) P is the pressure in the shock tube, Pa; V is the volume of the shock tube, m 3 ; n is the amount of air in the shock tube, mol; T is the absolute temperature of the environment, K; R is the gas constant, J/(mol-k). (3.2) v is the volume of the fuel when the concentration equivalence ratio o=1, ml; M is the molecular weight of the fuel; a is the fuel air-fuel ratio; p is the fuel density, g/cm³ (see Table 3.3 for the values). In view of the large differences in the physical performance indicators of the currently used aviation kerosene, by comparing the physical quantities in different data, it is found that the difference between the two is about 1%.

3.1.4 Result Analysis

3.1.4.1 Effect of spray pressure on kerosene cloud explosion velocity and pressure

In order to explore the influence of the initial pressure of compressed air on the explosion characteristics of RP-3 aviation kerosene cloud, especially the key parameters such as cloud particle size and specific surface area, and then how to regulate the pressure peak and speed of the explosion, a systematic study was designed. The experiment achieved five different levels of compressed air pressure in the air tank in the range of 0.2MPa to 0.6MPa by finely adjusting the operating parameters of the air compressor. These pressure levels directly correspond to different spray pressure conditions. Under fixed detonation conditions - using 1 8# industrial detonator combined with 5g explosives as the detonation source to ensure that the plane detonation energy E1 is constant at 1.12MJ/m² - the explosion pressure and speed of kerosene cloud under different spray pressures were measured. During the experiment, a uniform amount of 39ml of fuel was used, the equivalent ratio concentration was maintained at 0.91, and a delayed ignition time of 0.80 seconds was set to ensure the comparability and accuracy of the data. Tables 3.4 and 3.5 record the specific measurement results under these experimental conditions in detail. And the average explosion pressure and average explosion speed are used as the ordinate, and the spray pressure Ps is used as the horizontal axis, as shown in Figure 3.7. The average explosion overpressure is defined as: the average value of P2 to P6. Because the explosion overpressure measured by the 2# sensor is greatly affected by the detonation source, P1 is not included in the averaging range. The average explosion speed is defined as: the average value of D1 to D5.

$$\overline{D} = \frac{\sum D_i}{5} \qquad i=2,3,4,5,6$$

(3.3)

$$\overline{P} = \frac{\sum P_i}{5} \qquad i=2,3,4,5,6$$

(3.4)

Where P2 to P6 in (3.3) represent the pressure values measured from sensor 3# to sensor 7*, MPa. Where D1 to D5 in (3.4) represent the average explosion propagation speed from sensor 3# to sensor 7#, m/s.

Table 3.4 presents in detail the changes in explosion overpressure of aviation kerosene under different spray pressure conditions, revealing a significant correlation between pressure and overpressure. Specifically, at an initial spray pressure of 0.20 MPa, the explosion overpressure showed a large variability, ranging from 0.53 to 1.22 MPa, which suggests the instability of explosion energy under low pressure. As the pressure increased to 0.30 MPa, an obvious trend was that the explosion overpressure generally increased, with a peak value of 1.27 MPa, highlighting the direct effect of increasing spray pressure on increasing explosion intensity. Entering the 0.40 MPa interval, although the overpressure level continued to rise, its fluctuation range narrowed significantly, indicating that the spray pressure effect gradually tended to saturation. Finally, in the high pressure domain of 0.50 MPa to 0.60 MPa, the explosion overpressure stabilized between 1.28 and 1.31 MPa, indicating that under high spray pressure, the contribution of further increasing pressure to the increase in overpressure tended to be marginal. These data are of indispensable value for gaining a deeper understanding of the dynamic changes in the explosion behavior of aviation kerosene and guiding the formulation of safe operations and risk management strategies.

Spray pressure Ps/MPa	Explosion overpressure P(MPa)						
	P1	P2	P3	P4	P5	P6	$\overline{P}$
0.20	1.22	0.59	0.53	0.55	0.51	0.53	0.54
0.30	1.27	0.71	0.57	0.56	0.56	0.56	0.59
0.40	1.30	0.73	0.53	0.62	0.61	0.62	0.62
0.50	1.31	0.71	0.61	0.58	0.57	0.60	0.61
0.60	1.28	0.68	0.56	0.60	0.57	0.59	0.60

Table 3.5 Explosion velocity under different detonation energy conditions

Spray pressure	Explosion speed D(m/s)					
	D1	D2	D3	D4	D5	$\overline{D}$
0.20	622	615	592	589	543	592
0.30	647	631	592	579	556	601
0.40	673	624	604	578	561	608
0.50	657	618	584	596	560	603
0.60	642	631	589	589	569	604

Table 3.5 records in detail the changing trend of the explosion velocity of aviation kerosene under different

spray pressure environments, revealing the positive correlation between increased pressure and increased explosion velocity. Specifically, at a base pressure of 0.20 MPa, the explosion velocity fluctuates significantly, ranging from 543 to 622 m/s, indicating that pressure in this range has a significant effect on the explosion performance but is not yet stable. As the pressure climbs to 0.30 MPa, the overall level of the explosion velocity moves up significantly, with the highest value jumping to 647 m/s and the lowest value also stabilizing at 556 m/s, reflecting the direct promotion of the pressure increase on the explosion velocity. When further pressurized to 0.40 MPa, the explosion velocity continues to rise steadily, reaching a maximum of 673 m/s, while the lower limit remains at 578 m/s, showing stronger stability. However, when the pressure increases to 0.50 MPa and 0.60 MPa, although the explosion velocity fluctuations narrow, they remain within the range of 560 to 657 m/s, suggesting a possible nonlinear relationship between pressure and explosion velocity. These findings provide valuable data for a deeper understanding of the explosion behavior of aviation kerosene under different pressure conditions, and are of great significance for safety risk assessment and optimization of emergency measures.

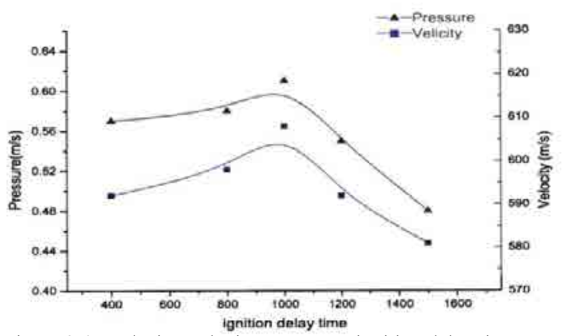


Figure 3.4 Explosion velocity, pressure - ignition delay time curve

The data in Figure 3.4 reveals a significant phenomenon: when the ignition delay time is exactly 1.00 seconds, the explosion speed and pressure of the aviation kerosene cloud both climb to the peak. It is worth noting that if the ignition delay time is lower than this threshold, the explosion overpressure and speed gradually increase with the increase of the delay, but the increase is relatively gentle; once the delay exceeds 1.00 seconds, both show a significant downward trend. This phenomenon can be attributed to the efficiency difference of the atomization process: when the atomization time is less than 1.00 seconds, the kerosene cloud is unevenly distributed, resulting in the failure of the fuel to fully mix and react, thereby limiting the growth of the explosion overpressure. On the contrary, when the delay exceeds 1.00 seconds, the cloud settles under the influence of gravity, the concentration is diluted, and some fuel fails to participate in the explosion reaction, thereby reducing the overall explosion overpressure. Therefore, based on the experimental conditions, it can be determined that 1.00 seconds is the ideal ignition delay time for aviation kerosene cloud to achieve the optimal explosion effect.

3.1.4.2 Effect of detonation energy on kerosene cloud explosion velocity and pressure

By changing the detonation source energy, the explosion pressure P and explosion velocity D data of RP-3 aviation kerosene in the shock tube were obtained at five detonation energies ranging from 0.37MJ·m -2 to 1.68MJm 2. The spray pressure of the experiment was 0.40MPa, and the concentration equivalence ratio was 1.28. The results are shown in Tables 3.6 and 3.7.

Table 3.6 Explosion overpressure under different detonation energy conditions

	Explosion overpressure P(MPa)						
	P1	P2	P3	P4	P5	P6	$\overline{p}$
0.37	0.35	0.29	0.27	0.23	0.25	0.26	0.26
0.56	0.81	0.40	0.38	0.35	0.34	0.35	0.36
0.75	0.82	0.47.	0.45	0.43	0.43	0.42	0.44
1.12	1.30	0.76	0.56	0.66	0.64	0.66	0.66
1.68	1.70	0.94	0.77	0.73	0.86	0.96	0.85

Table 3.6 records in detail the changes in explosion overpressure of aviation kerosene at different detonation energy levels, clearly revealing the positive correlation between energy and explosion power. Specifically, when the detonation energy is maintained at a low level of 0.37

MJ•m², the measured explosion overpressure generally hovers between 0.23 and 0.35 MPa, indicating that the explosion effect is relatively mild at this energy level. As the detonation energy jumps to 0.56 MJ•m², the explosion overpressure range is significantly widened, from a low of 0.34 MPa to a high of 0.81 MPa, which directly reflects the promotion of energy increase on explosion intensity. When the energy is further increased to 0.75 MJ•m² and above, the explosion overpressure continues to rise, especially under the condition of 1.12 MJ•m², the overpressure peak reaches 1.30 MPa, showing a stronger explosion characteristic. At the highest test energy of 1.68 MJ•m², the explosion overpressure soared to an astonishing 1.70 MPa, fully demonstrating that high energy input can greatly intensify the explosion reaction of aviation kerosene. This discovery is of indispensable value for a deeper understanding of the explosion behavior of aviation kerosene, optimizing aviation safety strategies and explosion-proof design.

Table 3.7 Explosion velocity under different detonation energy conditions

	Explosion speed D(m/s)					
	D1	D2	D3	D4	D5	$\overline{D}$
0.37	559	520	476	488	447	498
0.56	571	537	533	521	485	529
0.75	593	560	567	631	505	571
1.12	693	614	618	606	579	622
1.68	774	712	654	649	609	680

By analyzing the explosion velocity data of aviation kerosene in Table 3.7, we can clearly observe the close relationship between explosion performance and detonation energy. As the detonation energy gradually increases, the explosion velocity of aviation kerosene shows a clear increasing trend. At a lower detonation energy of 0.37 MJ•m², the explosion velocity hovers between 447 and 559 m/s, revealing its relatively mild explosion properties. When the detonation energy is increased to 0.56 MJ•m², the upper limit of the explosion velocity jumps to 571 m/s, and then at 0.75 MJ•m², this speed further accelerates to 631 m/s, indicating a significant increase in explosion intensity. As the detonation energy jumps to 1.12 MJ•m², the explosion velocity increases sharply, reaching a peak of 693 m/s, reflecting a more violent explosion behavior. Finally, at a detonation energy of up to 1.68 MJ•m², the explosion velocity soars to 774 m/s, demonstrating the extreme explosion performance of aviation kerosene under extreme conditions. This trend not only reveals the decisive role of detonation energy on explosion speed, but also provides valuable data support for safety assessment and the formulation of explosion-proof strategies.

Comprehensive analysis of the data in Table 3.6 and Table 3.7 shows that in the same experimental sequence, the pressure value experienced a significant drop from position P1 to P2. This is mainly because sensor No. 2 (P1) is close to the detonation point and is directly exposed to the direct impact of the explosion wave, while sensors No. 3 to No. 7 are minimally affected because they are at a sufficient distance from the detonation point. Further observation shows that the pressure value fluctuation between P2 and P6 is extremely small, and the floating range hardly exceeds 0.10MPa. This stable state indicates that after advancing to a position of about 1.9 meters in the shock tube, the explosion wave propagation of aviation kerosene has stabilized. In addition, Table 3.5 reveals an interesting phenomenon about the change of explosion velocity with distance: under a fixed detonation energy, the explosion velocity gradually decreases with the increase of distance. Although this decreasing trend is relatively gentle, the attenuation ratios from D1 to D5 (corresponding to energies from 0.37MJ/m² to 1.68MJ/m²) are 20.03%, 15.06%, 14.84%, 16.45% and 21.31%, respectively, showing a clear relationship between energy attenuation and distance.

