Support Vector Machine and Artificial Neural Network in Aircraft Engine Fault Diagnosis

Yinuo Yang[1*]

[1]The Experimental High School Attached to Beijing Normal University, Beijing, China
*evelyyn1227@gmail.com

Abstract. Nowadays, the aviation industry plays an important role in the development of the country, while the need for accurate prediction of aircraft engines is increasing. Among the numerous prediction methods and models, the Support Vector Machine Method and the Artificial Neural Network Method, which will be described in this essay, are capable of making relatively accurate predictions under various circumstances based on different principles. Following a comparative analysis, it can be concluded that the support vector machine (SVM) generally outperforms the artificial neural network (ANN) in terms of diagnostic accuracy when dealing with small sample sizes. However, if the ANN is appropriately trained and optimised, its robust learning capabilities may yield superior diagnostic results when a sufficient sample size is available. Although the experiments and applications of these two methods are not yet mature at present, they can be improved and widely applied through optimisation methods in the future, which can effectively reduce maintenance costs and enhance the reliability of aircraft.

Keywords: Aircraft Engine Fault Diagnosis, Support Vector Machine (Svm), Artificial Neural Network (Ann), Prognostics And Health Management (Phm), Data-Driven Diagnosis.

1 Introduction

With the rapid development of the modern aerospace industry, the requirements for the stability and durability of aircraft are getting higher and higher. As the core of the aircraft, the engine's internal fault diagnosis has become an important step in maintaining the performance of the aircraft. Ensuring flight safety through technical means has always been a highly valued issue in aviation-developed countries. For this reason, research on aircraft engine condition monitoring and fault diagnosis has continued since the 1950s.

As the complexity of aircraft engines has been constantly improving, it is difficult to predict and locate the faults accurately and quickly by relying on traditional methods, and it is also hard to guarantee the maintenance efficiency and overall benefits [1]. Therefore, engine health management technology characterised by diagnosis and prediction has become the most important approach at present. Its development process has gone through a process from simple to complex, from offline diagnosis to real-time

A. J. Moshayedi (ed.), *Proceedings of the 2025 2nd International Conference on Electrical Engineering and Intelligent Control (EEIC 2025)*, Advances in Engineering Research 279,
https://doi.org/10.2991/978-94-6463-864-6_65

monitoring, from single to integrated, and from simplified model-based to intelligent [2]. Due to the complexity of aircraft engine operation, traditional technology finds it difficult to achieve the purpose of predicting and diagnosing faults. This paper aims to introduce two mathematical-based diagnostic methods (support vector machine, artificial neural network), analyse and compare their advantages, disadvantages, practical application scenarios, and discuss their improvement of aircraft engine fault diagnosis technology.

Prognostics and health management (PHM) technology for aircraft engines and health management. The core of PHM is to use the integration of specific sensors and various prediction methods (such as neural networks, support vector machines, etc.) to monitor and manage the health status of equipment, providing a safe and scientific environment for equipment research, use, and repair. At present, the fault diagnosis, fault prediction, and related functions of engine health management in software and hardware of the whole engine and its components are continuously strengthened.

This paper will introduce the two main methods of using data-driven diagnosis of aircraft engine failures, their main working principles, practical applications, collaborative analysis, and related future development trends.

2 Two types of engine fault diagnosis methods

2.1 Support Vector Machine Method

Support vector machine (SVM) is a method that can achieve the purpose of controlling algorithm errors through adjustment. SVM is a representative method that starts from the idea of controlling the complexity of learning machines and proposes the principle of minimising structural risk, to better diagnose faults in highly dispersed aircraft engine systems with the lowest complexity method.

The support vector machine algorithm is specifically designed for limited sample situations (i.e., engine fault detection related information is limited). Its goal is to obtain the global optimal solution, not just the optimal value when the number of samples tends to infinity [2]. Additionally, it can employ a nonlinear transformation to turn the real problem into a high-dimensional space and ensure that the learning machine's complexity is always in line with the real problem, allowing it to tackle a variety of problems adaptively.

Basic Principles of Support Vector Machine Method. Figure 1 describes the working principle of SVM. It can be found that the SVM has a network topology structure, especially when the kernel function adopts a two-layer perceptual neural network kernel, it realises the neural network function with a specific network structure. The number of support vectors is automatically generated by the algorithm. This learning unit's capacity for learning is easily managed and does not have a tendency towards overlearning.

The weights are also determined by the global optimal algorithm, which better overcomes the problem of local extreme values.