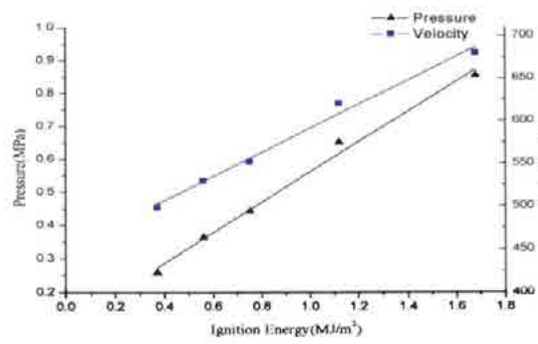


Figure 3.5 Average explosion velocity and pressure — Planar detonation energy trend chart

The data shown in Figure 3.5 clearly show that with the increase of detonation energy, the average explosion velocity D and the average explosion overpressure P both show a nearly linear and significant growth trend. This phenomenon can be attributed to the complex physical transformation process of the fuel cloud under the action of shock waves, including the rapid acceleration of droplets, morphological reshaping, evaporation, and subsequent heat transfer, which ultimately triggers oxidation reactions in the gas phase. The energy released by these reactions further enhances the leading shock wave, and the increase in detonation energy directly amplifies this effect. However, despite the increase in explosion intensity, the experimentally measured explosion velocity and pressure data show that at these five different detonation energy levels, the explosion of the aviation kerosene cloud did not reach the critical state of detonation. This is most likely due to the low saturated vapor pressure of aviation kerosene at room temperature, which limits its volatility and the amount of vapor generated during the detonation process, thereby making the energy released by the gas phase chemical reaction insufficient to maintain the energy level required for detonation.

3.1.4.3 Effect of concentration equivalence ratio on kerosene cloud explosion velocity and pressure

The explosion performance of fuel is deeply affected by its concentration equivalence ratio during reaction, and this law has been specifically verified in the experiment of RP-3 aviation kerosene. In the experiment, by adjusting the concentration equivalence ratio to seven different levels of 0.46, 0.63, 0.91, 1.28, 1.52, 1.67 and 1.98, while maintaining a constant plane detonation energy E1 of 1.12MJ/m², a spray pressure Ps of 0.40MPa, and an ignition delay time of 1.00 seconds, the average speed and pressure generated by the explosion were measured . These data are organized in Tables 3.8 and 3.9, and then graphically (as shown in Figure 3.6) to intuitively show how the average explosion overpressure P and the average explosion speed D fluctuate with the change of the concentration equivalence ratio, revealing the close relationship between them.

Table 3.8 Explosion overpressure at different concentration equivalence ratios

	Explosion overpressure P(MPa)						
	P1	P2	P3	P4	P5	P6	$\overline{p}$
0.46	1.04	0.65	0.57	0.56	0.57	0.59	0.56
0.63	1.30	0.68	0.60	0.59	0.56	0.53	0.59
0.91	1.28	0.69	0.57	0.62	0.59	0.58	0.61
1.28	1.30	0.76	0.56	0.66	0.64	0.66	0.66
1.52	1.28	0.61	0.61	0.75	0.62	0.63	0.65
1.67	1.27	0.72	0.59	0.68	0.61	0.66	0.65
1.98	1.28	0.72	0.60	0.58	0.58	0.59	0.61

Table 3.8 records in detail the overpressure data generated by the explosion of aviation kerosene at different concentrations and equivalence ratios, revealing the close connection between the overpressure value and the equivalence ratio. Specifically, when the equivalence ratio is at a low level (such as 0.46), the explosion overpressure is stable at around 1.04 MPa; however, as the equivalence ratio gradually increases, the explosion overpressure also increases significantly, reaching a peak of 1.30 MPa at an equivalence ratio of 0.63, showing a significant increase in the explosion power. Thereafter, in the range close to the stoichiometric ratio (about 0.91 to 1.28), the explosion overpressure remains at a high level of 1.28 to 1.30 MPa, reflecting the relative stability of the explosion performance. However, when the equivalence ratio further increases to 1.52, the overpressure value drops slightly, and then maintains a small fluctuation in the range of 1.67 to 1.98, maintaining between 1.27 and 1.28 MPa. This trend of change not only deepens the understanding of the explosion characteristics of aviation kerosene, but also provides valuable experimental data support for subsequent related research.

Table 3.9 Explosion velocity at different concentration equivalence ratios

	Explosion speed D(m/s)					
	D1	D2	D3	D4	D5	$\overline{D}$
0.46	639	633	609	578	548	601
0.63	651	625	600	578	546	598
0.91	667	638	611	581	546	608
1.28	693	614	618	606	579	622
1.52	632	674	606	603	559	615
1.67	638	676	625	594	558	618
1.98	659	630	600	598	565	610

From the detailed data in Table 3.9, it can be found that the explosion velocity presents a specific evolution pattern with the change of the aviation kerosene equivalence ratio. At first, at a lower equivalence ratio (0.46), the explosion velocity was stable at around 601 m/s. Subsequently, a small increase in the equivalence ratio (to 0.63) did not bring about a significant change in the velocity, but instead dropped slightly to 598 m/s. However, when the equivalence ratio further increased to the range of 0.91 to 1.28, the explosion velocity experienced a significant jump, reaching peak values of 608 m/s and 622 m/s, respectively, indicating that this range is the key area for optimizing explosion performance. Afterwards, although the velocity slightly dropped to 615 m/s at an equivalence ratio of 1.52, the explosion velocity remained at a high level at higher equivalence ratios (1.67 and 1.98), fluctuating between 618 m/s and 610 m/s. These data not only reveal the direct effect of equivalence ratio on explosion velocity, but also provide valuable insights into the explosion behavior of aviation kerosene under different concentration conditions.

According to the data in Table 3.8 and Table 3.9, except for P1, the maximum explosion overpressure is 0.76 MPa, the maximum average explosion rate max is 693 m/s, and the maximum average velocity max is 622 m/s. These four maximum values all appear in the test group with a concentration ratio of 1.28. Compared with the six test groups (with concentration equivalent ratios of 0.46, 0.63, 0.91, 1.52, 1.67 and 1.98, respectively), the average explosion overpressure of this group increased by 17.9%, 11.9%, 8.2%, 1.5%, 1.5% and 11.8%, respectively; the average explosion rate increased by 3.5%, 4.0%, 2.3%, 1.1%, 0.6% and 2.0%, respectively. The results show that the effect of the equivalent ratio on pressure is greater than that on flow rate.

Figure 3.6 shows that when the concentration equivalence ratio is less than 1, the explosion speed and pressure rise rapidly with the increase of the concentration equivalence ratio, and reach a peak value when it is close to 1.3, and then gradually decrease, presenting an "inverted U" curve as a whole. The study found that in the RP-3 aviation kerosene-air mixture, there is an optimal combustion mass fraction, at which the energy generated

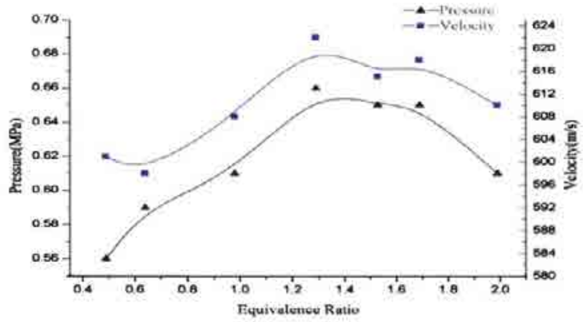


Figure 3.6 Average explosion velocity and pressure − concentration equivalent ratio trend chart

is the largest.

3.2 Determination of aviation kerosene vapor deflagration parameters

In the petrochemical industry, liquid fuel vapor explosion constitutes the most common dangerous scenario. Its core mechanism lies in the mixture of fuel vapor and oxygen. When the ratio is appropriate and encounters ignition energy, it will cause a violent explosion. Such incidents have serious consequences and pose a huge threat to public safety and property. Therefore, in-depth exploration of the reaction characteristics of fuel vapor explosion and accurate acquisition of its key parameters of combustion and explosion have become the key to preventing and controlling such industrial accidents and avoiding the recurrence of tragedies. This study used a horizontal shock tube platform to carry out a series of experiments specifically for RP-3 aviation kerosene vapor, successfully determined the explosion pressure and velocity of kerosene vapor at different concentrations, and analyzed the specific effect of ambient temperature on the explosion pressure. In addition, the explosion pressure change trend of kerosene vapor in a specific concentration range under different volatile components was carefully analyzed, and the explosion limit under different volatile temperatures and initial ambient temperatures was clearly defined. These valuable data not only provide an important basis for preventing aviation kerosene vapor explosion accidents, but also lay a solid foundation for subsequent safety research in this field.

3.2.1 Experimental setup

The core structure of the experimental device includes a horizontal shock tube system, a special gas supply unit, an efficient heating module, a precise ignition device, and a pressure measurement system that is consistent with the previous experiment. In particular, the ignition link uses a chemical ignition head with energy precisely controlled to 20 joules, which is triggered by an advanced detonation controller to ensure the stability of the experimental operation. As for pressure measurement, this experiment uses the same but verified pressure measurement system as the experiment in the previous chapter.

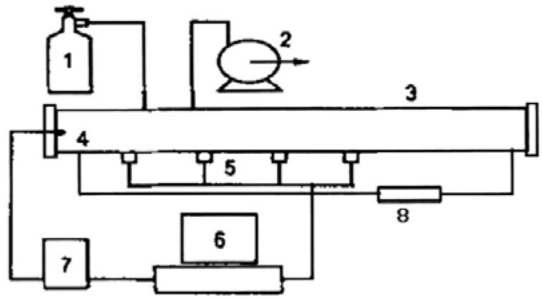


Figure 3.7 Schematic diagram of horizontal shock tube system

2.2.1. Horizontal shock tube system

The shock tube used in this experiment is uniquely designed, with a total length of 2 meters, an outer diameter of 90 mm, an inner diameter reduced to 70 mm, and an effective volume of approximately 7.69 liters. The tube is tightly sealed at both ends through a sturdy flange structure to ensure a highly airtight experimental environment. Four precision pressure sensors are arranged at equal intervals along the bottom of the tube, 30 cm apart from each other, and are marked as 1#, 2#, 3#, and 4# in order to accurately monitor the pressure changes at different positions in the tube. In particular, there are two interfaces above the tube, located 30 cm and 170 cm away from the ignition end, respectively. These two interfaces are connected to the circulation pump system to evenly mix the gas components in the tube. In addition, the vacuum gauge and vacuum pump are also cleverly installed above the tube, and are flexibly controlled by a ball valve to meet the specific vacuum conditions required for the experiment. It is worth mentioning that a circular transparent observation window is embedded on the right side of the tube, providing an intuitive perspective for the experimenter to clearly observe the dynamic changes of the flame at the moment of explosion. For the specific layout, please refer to the schematic diagram of the horizontal shock tube shown in Figure 3.7.

3.2.2.2 Gas generating device

The gas generation device required for the experiment cleverly utilized abandoned fire extinguishers for modification. Its main structure has a diameter of 15 cm and a height of 45 cm. It is calculated that its internal space can accommodate about 7.96 liters of gas. A pressure gauge is cleverly installed on the top of the device, and its measurement range covers -0.1MPa to 0.1MPa, which can intuitively reflect the pressure state inside the container. In addition, the device is carefully designed with three interfaces with valves, one of which is specifically used to connect the shock tube to ensure that the experimental gas can be transmitted smoothly; the second valve is set as a vent valve to release the gas in the container to adjust the pressure when necessary; and the third valve is used as a reserved interface.

3.2.2.3 Heating system

The experiment used two different heating methods to independently control the temperature of the shock tube and kerosene vapor. Each heating system device consists of three components: a heater, a thermostat, and an insulation layer.

(1) The core of the heating system is a 3 cm wide heating belt that can output 100 watts of heat per meter. It is cleverly wrapped around the outer circumference of the container and closely connected to an advanced temperature control device. This heating belt uses a nickel-chromium alloy electric heating flat wire that is resistant to high temperatures up to 450°C as a heat source, and the outer layer is carefully wrapped with durable glass fiber to ensure safety and durability.

(2) Temperature Control Center - A professional device from Shanghai Huajian Electric Heating Equipment Co., Ltd., it not only has a load bearing capacity of up to 40 amps and 8,000 watts, but is also equipped with a high-precision thermocouple sensor with an accuracy of up to 0.5%. The controller monitors the container temperature in real time and compares it with the preset temperature

value, intelligently adjusts the working state of the heating belt, and accurately achieves temperature control.

(3) To further enhance the thermal insulation effect, a two-layer thermal insulation structure is cleverly designed on the outside of the container: the inner layer uses a high-efficiency thermal insulation material - glass wool tube, which effectively reduces heat loss and accelerates the heating process; the outer layer is covered with a highly reflective tin foil layer, which not only effectively blocks the escape of thermal radiation, but also further improves the overall thermal insulation performance.

3.2.2 Experimental methods

(1) Selection of kerosene injection method

Given the significant adsorption characteristics of kerosene on the shock tube wall, the vapor introduction method of kerosene as a liquid fuel is directly related to the accuracy of the kerosene vapor concentration in the reaction vessel, so it is crucial to choose the appropriate kerosene injection technology . In experiments to explore the explosion characteristics of combustible gas (vapor), researchers generally use three different injection strategies. First, one method is to drive kerosene into fine aerosol particles by high-pressure gas and evenly disperse them in the reaction space. Although this method can effectively promote mixing uniformity, kerosene droplets tend to adhere to the tube wall during high-pressure injection, affecting the accuracy of concentration measurement. Secondly, directly injecting a certain amount of kerosene into the container and heating it for evaporation, although it is simple and direct, the incomplete fuel conversion makes it difficult to accurately control the amount of steam actually participating in the reaction. Finally, the premixed gas distribution method is to fully mix the kerosene vapor with oxygen and dilution gas in the gas distribution chamber before the reaction, and then introduce it into the reaction vessel. Although this method can ensure uniform mixing, the strong adsorption of the inner wall of the gas distribution equipment also introduces measurement errors.

The innovative sampling process of this experiment is cleverly designed. First, an appropriate amount of kerosene is injected into the gas generation system as the starting material. Subsequently, the launch device is heated using an external heat source to convert the kerosene partially into a vapor state. Next, the partial pressure gas distribution technology is finely controlled to ensure that the vapors can be efficiently and completely introduced into the shock tube. This strategy not only avoids the drawback of incomplete evaporation of kerosene in traditional methods, but also significantly reduces the adsorption effect of the gas distribution container on the kerosene components, thereby greatly improving the accuracy and reliability of the experimental data.

(2) Determination of temperature

Since the thermocouples of the heating system only monitor the temperature of the outer wall of the container, when the outer wall reaches the preset experimental temperature (such as 150°C for the shock tube and 100°C for the gas generator), the control system will instruct the heating belt to stop working. However, this design ignores the temperature difference between the inside and outside of the container, the so-called temperature gradient, which is particularly significant in the internal environment of the shock tube. In order to accurately grasp the real temperature dynamics inside the container, the research team adopted a multi-point thermocouple arrangement strategy, and tracked the evolution of the inner and outer wall temperatures of the shock tube and its supporting gas generator over time during the heating process, as shown in Figure 3.8, thereby providing more comprehensive temperature distribution information.

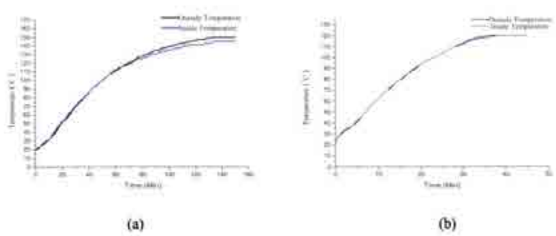


Figure 3.8 Temperature changes over time of (a) shock tube and gas generator (b) inside and outside of the device during heating

Observe the data presented in Figure 3.8 (a). When the heating temperature does not exceed 80°C, the temperature inside and outside the shock tube is almost the same, indicating balanced heat transfer. However, once the temperature rises to the range of 80°C to 105°C, the outer wall temperature is significantly higher than the inner wall by about 4°C, and this temperature difference gradually increases with the heating process. Until the tube wall temperature reaches 150°C, the temperature inside the tube stabilizes at 145°C and no longer rises. In view of this, when setting the target value of the temperature control device, it is necessary to refer to the data in the figure for appropriate adjustments.

Figure 3.8(b) reveals the significant difference in the heating behavior between the gas generator and the shock tube. The temperature rise is more rapid, which is attributed to the smaller surface area that reduces heat loss and the excellent thermal insulation performance of the insulation layer. It is worth noting that during the heating period, the temperature curves inside and outside the container are closely matched, with only a small (about 1°C) difference at individual temperature points, which can be inferred that the external wall temperature is similar to the internal ambient temperature. Therefore, in the experiment on the gas generator, no additional correction is required when setting the temperature.

(3) Experimental procedures

Before the experiment starts, the first step is to use a vacuum pump to reduce the internal pressure of the shock tube to -0.08MPa, so as to fully test and adjust the sealing performance of the tube body to ensure that it meets the experimental standards. Once the airtightness is verified, according to the guidance of Figure 3.8 (a), an appropriate amount of kerosene is injected into the gas generating unit, and the inside of the generator is further evacuated to an extremely high vacuum state by a vacuum pump. Subsequently, the temperature control system is activated to heat the gas generator and the shock tube to the preset experimental temperature at the same time, so that the kerosene is converted into a certain concentration of steam. After all equipment reaches the target temperature, the shock tube is subjected to high vacuum treatment again, and the valve leading to the gas generator is carefully opened to accurately control the injection amount of kerosene steam. Next, by introducing an appropriate amount of air, the vacuum degree in the shock tube is gradually reduced to almost zero. Subsequently, the circulation pump is started and operated for 10 minutes to ensure that the gas in the tube is fully mixed and evenly mixed. Finally, the ignition device is connected to trigger the explosion, and the experimental data is collected in real time. After each experiment, the vacuum pump is used to extract the exhaust gas several times to thoroughly clean the tube body in preparation for subsequent experiments.

3.3 Summary of this chapter

This chapter deeply analyzes the complex mechanism of the anti-knock performance of aviation kerosene, and comprehensively explores its deflagration characteristics and the influencing factors behind it with the help of a series of carefully designed experiments. In the experimental exploration of the cloud deflagration phenomenon of aviation kerosene, not only the construction of the experimental equipment, the selection of fuels and the experimental process are elaborated in detail, but also the experimental data are deeply analyzed to reveal the deflagration response mode of aviation kerosene under different environmental variables and its potential safety challenges. Subsequently, through a high-precision steam deflagration parameter measurement system, the key indicators that determine the safety of the fuel are successfully captured, and a solid data foundation is built for safety assessment. Furthermore, by adjusting the chemical composition of aviation kerosene and introducing anti-knock additives containing isoparaffins and metallic ash, it is observed that these improvement measures have a significant effect on the anti-knock performance of kerosene, opening up a new path for improving the safety performance and application breadth of aviation fuel. This series of research results not only strengthens the understanding of the anti-knock performance of aviation kerosene, but also provides valuable theoretical basis and practical guidance for future technological innovation and safety upgrades of aviation fuel.

Among the strategies for enhancing the anti-knock capability of aviation kerosene, the core means include process optimization, additive formulation, and the introduction of high-efficiency anti-knock components. Specifically, through complex isomerization and alkylation technology innovations, the anti-knock performance of aviation kerosene has been significantly improved, although this method is accompanied by a high economic cost. On the other hand, the incorporation of isooctane as an additive, although the improvement in anti-knock performance is relatively mild, also provides an effective way to increase the octane number. At the same time, the addition of isopentane helps to adjust the vapor pressure characteristics of kerosene. It is worth noting that studies have shown that metal ash anti-knock agents MMT have shown excellent effects in improving the anti-knock performance of aviation kerosene, and their optimal use concentration is locked between 200 and 300 ppm. In view of increasingly stringent environmental protection requirements, exploring green and harmless alternative anti-knock agents has become the focus of current research, opening up new paths for safety improvement and environmentally friendly transformation in the field of aviation fuel.

4 Research on Forecast of Aviation Kerosene Consumption

4.1 Deep Learning

Deep learning is a technology based on an artificial neural network model, which consists of multiple levels of nodes (or neurons) that have the functions of receiving (input) and transmitting (output) information, and is interspersed with possible multiple hidden layers. In the process of deep learning, the system first focuses on the preliminary features of the data, and then uses these basic features to build more advanced and abstract feature representations in a layer-by-layer progressive manner. This process is similar to the human brain's understanding of complex information. Compared with traditional machine learning, deep learning is widely used in both supervised learning and unsupervised learning. The artificial neural network (ANN), as its cornerstone, realizes the adaptability and nonlinear characteristics of information processing based on the latest research in neuroscience. It uses computer simulation technology to process, convert and store information by simulating the connection and interaction between neurons. The system includes three units: output, input, and implicit. In the figure below, we see an input, which is a nonlinear one with a large number of neurons, usually called x. Here, the x input is usually an input vector. At the output level, after being transmitted by specific nerve cells, it is usually called the output of y. Here, the output of y is an output vector, usually with a multi-point input and a multi-point output. A hidden layer (often referred to as a "hidden layer") is a hierarchy consisting of many neurons and connections between inputs and outputs. A hidden layer can be multiple layers, usually as a layer.

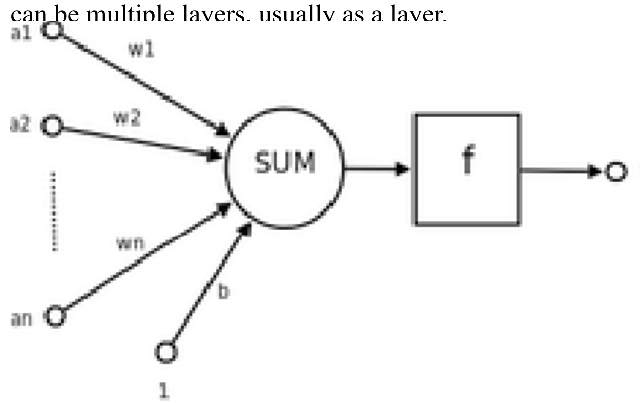


Figure 4.1 Simple neural network

The total input is from a1 to an, and the corresponding neuron weights are w1 to wn, b represents the bias, f is the transfer function (usually nonlinear, such as ansig (), traingd (), thardlim (), etc.), and t represents the output of the neuron.

Convolutional neural network (CNN) is a feed-forward neural network with multiple layers, which has strong learning and adaptive capabilities, high fault tolerance and fast computing speed. Currently, it has been widely used in speech recognition, image recognition and target recognition.

Neural networks usually consist of convolutional layers, input layers, activation layers, fully connected layers, and pooling layers. Commonly used convolutional neural network models include AlexNet, LeNet, ZF Net, VGGNet, Google Network (Inception), and ResNet . Among them, AlexNet won the first prize in the 2012 Image Classifier Competition and became one of the most representative image classification models. It achieved this goal through training. Figure 4.2 shows the hierarchical structure of AlexNet .

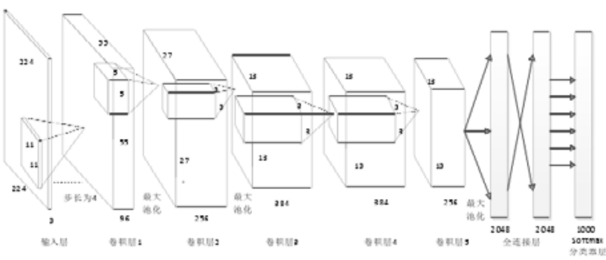


Figure 4.2 Schematic diagram of the hierarchical structure of the AlexNet model

AlexNet has an eight-layer architecture consisting of five convolutional layers focused on feature extraction alternating with three fully connected layers responsible for information integration. Each convolutional layer is followed by an activation layer that enhances the network's representation capabilities through nonlinear transformations. In addition, to control the data size and enhance the robustness of the features, the convolutional layers are cleverly embedded with pooling layers. Regarding the input data, AlexNet expects to receive a 224x224 pixel color image with three RGB channels. However, before actual processing, the image is preprocessed to a size of 227x227x 3 to accommodate the processing requirements of the first layer of the network. When entering convolutional layer 1, the network uses 96 convolutional kernels of exact size 11x11x 3 for feature mapping, which are specially designed to capture the details of the image in the three RGB color channels. It is worth noting that the convolution operation uses a stride of 4 when sliding on the image, so as to efficiently traverse the entire image area and generate a rich feature map, so the number of new image features extracted is:

Kannaiyan conducted an in-depth analysis of the drawbacks of low-altitude flight of aircraft, and successfully constructed an exponential relationship model between fuel consumption and flight altitude by integrating actual flight records with advanced genetic algorithm technology (Kannaiyan, 2020). In contrast, Berger took a different approach, introduced the receiver operating characteristic curve as an optimization method, and designed an innovative support vector machine network model to predict fuel consumption. This model uses detailed flight data collected on the route as a training basis, which significantly improves the prediction accuracy (Berger, 2021). Kreyer focused on fuel management during the flight climb phase, and through genetic algorithm technology, developed a new fuel flow prediction model that comprehensively considers flight altitude and true airspeed, providing a new perspective for aviation fuel efficiency management (Kreyer, 2020).

4.2 Fuel consumption prediction model based on RBF neural network

Based on the core research objectives of this paper, this section focuses on building a practical fuel consumption prediction model suitable for the tactical phase. Through a detailed analysis of the factors affecting fuel consumption in each flight phase in the QAR data, the unique impact of each key factor on fuel consumption in different flight phases is determined. Based on this, the advanced technology of radial basis function neural network is used to tailor a high-precision fuel consumption prediction model for each flight phase. At the same time, the robustness of the established model is verified.

As an efficient feedforward network architecture, radial basis function (RBF) neural network has shown excellent approximation ability, simplified training process, fast learning convergence speed, and the ability to effectively solve the local optimal trap. In view of these significant advantages, RBF neural network has been widely used in many fields such as pattern recognition tasks, complex nonlinear control system design and image processing applications.

Its value depends only on the distance from the origin, that is, Φ(x)=Φ(‖x‖), or it can be the distance from any point c, where point c is called the center of the circle, that is, Φ(x,c)=Φ(‖xc ‖). φ with this property is called a radial basis function.

Although other distance metrics are available, the Euclidean distance is the most commonly used standard. In the structure of neural networks, it can be used as the main function of fully coupled layers and ReLU layers.

When N pairs of input and output data $\left(x^k, y^k\right)$, k = 1, 2, ..., N are given, an RBF neural network with arbitrary accuracy can be constructed. The hidden layer unit in the RBF network is calculated as follows:

$$R_i(x) = \exp\left[\frac{(x-c_1)^2}{2R^2}\right]$$

The learning process of the RBF neural network for the aviation kerosene fuel process is as follows:

(1) Select an appropriate radius r to determine the complexity of the network. R is a one-dimensional parameter, and a suitable value can be obtained based on experimental results and error data. The vector S(l) is used to store the sum of different types of output media. Then, the count value CT(L) is determined to count the number of samples of each type.

(2) Starting from the first data $\left(x_{1,} y_1\right)$, pair, set the cluster center with $c_1 = x^1$, S(1)= y^1, CT(1)= 1. The RBF network has only one hidden unit, the center of the hidden unit is the weight vector from the hidden unit to the output layer $w_1 = S(1)/CT\ (1)$.

(3) Starting from the second data pair $\left(x^2, y^2\right)$, find the distance x^2 to c_1 this cluster center $\left|x^2 - c_1\right|$. If $\left|x^2 - c_1\right| \in R$, then it c_1 x_2 is the nearest neighbor cluster, and let S(1) = $y^1 + y^2$, CT(1) =2, w_1 = S(1) / CT(1); if $\left|x^2 - c_1\right|$<R, then it will x^2 be used as a new cluster center, and let $c_2 = x^2$, S(2)= y^2, CT(2)=1. The hidden units are added to the RBF network, and the weight vector from the hidden units to the output layer w_2 = S(2) /CT(2).

(4) Starting from the kth data pair $\left(x^k, y^k\right)$, we find that there are cluster centers n_h with the center points being c_1, c_2,,, c_h, and there are n_h hidden units added to the RBF network. We find the distance of the cluster center | x^k - c_i |, i =1,2,,, n_h, let | x^k - c_j | be the minimum distance among these distances, that is c_i x^k, the nearest neighbor cluster of, then:

If | x^k - c_j |>R, it will be x^k used as a new cluster center and set $c_{n_h+1} = x^k$, $n_h = n_h + 1$, S(n_h) = y^k, CT(n_h) = 1. And keep the values of S(i), CT(i) unchanged, i = 1, 2,,, n_h -1. n_h A hidden unit is added to the RBF network, and the weight vector from the hidden unit to the output layer w_{n_h} = S(n_h) /CT(n_h).

If $\left|x^2 - c_1\right|$<R, then S (j) = S (j) + y^k, CT (j) = CT (j) + 1. When i > j, i = 1, 2,,, n_h, and keep the values of S (i) and CT (i) unchanged. The weight vector from the w_i hidden unit to the output layer is = S (i) / CT (i), i = 1,,, n_h.

(5) Based on the above rules, the RBF neural network for aviation kerosene fuel consumption is established. The network output is

$$f\left(x^k\right) = \frac{\sum_{i=1}^{n_h} w_1 \exp\left(-\frac{\left|x^k - c_i\right|^2}{R^2}\right)}{\sum_{i=1}^{n_h} \exp\left(-\frac{\left|x^k - c_i\right|^2}{R^2}\right)}$$

RBF is a three-layer feed-forward network with a single hidden layer .

The first layer is the input layer composed of signal source nodes.

The number of nodes in the second layer of the network, the hidden layer, is flexibly configured according to the characteristics of the problem. The activation of neurons in the hidden layer depends on a special radial basis function, which has a non-negative linear characteristic that gradually weakens from the center to the periphery, showing a local sensitive response in space. This localized response mechanism emphasizes the changes in the input data in a specific area, which is different from the previous global response transfer function.

In the neural network architecture, the third layer, as the output layer, directly reflects the response results of the input layer. The input layer plays the role of a signal transmitter, transmitting information to the network. In particular, the input layer and the hidden layer that follows it can be regarded as a direct path with fixed connection weights (i.e., weight 1). It is worth noting that there are significant differences in the functions and processing methods of the output layer and the hidden layer: the output layer focuses on the adjustment of linear weights, which is achieved through linear optimization techniques. This process leads to a faster resource (such as computing resources or hypothetical "kerosene") consumption rate due to its directness. In contrast, the hidden layer is committed to optimizing the parameters of the activation function (such as the Gaussian function, as a common choice), which involves nonlinear optimization strategies.

In other words, the radial basis function constitutes a two-layer neural network. In this network model, the RBF network is used as the activation function, and the output adopts a linear method.

When reconstructing the data, the hidden layer uses the radial basis function and uses Φ (||X- Xp ||) to replace the original data vector representation. Since there are P centers in total, the dimension of the new data is P. Next, the data is classified again.

The RBF network can be divided into three parts: input layer, hidden layer and output layer. The specific structure is shown in Figure 4.1. This method first takes the main factors as input, then trains through the hidden layer, and finally obtains the final prediction result in the output layer.

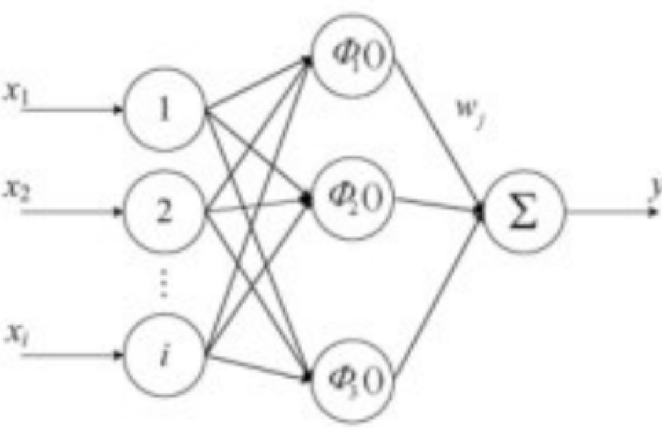


Figure 4.3 Schematic diagram of radial basis function neural network structure

$$y_i = \sum_{i=1}^{n} w_j \times exp\left(\frac{1}{-2\delta^2}\left\|x_p - x_i\right\|^2\right) \quad (4.1)$$

Among them, y_i represents the output of the model; x_i represents the input of the model; x_ρ represents the center of the basis function; w_j represents the weight value; and δ represents the smoothness parameter.

4.2.3 Verification Analysis

The key factors that have a significant impact on fuel consumption in each flight phase from the tactical phase QAR data carefully analyzed in Chapter 2 are cleverly integrated into the aviation kerosene fuel consumption prediction model based on the radial basis function (RBF) neural network. Subsequently, detailed prediction results are generated and cleverly compared with the predictions using the convolutional neural network (CNN) model and the multi-layer perceptron (MLP) model. As shown in Table 4.1, the comparison results are particularly striking: in the critical takeoff and climb phase, the RBF neural network model shows excellent performance, with an average error rate of only 5.73%, significantly lower than the 15.01% of the CNN model and the 17.68% of the MLP model.

Table 4.1 Error rate comparison table

	RBF Model	CNN Model	MLP Model
Takeoff climb phase	5.73%	15.01%	17.68%
Air cruise phase	3.36%	8.09%	10.33%
Descent approach phase	14.04%	18.20%	20.74%

The prediction results shown in Figure 4.4 reveal the excellent performance of the RBF neural network in predicting the fuel consumption during the aircraft climb phase. The model not only accurately tracks the actual fuel consumption trend, but also shows a high degree of fit, although there are slight fluctuations at certain moments.

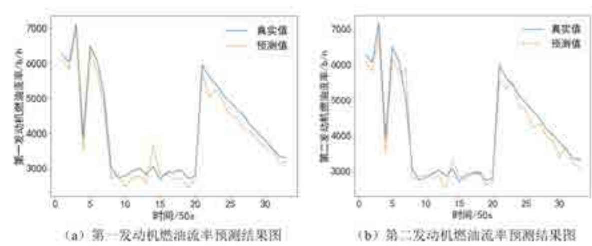
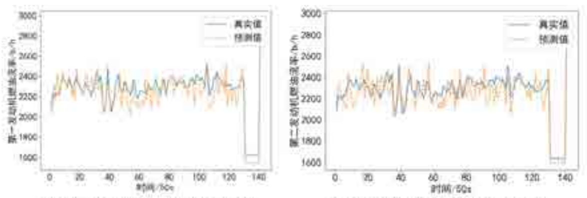


Figure 4.4 Engine fuel flow rate prediction results during takeoff and climb

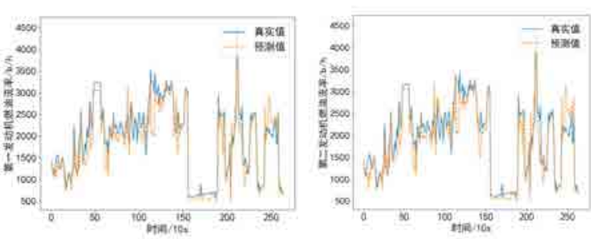
During the flight, the RBF network was used to predict fuel consumption, and its prediction error rate was only 3.36%, while the errors of CNN and MLP were 8.09% and 10.33% respectively. This shows that the fuel consumption prediction model established using the RBF network can more accurately predict the fuel consumption during the flight and has a higher accuracy.



（a）第一发动机燃油流率预测结果图 （b）第二发动机燃油流率预测结果图

Figure 4.5 Fuel flow rate prediction results during air cruising

When discussing the prediction of fuel consumption during the descent approach phase, the model constructed using the RBF neural network showed significant advantages, with an average error rate of only 14.04%, significantly lower than the 18.20% of the convolutional neural network (CNN) and the 20.74% of the multi-layer perceptron (MLP). As shown in Figure 4.6, although the prediction error of the model in the descent approach phase has increased compared to the air cruise phase, it still maintains a high prediction accuracy, significantly better than the other two models.



（a）第一发动机燃油流率预测结果图 （b）第二发动机燃油流率预测结果图

Figure 4.6 Fuel flow rate prediction results during descent approach

During the flight of the aircraft, the fuel consumption prediction error of the air cruise phase is generally at a low level due to its continuous stability of flight status and the scarcity of maneuvering operations, and this phase occupies most of the total flight time. In particular, the fuel prediction model constructed using the RBF neural network shows the smallest prediction error in this phase, demonstrating its excellent performance. In contrast, the aircraft needs to frequently respond to control instructions and perform various maneuvers during the descent approach phase. The flight status changes rapidly and the time is tight, which naturally leads to a general increase in the prediction error in this phase. Despite this, the RBF neural network model still maintains the smallest prediction error among the three comparison models, further verifying its advantage in fuel consumption prediction compared with other models.

4.2.4 Generalization Analysis

4.2.4.1 Ten- fold cross validation analysis

When evaluating the robustness of the fuel consumption prediction model based on the radial basis function (RBF) neural network, a rigorous ten-fold cross-validation strategy was adopted. This strategy involves evenly dividing the existing 44 flight QAR data into ten parts. In each round of validation, one subset is independently selected as the test set, and the remaining nine subsets are integrated as the training set. This method ensures that each training and testing process is based on different data combinations, thereby comprehensively testing the performance of the model under diverse data conditions. Table 4.2 records the results of this series of cross-validation in detail, providing solid data support for evaluating the robustness of the model.

Table 4.2 Ten- fold cross validation results

From the detailed data in Table 4.2, we can clearly observe the performance of the fuel consumption prediction model constructed using the RBF neural network in the three key flight stages of takeoff and climb, air cruising, and descent and approach. Specifically, the average error rate in the takeoff and climb stage is 6.08%, showing a high prediction accuracy; and the average error rate in the air cruising stage is 3.68%, which demonstrates the excellent prediction ability of the model in this stable flight stage. Although the error rate slightly increased to 14.03% in the descent and approach stage, overall, the error variance of the three stages remained at a low level, which is not only a reflection of the accuracy of the model, but also further strengthens its strong robustness and multi-stage adaptability.

4.2.4.2 Verification and analysis of influencing factor sets

As QAR data is confidential and difficult to obtain, this project intends to subdivide the combinations of various influencing factors according to the types of parameter values and the difficulty of obtaining them. The detailed divisions are shown in Figure 4.3 below.

Table 4.3 Parameter set table

	Parameter composition
Less parameter set	Ground speed, longitude, latitude, altitude, heading
Parameters collection	Ground speed, longitude, latitude, altitude, heading, wind direction, wind speed, temperature
Multiple parameter sets	Ground speed, longitude, latitude, altitude, heading, wind direction, wind speed, temperature, Mach number, vertical acceleration, lateral acceleration, engine exhaust temperature, gross weight, fuel quantity in each tank.

In the prediction of fuel consumption, three different parameter sets are used as input, namely ADS-B (Automatic Dependent Surveillance-Broadcast) data, ADS-B combined with meteorological data, and complex parameters that can only be extracted from QAR (Quick Access Recorder) data. These parameter sets are divided into three categories according to the difficulty of data acquisition: easy to obtain (ADS-B), relatively easy to obtain (ADS-B + meteorological) and difficult to obtain (QAR). Subsequently, these parameter sets are input into the RBF (Radial Basis Function) neural network model for the three flight stages of takeoff, cruising and landing to predict fuel consumption. In order to comprehensively evaluate the performance of the model, the prediction results are compared with the CNN (Convolutional Neural Network) and MLP (Multi-layer Perceptron) models. Table 4.4 shows in detail the prediction error rate of each model under different parameter sets, showing the difference in applicability of each model under different data conditions.Observing the data in Table 4.4, it can be found that when the input parameter set is relatively limited, the error rates of the three prediction models

Table 4.4 Comparison of error rates of different parameter sets

	Takeoff climb phase			Air cruise phase			Descent approach phase		
	RBF Model	CNN Model	MLP Model	RBF Model	CNN Model	MLP Model	RBF Model	CNN Model	MLP Model
Less	5.58%	19.18%	16.41%	8.55%	19.42%	12.37%	27.16%	44.21%	40.46%
	4.63%	8.87%	13.97%	2.54%	9.07%	8.31%	25.57%	51.77%	38.49%
	1.70%	3.15%	3.47%	0.49%	3.36%	3.43%	9.17%	18.38%	9.42%

are all at a high level. However, with the increase in the number of parameters, the prediction accuracy of all models has been significantly improved, especially the performance of the RBF neural network in fuel consumption prediction, with a significantly lower error rate than the other two models, which strongly proves the superiority of the RBF neural network model in fuel consumption prediction. Further analysis of the flight phase shows that the overall prediction error is high in the descent approach phase due to the frequent changes in flight status and short duration of the aircraft. In contrast, the prediction error is relatively low in the air cruising phase due to the stable flight status, few maneuvers and most of the flight time. It is worth noting that in the three flight phases, the RBF neural network model shows the lowest prediction error, which once again confirms its excellent performance and stronger robustness in fuel consumption prediction.

In summary, the improvement of model prediction accuracy significantly depends on the diversity and richness of input parameters, which is directly reflected in the reduction of prediction errors. Furthermore, through verification, the fuel consumption model constructed by radial basis function (RBF) neural network shows strong robustness and can maintain stable prediction performance even in the face of complex and changing input conditions. It is worth noting that compared with the key variable set obtained through careful screening, a new strategy was tried, that is, to reorganize the set of influencing factors as model input based on the nature of the parameters and the difficulty of obtaining them. This attempt revealed the subtle deviations in the prediction effects of different sets of influencing factors, thus emphasizing the indispensability of in-depth analysis of influencing factors for optimizing model performance.

4.3 Analysis of aviation fuel consumption patterns and fuel efficiency evaluation

Analyzing the phenomenon of "fuel consumption" in aviation and focusing on the fuel consumption characteristics of each flight stage (take-off, cruising, landing) and the complex factors behind it is a key step in improving aviation fuel efficiency. Studies have found that the cruising stage enjoys lower fuel consumption efficiency due to its stable flight attitude and high-speed characteristics, while the fuel consumption rises sharply during the take-off and landing stages due to the need to overcome strong gravity and air resistance. At the same time, factors such as the choice of flight altitude, changes in meteorological conditions, the rationality of route design, and the cargo or passenger capacity of aircraft all have a profound impact on fuel consumption. Based on these insights, airlines can optimize flight path planning, implement more sophisticated fuel management plans, and improve fuel efficiency with the help of data analysis. This move not only helps to reduce operating costs, but also plays a positive role in reducing carbon emissions and promoting the green transformation of the aviation industry. Therefore, a systematic study of aviation fuel efficiency and fuel consumption patterns is not only a strategic choice for airlines to enhance their competitiveness, but also an important way to promote the entire aviation industry to develop in a more environmentally friendly and efficient direction .

In the framework of in-depth exploration of aircraft fuel economy, this chapter focuses on analyzing the complex dynamics of "extra fuel consumption caused by carrying too much fuel" and analyzes fuel efficiency in detail. Relying on the realistic fuel consumption prediction model carefully constructed in Section 4.2, a series of strategies are adopted to simulate a variety of fuel consumption prediction scenarios by flexibly adjusting the model input parameters. This process not only reveals how the aircraft carrying too much fuel indirectly affects the fuel consumption level during the flight, but also promotes a deep understanding of the subtle relationship between "carrying more fuel" and "consuming more fuel". Furthermore, for the same model, an innovative fuel efficiency comparison and evaluation mechanism before and after the flight, as well as a real-time fuel efficiency monitoring scheme during the flight, are designed.

4.3.1 Experimental simulation

In order to accurately grasp the phenomenon of "fuel consumption" of aircraft and evaluate its fuel economy, a comprehensive analysis method was adopted, which relies on a total of 135 actual flight data of a specific A321 model from Beijing Daxing Airport to Guangzhou Baiyun Airport in February 2022. These data were carefully selected to drive two fuel consumption models at the same time: one is a prediction model based on the flight plan, and the other is closely matched with the actual QAR (Quick Access Recorder) data. Through this parallel processing strategy, it is possible to directly compare the model prediction with the fuel consumption in actual operation, so as to accurately verify the accuracy of the prediction model. Table 4.5 shows in detail the error rate of the plan-oriented fuel consumption prediction model, which provides a solid foundation for subsequent model optimization and efficiency improvement.

Table 4.5 Prediction result error rate table

	Average error rate	Maximum error rate	Minimum error rate
CNN Model	5.21%	13.02%	0.29%

From the data analysis in Table 4.5, it can be clearly observed that even after changing the aircraft model and adopting the new data set, the fuel consumption prediction model based on the convolutional neural network (CNN) still shows its excellent stability, and its prediction error rate remains at an average level of 5.21%. Figure 4.7 intuitively depicts the prediction performance of this model, which compares the distribution between the model prediction value and the actual fuel consumption value. In the figure, the blue dotted line marks the ideal line of y=x. The closer the prediction point is to this line, the higher the prediction accuracy. Obviously, the prediction results in the figure are closely around this blue line, which fully proves that the CNN model is not only highly accurate in predicting fuel consumption, but also has good robustness and can adapt to changes in data of different aircraft models.

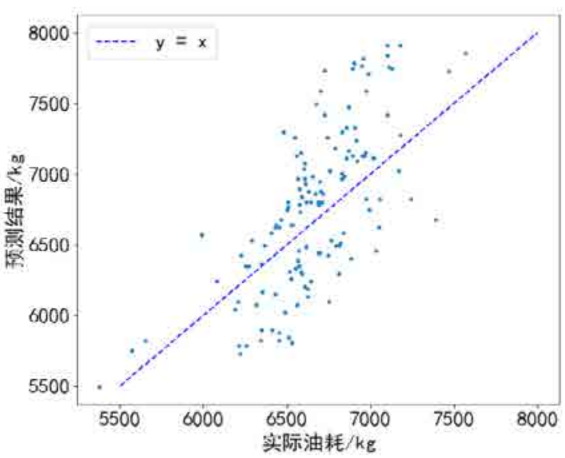


Figure 4.7 Distribution of prediction results

Using the actual fuel consumption prediction model, the prediction error rate is shown in Table 4.6

Table 4.6 Prediction result error rate table

Analyzing the data in Table 4.6, compared with the results in Section 4.2, after using the updated aircraft data set, the kerosene fuel consumption prediction model based on the radial basis function (RBF) neural network showed stable prediction performance. Specifically, during the take-off and climb phase, the average error rate of the model remained at 6.34%, while it dropped to 3.71% during the air cruise phase. During the descent and approach phase, although the error rate rose to 13.56%, overall, the prediction error rate of this model did not fluctuate much in different flight phases, which fully verified its strong robustness and adaptability to different aircraft models.

4.3.2 Analysis of aviation fuel consumption patterns

As we all know, there is a direct positive correlation between the load and kerosene consumption of an aircraft: as the load increases, fuel consumption also rises. Under this principle, if one intends to increase the endurance by increasing kerosene reserves, it is actually counterproductive, because the increased kerosene itself increases the burden on the aircraft, which in turn increases fuel consumption. This phenomenon is vividly called the “fuel consumption” effect. This section focuses on analyzing this unique phenomenon, aiming to reveal how changes in additional kerosene (whose weight is deeply affected by human scheduling and meteorological conditions) affect the overall fuel efficiency of the aircraft and explore the quantitative relationship between the two. By abstracting this complex relationship into a mathematical model (such as Equation 4.2 and its variants), it is possible to more clearly understand and optimize the management strategy of the “fuel consumption” phenomenon.

$$\Delta y = f(\Delta x) \quad (4.2)$$

Among them, Δy represents the change in kerosene fuel consumption;

Δx represents the additional oil change .

In the process of exploring the prediction of kerosene fuel consumption, we focus on observing the impact of the strategy of adjusting the amount of extra fuel on the fuel consumption prediction results, aiming to reveal the intrinsic connection between the two, and then extract the key coefficient c that affects the phenomenon of “fuel consumption” of aircraft. In view of complex factors such as weather fluctuations and differences in human operations, even the same type of aircraft on the same route have diverse characteristics in terms of the amount of extra fuel carried. Therefore, we first deeply analyzed the distribution profile of the extra fuel in the flight plans of these 135 flights, as shown in Figure 4.8, which laid a data foundation for the subsequent correlation analysis.

It can be seen from Figure 4.8 that among these 135 flights, the number of flights carrying 800kg of extra fuel is the largest, accounting for 37.04% of the total number of flights; the second largest number of flights is carrying 1200kg, accounting for 20.74% of the total number of flights. 83.70% of the flights carry extra fuel between [800,1200]kg.

Furthermore, by adjusting the weight of the additional

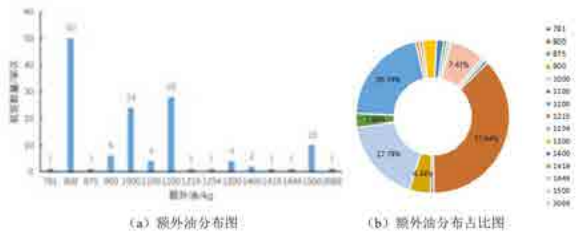


Figure 4.8 Extra oil statistics

fuel and inputting it into the actual kerosene consumption prediction model, a series of prediction results were obtained, some of which are shown in Table 4.7. The kerosene consumption prediction without adjusting the additional fuel was used as the baseline, and any subsequent adjusted prediction results were subtracted from this baseline, and the difference was used as a quantitative representation of the change in kerosene consumption .

Table 4.7 Partial table of prediction results

Extra Oil Change value	…	-10Kg		0	+10 kg		…
flight	…	Predicted value/kg	Change/ kg	Predicted value/kg	Predicted value/kg	Change/ kg	…
1		6825.077	-0.796	6825.873	6826.669	0.796	
2		6746.977	-0.796	6747.773	6748.568	0.795	
3	…	7020.093	-0.795	7020.888	7021.684	0.796	…
4		6801.350	-0.797	6802.147	6802.942	0.795	
5		7192.984	-0.796	7193.780	7194.576	0.796	

Table 4.7 shows in detail the subtle changes in the flight fuel consumption forecast as the additional fuel is adjusted. Specifically, when the additional fuel is reduced by 10 kg, the expected fuel consumption of the flight decreases slightly, and this change is concentrated between -0.796 kg and -0.795 kg, which clearly reflects the direct response of fuel consumption to the reduction in fuel. Conversely, adding the same amount of additional fuel causes the predicted fuel consumption to rise slightly, ranging from 0.795 kg to 0.796 kg. This regular change proves the clear linear relationship between fuel consumption and additional fuel. It is worth noting that the range of variation of the fuel consumption forecast values of all flights under similar conditions is relatively constant, revealing the stability of aircraft fuel consumption performance under similar loads. This finding is a valuable reference for airlines to optimize fuel configuration and flight scheduling, and emphasizes the key role of accurate fuel management in controlling operating costs and efficiency.

The changes in kerosene fuel consumption for some flights are then plotted as shown in Figure 4.9.

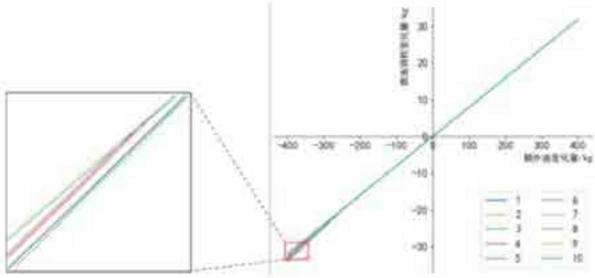


Figure 4.9 Changes in "fuel consumption" of some flights

In the display of Figure 4.9, the horizontal axis depicts the increase or decrease of the additional fuel, while the vertical axis reflects the corresponding change of kerosene fuel consumption. It is striking that most of the flight data points are closely distributed around a straight line, revealing a significant linear relationship between the two. Therefore, through linear fitting, the coefficient c=0.0809 can be obtained, that is: Ay=0.0809Ax, and the fitting degree is 0.99.

This section of the study focuses on adjusting the additional kerosene load of flights, combined with a practical application-oriented kerosene consumption prediction model, to explore how this variable affects the kerosene consumption of the A321 model. The experimental results show that every 100 kg of additional kerosene change, whether it is an increase or decrease, will result in a corresponding change of about 8.09 kg in aircraft kerosene consumption. This linear relationship not only reveals the direct connection between kerosene consumption and additional load, but also provides strong support for airlines to formulate more accurate kerosene loading strategies. By accurately calculating and controlling the kerosene loading, airlines can significantly reduce flight costs while promoting environmental protection and reducing greenhouse gas emissions caused by kerosene combustion.

4.3.3 Kerosene fuel efficiency evaluation indicators

Firstly, from both overall and stage perspectives, an evaluation method of aviation kerosene fuel utilization is proposed, and based on the actual flight conditions in actual flights and combined with pre-flight/post-flight QAR data, a study on aviation kerosene fuel efficiency evaluation is carried out.

4.3.3.1 Overall indicators

1) Hourly fuel consumption

Hourly fuel consumption is an important measure to evaluate the fuel efficiency of an aircraft. It indicates the amount of kerosene consumed by an aircraft in one hour of flight. The reduction of this value is equivalent to a significant increase in the distance or time that the aircraft can fly under the same kerosene consumption conditions, whic ient use of kerosene by the aircraft.

$$ET_i = \frac{F_i}{T_i} \quad (4.3)$$

Among them, ET i is the hourly fuel consumption of flight i, in kg/h;

F i is the kerosene fuel consumption of flight i, in kg;

Ti is the flight time of flight i, in h.

2) Mileage and fuel consumption

Mileage fuel consumption rate, as a key indicator to measure flight economy, reflects the amount of kerosene consumed by the aircraft for every kilometer it travels. This ratio is directly related to fuel efficiency. The lower the value, the farther the aircraft can cover with the same amount of kerosene consumed, thus reflecting higher fuel efficiency. In short, it is an in-depth analysis of the aircraft's kerosene utilization efficiency from the pers ion capability .

$$EL_i = \frac{F_i}{L_i} \quad (4.4)$$

Among them, EL i is the mileage fuel consumption rate of flight i, in kg/km;

F i is the kerosene fuel consumption of flight i, in kg;

Li is the flight distance of flight i, in km.

3) Range kerosene fuel ratio

Specific range, as a quantitative indicator of the ratio of range to kerosene fuel consumption, directly reflects the distance an aircraft can fly per unit of fuel consumption. It is essentially a measure of the range corresponding to each unit of kerosene consumption, which is in sharp contrast to the mileage fuel consumption rate. Specifically, when the specific range value increases, it means that the flight distance that the aircraft can cover has increased significantly while consuming the same amount of kerosene, which indicates that the efficiency of the aircraft in k ptimized and improved.

$$W_i = \frac{1}{EL_i} \quad (4.5)$$

Wherein, Wi is the range kerosene fuel ratio of flight i, in km/kg.

4) Passenger-kilometers

Passenger kilometers are an important indicator for measuring the kerosene fuel efficiency of aircraft. In essence, it is the ratio of the passenger transport volume supported by a unit of kerosene fuel to the product of the flight distance. The increase in this value directly reflects that under the same kerosene fuel consumption, the aircraft can carry passengers to cover a longer distance, which in turn reflects higher fuel economy. In other words, the increase in passenger kilometers is an effective means to comprehensively evaluate the kerosene utilization efficiency of aircraft from the two dimensions of p ht range.

$$K_i = \frac{P_i \times L_i}{F_i} \quad (4.6)$$

Where Ki is the passenger-kilometers of flight i, in person·km/kg;

Pi is the number of passengers on flight i, in persons;

Li is the flight distance of flight i, in km;

Fi is the kerosene fuel consumption of flight i, in kg.

5) Kerosene fuel consumption fluctuation rate

Based on the past flight data of a specific route and aircraft model, an average benchmark value of kerosene fuel consumption is established. Subsequently, by comparing the actual fuel consumption of each current flight with this benchmark, the change ratio of kerosene fuel consumption can be calculated. The specific calculation method is shown in Formula 4.7. The level of this change ratio directly reflects the degree of deviation of the aircraft's fuel efficiency from the historical average level: the higher the ratio, the more significantly the aircraft's kerosene consumption is reduced compared to the historical average when flying this route, thereby demonstrating a higher kerosene utilization efficiency. This statistical analysis provides a powerful tool for multi-dim

$$E_i = \left[1 - \frac{(F_i - F)}{F}\right] \times 100\% \tag{4.7}$$

Where: Ei is the kerosene fuel consumption floating rate of flight i ;

Fi is the actual fuel consumption of flight i, in kg;

Fi is the fuel consumption benchmark for this route, in kg.

4.3.3.2 Phased indicators

1) Instantaneous kerosene fuel efficiency

At any time t, the kerosene fuel efficiency of an aircraft can be embodied as the true airspeed capability converted from kerosene combustion per unit time. This efficiency is measured by the direct proportional relationship between true airspeed and kerosene consumption rate, as explained in formula 4.8. When the instantaneous kerosene fuel efficiency is improved, it means that the aircraft can obtain a higher speed increment when consuming the same amount of kerosene, thus nt improvement in its fuel utili

$$SF_{it} = \frac{TAS_{it}}{FF_{it}} \tag{4.8}$$

Where: SFit is the instantaneous kerosene fuel efficiency of flight i at time t, in km/kg;

TASit is the true airspeed of flight i at time t, in km/h;

FFit is the kerosene fuel flow rate at flight i at time t, in kg/h.

2) Cumulative kerosene fuel efficiency

Cumulative kerosene fuel efficiency is a key indicator to measure the flight economy of an aircraft at a specific time point t. It is obtained by comparing the cumulative flight distance to date with the corresponding total kerosene fuel consumed. As shown in formula 4.9. In short, the higher this ratio is, the longer the flight distance the aircraft can cumulatively cover when consuming the same amount of kerosene fuel, which reflects the aircraft's excellent efficiency in fuel utilization. This analysis method focuses on historical cumulative data and provides an intuitive quantitative basis for evaluating the fuel effic

$$LF_{it} = \frac{L_{it}}{F_{it}} \tag{4.9}$$

Where: LFit is the cumulative kerosene fuel efficiency of flight i at time t, in km/kg;

Lit is the cumulative flight distance of flight i at time t, in km;

Fit is the cumulative kerosene fuel consumed by flight i at time t, in kg.

4.3.4 Example Analysis

This paper takes one of the 135 flights as the research object and evaluates the fuel utilization before and after the flight by using flight time series and QAR data.

According to the planned fuel consumption prediction model described in Section 4.2, the fuel consumption of the aircraft under the current schedule is input and compared with the fuel consumption of the original route, so as to evaluate the fuel utilization efficiency of the aircraft from multiple perspectives, assuming that the number of passengers is 180. The results are shown in Table 4.8.

From the data comparison in Table 4.8, we can clearly see the optimization effect of the fuel consumption strategy. Under the original setting, the aircraft needs to consume 2192.042kg of fuel per hour, while the adjusted plan reduces this value to 2076.721kg, saving 115.320kg of fuel per hour. In terms of mileage efficiency, the fuel consumption per kilometer is reduced from 3.119kg to 2.955kg, and the fuel consumption per kilometer is reduced by 0.164kg. Further analysis shows that the flight distance per kilogram of fuel is increased from the original planned 0.321km to 0.338km, which means that the fuel utilization efficiency has increased by 0.018km/kg. In terms of passenger efficiency, the number of passenger kilometers that can be carried per kilogram

Table 4.8 Pre−flight fuel efficiency comparison table

Evaluation indicators	Original plan	Current plan	
Hourly fuel consumption (kg/h)	2192.042	2076.721	-115.320
Mileage fuel consumption (kg/km)	3.119	2.955	-0.164
Range fuel ratio (km/kg)	0.321	0.338	0.018
Passenger kilometers (person km/kg)	57.710	60.914	3.204
Fuel consumption fluctuation rate (%)	96.724	102.157	5.433

of fuel has increased from 57.710 person-km to 60.914 person-km, showing a stronger transportation efficiency, which is equivalent to an additional 3.204km journey for 180 passengers per kilogram of fuel. In addition, the fuel consumption fluctuation rate also increased from 96.724% to 102.157%, an increase of 5.433 percentage points, reflecting the flexibility and adaptability of the fuel management strategy. This series of data shows that the use of a plan-oriented fuel consumption forecasting model not only accurately estimates fuel demand, but also significantly promotes fuel savings and efficiency improvements.

Based on the reality-oriented fuel consumption prediction model constructed in Section 4.2, the actual fuel consumption of a flight (i.e., the current plan) is obtained by analyzing the QAR data of a certain flight, and compared with the original QAR data (i.e., the original plan), so as to comprehensively evaluate the fuel utilization efficiency of this flight. It is assumed that the number of passengers is 180, and the results are shown in Table 4.9.

Table 4.9 Post-flight fuel efficiency comparison

Evaluation indicators	Original plan	Current plan	Difference
Hourly fuel consumption (kg/h)	2304.089	2101.338	-202.751
Mileage fuel consumption (kg/km)	3.089	2.825	-0.273
Range fuel ratio (km/kg)	0.323	0.354	0.031
Passenger kilometers (person km/kg)	58.104	63.710	5.606

Analyzing the data in Table 4.9, it is found that the fuel efficiency has been significantly improved. Specifically, in terms of hourly fuel consumption, the current plan saves 202.751 kg of fuel per hour compared with the original plan, that is, from 2304.089 kg to 2101.338 kg. Further observation shows that the fuel consumption per kilometer has also been reduced from 3.089 kg in the original plan to 2.825 kg in the current plan, which means that the fuel consumption per kilometer has been reduced by 0.273 kg. From the perspective of the range-to-fuel ratio, the flight distance per kilogram of fuel in the current plan has increased from 0.323 km in the original plan to 0.354 km, achieving a breakthrough of 0.031 km more flight per kilogram of fuel. In terms of passenger-kilometer efficiency, the passenger-kilometers that can be generated by each kilogram of fuel in the current plan have increased to 63.710 person-km, compared with 58.104 person-km in the original plan, which means that each kilogram of fuel can provide an additional 5.606 km of transportation services for 180 passengers. In addition, the fuel consumption floating rate has also been adjusted, and the current plan has reached 106.451%, an increase of 9.026 percentage points from the original plan of 97.424%.

In conclusion, by using the fuel consumption prediction method based on actual data to estimate the aircraft's fuel consumption, fuel consumption can be effectively reduced and fuel efficiency can be improved.

4.4 Summary of this chapter

Through in-depth research on the prediction of aviation kerosene consumption, this chapter constructs a prediction model with RBF neural network as the core, and verifies its effectiveness through a series of rigorous verification processes and extensive applicability analysis. Taking 135 actual flights as samples, the whole process of fuel use is carefully analyzed using detailed flight planning and QAR monitoring data. In the flight preparation stage, the plan-driven model is used to estimate fuel consumption. The results show that the optimized flight plan can significantly reduce fuel consumption and effectively improve fuel efficiency. After the flight, combined with the retrospective verification of actual flight data, the results of fuel consumption reduction and efficiency improvement are once again confirmed. Further, the fuel efficiency during the flight was evaluated in stages, and it was found that whether it was takeoff acceleration, stable cruising or deceleration descent, the new scheme showed a better fuel consumption control ability, and the overall operation was stable and efficient. In addition, the study also pointed out that the slight adjustment of the amount of extra fuel carried has a significant impact on fuel consumption. Specifically, every increase or decrease of 100 kg of extra fuel will result in a corresponding increase or decrease of about 8.09 kg in fuel consumption. These findings not only emphasize the important role of fuel consumption prediction models in aviation energy conservation and emission reduction, but also provide valuable theoretical basis and practical path for the optimization and upgrading of future aviation management.

5 Conclusion and Outlook

5.1 Conclusion

Faced with the rapid development of the global aviation industry and the sharp increase in fuel demand, as an important energy source supporting this industry, the optimization of the anti-explosion performance and the accuracy of consumption prediction of aviation kerosene have become the focus of industry attention. Anti-explosion performance is not only an important indicator to measure fuel safety, but also directly affects the stable operation ability of aircraft in various complex environments. At the same time, in order to achieve cost control and operation optimization of airlines, accurate prediction of fuel consumption is crucial, which is not only related to economic benefits, but also an important way to reduce carbon emissions and practice environmental protection concepts. Therefore, combining multidisciplinary knowledge such as materials science, fluid mechanics, and thermodynamics, in-depth research on the mechanism of improving the anti-explosion performance of aviation kerosene under the action of additives, as well as the influence of different flight parameters on fuel consumption, has become a hot topic of current research. By constructing a refined prediction model, it can provide a scientific basis for the selection and consumption management of aviation fuel, and promote the aviation industry to move towards a more efficient and greener future. This research not only has far-reaching theoretical exploration value, but also has a strong demand for practical applications.

(1) In the study of the explosion characteristics of RP-3 aviation kerosene mist, the effects of three key parameters, spray pressure, detonation energy and concentration equivalence ratio, were systematically investigated. The experiment found that as the spray pressure gradually increased to 0.40 MPa, the overpressure and velocity generated by the explosion showed a significant increase, and tended to a stable high level near this pressure point, highlighting the importance of pressure regulation on explosion intensity. At the same time, the enhancement of detonation energy cannot be ignored, especially when it reached 1.68 MJ/m², the explosion velocity soared to 774 m/s, highlighting the direct effect of energy input on the intensity of the explosion. In addition, the change in concentration equivalence ratio showed a unique "inverted U" effect, and the maximum explosion efficiency appeared at an equivalence ratio of 1.28, which provided key parameters for optimizing the explosion performance of fuel mist. This series of findings not only deepened the understanding of the safety margin of aviation kerosene under different working conditions, but also provided a solid experimental basis for the application optimization and risk prevention and control strategy formulation of related industries .

(2) When analyzing the explosion potential of aviation kerosene vapor in depth, it was observed that its explosion characteristics were significantly regulated by both concentration and ambient temperature. Specifically, at 90°C, the kerosene vapor concentration of 5.0% exhibited the best explosion efficiency, at which the explosion overpressure reached a peak of 301.75 kPa, but as the concentration increased further, the efficiency showed signs of attenuation. On the other hand, the increase in ambient temperature not only failed to increase the explosion overpressure, but instead caused it to decrease and accelerated the arrival of the peak pressure, which highlights the acceleration effect of temperature on the chemical reaction rate and its profound influence on the explosion dynamics. The discussion on the explosion limit reveals another level of complexity: as the temperature rises, the lower explosion limit gradually decreases, while above 120°C, the upper explosion limit tends to stabilize. This finding deeply reflects the complex evolution of the explosiveness of kerosene vapor under the dual effects of

concentration and temperature. Is it necessary to conduct a more in-depth exploration of the specific test results and conclusions?

(3) In exploring ways to improve the anti-knock performance of aviation kerosene, we focus on three major strategies: process optimization, component enhancement, and additive application. First, we use deep secondary processing technologies, such as advanced catalytic reforming and isomerization treatment, to successfully optimize the quality of kerosene, ensuring that it can meet the stringent requirements of high-compression ratio aircraft engines. Second, experimental exploration found that although isooctane as an additive can moderately increase the octane number of kerosene, its effect has an upper limit, while isopentane shows a unique advantage in increasing the vapor pressure of kerosene. Finally, for RP-3 aviation kerosene, we conducted in-depth research on the metal ash anti-knock agent MMT and found that its optimal addition concentration range is between 200 and 300 ppm. At this concentration, it can significantly enhance the anti-knock properties of kerosene, laying a solid foundation for the efficient and stable operation of aircraft engines. In short, by combining refined processing technology with the scientific and reasonable use of additives, we have successfully achieved a significant improvement in the anti-knock performance of aviation kerosene.

(4) Using radial basis function (RBF) neural network technology, an efficient aviation kerosene fuel consumption prediction system was designed and implemented. The system showed extremely high prediction accuracy and stability in different stages of the flight cycle, including takeoff climb, air cruising, and descent approach. The experimental data clearly showed that the average error rate of the RBF model in these stages was better than that of the CNN and MLP models, specifically 5.73%, 3.36%, and 14.04%, respectively, highlighting its significant improvement in prediction accuracy. More importantly, by implementing a strict ten-fold cross-validation process, it was confirmed that the model performed uniformly on different test sets and had small error fluctuations, proving its wide applicability and reliability. In addition, an in-depth study of the impact of different parameter configurations on model performance found that the richness of the parameter set was positively correlated with the prediction accuracy of the model. In particular, when dealing with complex and variable parameter combinations, the RBF neural network showed the best prediction ability and minimized the error. This discovery not only strengthened the dominant position of the RBF neural network in the field of fuel consumption prediction, but also provided strong technical support and innovative ideas for researchers in related fields.

(5) This study focuses on analyzing the phenomenon of "fuel consumption" of aircraft and the dynamic changes of its fuel efficiency, and deeply explores the specific impact of additional fuel carried on overall fuel consumption. By constructing a fuel consumption prediction model that takes into account both the planning stage and the actual operation scenario, and relying on the detailed flight planning and QAR (Quick Access Recorder) data of 135 flights, the high accuracy of the model was successfully verified. The study found that for every 100 kg increase in additional fuel, the aircraft's fuel consumption will increase by approximately 8.09 kg. This clear linear correlation reveals the unique performance of fuel efficiency when the aircraft load is adjusted. Combined with the fuel efficiency evaluation of the entire flight cycle - covering the flight preparation, execution and subsequent analysis stages, this study shows that the constructed prediction model can significantly promote fuel savings, carbon emissions reduction and fuel efficiency improvement, providing a powerful tool and reference for airlines to optimize flight fuel planning and achieve refined management, and further promoting the green development and cost control strategies of the aviation industry.

5.2 Implications

In order to optimize the anti-explosion performance of aviation kerosene and improve its utilization efficiency, the following countermeasures can be considered:

5.2.1 Improve fuel formulation and additives

In the journey of improving the anti-knock performance of aviation kerosene, it is crucial to select base oil as a core strategy. The quality of base oil is directly related to key properties of fuel such as flash point stability, density distribution and energy density. Airlines and fuel supply companies should work together to conduct in-depth market research and explore innovative and high-efficiency base oil resources, aiming to customize the optimal ratio of aviation kerosene. Synthetic base oils and ultra-refined petroleum products have attracted much attention for their outstanding ability to resist oxidation and maintain stable performance under high temperature and pressure. Through a series of scientific and rigorous performance evaluations and comparative analyses, base oil types with significantly enhanced anti-knock performance can be identified. In addition, combined with the specific operational needs of the aviation industry, explore strategies to maximize cost-effectiveness to ensure that the selected new base oils are not only technologically advanced, but also can be used sustainably at the economic level to promote their widespread adoption.

In order to significantly improve the anti-knock properties of aviation kerosene, incorporating high-efficiency anti-knock additives has become a key strategy. The formulas of these additives often combine multiple ingredients such as antioxidants, anti-corrosion and performance enhancements, aiming to enhance the stability and safety of the fuel in all aspects. Specifically, antioxidant ingredients can significantly inhibit the oxidation process of fuel during storage and transportation, effectively curb the generation of flammable substances, and thus weaken the potential threat of explosion. At the same time, anti-corrosion agents play the role of protectors of fuel systems and engine components, extending the service life of these key components by slowing down corrosion, and indirectly reducing maintenance and replacement costs. Enhancers are committed to optimizing the combustion process of fuel, which not only improves energy output efficiency, but also significantly reduces the generation of harmful emissions. Therefore, airlines should actively carry out multi-dimensional evaluation and actual testing of additive performance to screen out the optimal additive combination solution to ensure that it is perfectly adapted to aviation kerosene and is used efficiently in actual operations.

In order to continuously enhance the explosion-proof performance of aviation kerosene and optimize its use efficiency, airlines need to build a rigorous fuel efficiency monitoring system. This system should cover the collection of real-time operating data and the integration of precise laboratory test results, aiming to deeply analyze the specific performance of the current fuel formula in the actual operation of the aircraft. Based on these detailed evaluation feedback, companies need to flexibly adjust and improve the fuel formula to ensure that it keeps pace with the latest developments in aviation technology and equipment upgrades. At the same time, we advocate close cooperation with academia and research institutions to jointly promote scientific research and innovation in the field of aviation fuel, try to introduce cutting-edge materials and technologies, and lead the performance of aviation kerosene to new heights. This continuous evolutionary strategy will not only enhance the explosion-proof capability of the fuel, but will also effectively reduce fuel consumption, optimize operational processes, and lay a solid foundation for the sustainable development of airlines.

5.2.2 Strengthening fuel management and monitoring systems

Building an intelligent management system optimized for aviation kerosene is a key measure to improve the anti-explosion performance and utilization efficiency of fuel. The system seamlessly integrates multi-dimensional data sources inside and outside the airline, covering comprehensive information such as fuel consumption, aircraft operating parameters, maintenance history, and environmental weather. With the help of cutting-edge data analysis and machine learning algorithms, it can realize dynamic monitoring of fuel status and keenly capture potential problems such as abnormal consumption and quality degradation. In addition, the platform intelligently plans flight fuel loading strategies, accurately matches demand, and effectively curbs the waste of resources caused by excessive loading. Its intuitive visual interface provides management with instant and comprehensive data insights, helps to make quick decisions, and ensures the refinement and safety of fuel management.

Strengthening the quality monitoring system of aviation kerosene is a key link in ensuring its anti-explosion ability. Airlines need to work with fuel suppliers to jointly establish and implement strict quality assessment and inspection procedures to ensure that the aviation kerosene used meets both domestic standards and international specifications. Through periodic chemical testing, the core parameters of fuel samples such as anti-explosion ability, flash point stability and density are accurately measured to ensure that the fuel is maintained at the best quality at every stage from storage to use. In addition, cutting-edge online monitoring technology is used to continuously monitor the dynamics of fuel quality, quickly capture any signs of quality degradation, and effectively prevent safety risks caused by deterioration in fuel quality. Furthermore, a fuel quality tracking system is established to cover the entire chain from procurement, storage to use, laying a solid data support for problem tracing and subsequent analysis.

Building a comprehensive aviation kerosene usage specification system is the core cornerstone for improving management effectiveness and efficiency. This specification should cover the entire chain from fuel source procurement, safe storage, seamless transportation to efficient use, to ensure that each link can achieve optimal control of fuel quality and consumption. When purchasing, priority should be given to the anti-explosion characteristics and quality of the fuel, and high-quality suppliers that meet international standards should be strictly selected to ensure fuel quality from the source. During the storage and transportation stages, a regular and detailed tank and pipeline inspection mechanism should be implemented to prevent any possible leakage and pollution risks. As for the use stage, by establishing standardized refueling procedures, the refueling volume can be accurately controlled to prevent waste. In addition, employee training and education should be strengthened to enhance the awareness of all employees on the importance of fuel management and ensure that the specifications are implemented without blind spots. The implementation of this series of measures will significantly promote the economic use of aviation kerosene while significantly reducing safety risks in operations.

5.2.3 Strengthen flight operations and training

In order to significantly improve the energy efficiency and anti-explosion performance of aviation kerosene, optimizing the flight operation process has become an indispensable part. This requires airlines to conduct a comprehensive and detailed review and innovation of existing flight procedures, aiming to guide pilots to achieve a double leap in fuel economy and safety at the practical level. Specifically, airlines can adopt a data-driven flight optimization platform, which deeply integrates historical flight data, real-time weather forecasts and detailed route planning to tailor efficient flight plans for pilots, including optimal flight trajectories, flexible climb and descent strategies, etc., to dynamically adapt to environmental changes and minimize fuel consumption. At the same time, establish and continuously improve standardized flight operation guidelines to ensure that pilots master and implement the most cutting-edge flying skills to avoid fuel waste. In addition, strengthen pilots' awareness of fuel management, and advocate strategies such as fine-tuning engine output and accurately selecting cruising layers to further improve the efficiency of aviation kerosene use.

To ensure that pilots have a high level of awareness of fuel efficiency and anti-explosion performance, it is particularly important to implement a comprehensive training program. The training needs to cover in depth the basic properties of aviation kerosene, the evaluation of its anti-explosion ability, and efficient fuel management strategies and flight operation optimization techniques. By integrating classroom teaching and practical simulation, it aims to deepen pilots' understanding of aviation kerosene, especially how to strategically allocate fuel resources at various stages of flight. Using advanced flight simulators, pilots can practice and master fuel optimization techniques in a near-realistic scenario, while exercising their rapid response and decision-making capabilities in complex situations. In addition, senior experts and engineers in the aviation industry will be invited to hold special seminars regularly. They will share the latest research results and successful cases in fuel management, prompting pilots to keep up with international trends and master cutting-edge technologies and applications. This series of carefully designed training activities aims to comprehensively enhance pilots' professional capabilities and strengthen their understanding of the importance of fuel management, so that they can take more savvy and effective measures in actual flights to improve fuel efficiency .

Building a comprehensive flight operation performance evaluation framework is essential to ensure efficient and safe training for flight operations. This framework needs to meticulously incorporate pilots' multi-dimensional indicators in the field of fuel management, such as fuel economy, range and fuel consumption ratio, and overall flight efficiency, so as to accurately measure the performance of each pilot. By implementing regular performance evaluations, airlines can keenly capture potential shortcomings and quickly adjust training programs to meet challenges. In addition, integrating such evaluations directly into the pilot's performance evaluation system can not only inspire pilots to pay attention to fuel efficiency optimization, but also enhance their professional responsibility and enthusiasm. At the same time, the evaluation results, as a valuable learning resource, should be used to commend and share best practice cases, and encourage peer pilots to learn from each other and make progress together. To achieve this goal, airlines also need to rely on advanced data analysis tools, deeply integrate flight data and evaluation standards, conduct in-depth analysis, build a closed-loop feedback mechanism, and continuously iterate flight operation specifications and training content to ensure that aviation kerosene resources are maximized and efficiency is improved.

5.2.4 Carry out technological innovation and R&D

In order to improve the key performance indicators of aviation kerosene, especially the anti-explosion ability and efficiency of use, exploring and developing efficient additives has become the core task in the field of scientific research. These additives are designed to directly enhance the anti-explosion properties by finely controlling the chemical composition and physical state of the fuel. The research team should focus on the development of innovative additives, which must take into account the three major advantages of improving combustion efficiency, reducing pollutant emissions and stabilizing fuel quality. For example, the optimized antioxidant technology can significantly extend the shelf life of kerosene, inhibit impurity deposition, and improve fuel quality in all aspects. At the same time, in response to the call for environmental protection, the development of additives based on bio-based raw materials or renewable resources has become a new trend, aiming to reduce dependence on fossil fuels and effectively reduce the environmental impact of the aviation industry. In this process, strengthening cross-border cooperation with academia, research institutions and industry leaders, and building an innovation system with deep integration of industry, academia and research will be an effective way to accelerate technological breakthroughs and promote market transformation.

Innovation of the production process of aviation kerosene, especially focusing on enhancing its anti-explosion performance and utilization efficiency, is a key link in promoting the progress of the industry. Faced with the challenges of high energy consumption, insufficient resource utilization and product quality fluctuations common in traditional processes, the introduction of advanced production technologies, such as high-efficiency catalytic cracking technology and efficient synthesis gas conversion technology, has become an important way to improve the quality of aviation kerosene. By finely controlling the reaction environment, selecting high-efficiency catalysts and optimizing the overall process layout, it is possible to significantly improve production efficiency and effectively reduce energy consumption while ensuring excellent product quality. In addition, actively promoting environmentally friendly production processes and integrating waste resource utilization technologies will not only help reduce costs, but also actively promote environmental protection and achieve a win-win situation of economic and ecological benefits.

It is important to conduct comprehensive and rigorous testing and evaluation of emerging technologies to ensure their reliability and economy in practical applications, thereby leading aviation kerosene production to a greener and more sustainable direction and laying a solid foundation for the long-term prosperity of the industry .

In order to enhance the efficiency of aviation kerosene use, it is particularly important to promote the innovation of fuel consumption prediction technology. This strategy focuses on integrating big data, AI and machine learning cutting-edge technologies to achieve refined estimates of fuel consumption. By deeply exploring past flight records, current weather conditions, aircraft load and specific route parameters, an intelligent prediction model is constructed to cope with the challenges of fuel consumption under variable flight distances and flight environments. This not only lays a solid data foundation for flight planning, but also helps airlines to fine-tune route layout and fuel procurement strategies to maximize cost-effectiveness. At the same time, the prediction model is continuously iterated and optimized, and a real-time data monitoring mechanism is integrated to ensure that the prediction results are both accurate and timely. During the implementation process, airlines should strengthen cross-departmental collaboration, closely link technology research and development, practical application and feedback optimization, and build a closed-loop fuel management ecosystem, so as to achieve a dual improvement in aviation kerosene utilization efficiency and anti-explosion performance.

5.3 Outlook

In the face of the continued growth in demand in the aviation industry, the enhancement of the anti-explosion performance of aviation kerosene and the accuracy of consumption prediction have become core issues for future exploration. In view of the increase in transportation volume, the requirements for fuel quality have reached an unprecedented level. In order to enhance the anti-explosion ability of aviation kerosene, the scientific research community is focusing on the development of new additives, striving to fine-tune its chemical and physical properties by adjusting the fuel composition. At the same time, the innovation of production processes is also regarded as a key breakthrough point, with the help of cutting-edge catalytic technology and efficient synthesis pathways, aiming to improve the production efficiency and quality standards of aviation kerosene. In addition, a new model of interdisciplinary cooperation is booming, and the integration of wisdom in fields such as chemistry, engineering and data science will promote the production of aviation kerosene towards intelligent and refined management, and comprehensively optimize its comprehensive performance in actual flight.

In the aviation field, in-depth exploration of kerosene consumption prediction technology is particularly urgent. With the vast resources of big data and cutting-edge technologies of artificial intelligence, it is expected to build an accurate prediction system for aviation kerosene consumption, which will become a strong support for airlines to formulate strategies and optimize operations. Looking to the future, the scientific research community needs to focus on the deep mining of historical data and the continuous optimization of prediction models to improve the accuracy and stability of prediction results. At the same time, building a real-time monitoring system and incorporating a feedback mechanism will greatly promote the refinement and efficiency of fuel management, and help aviation companies find the best balance between economic benefits and environmental protection. This series of research efforts will not only promote an efficiency revolution in the use of aviation kerosene, but also lay a solid foundation for the industry's green transformation and sustainable development .

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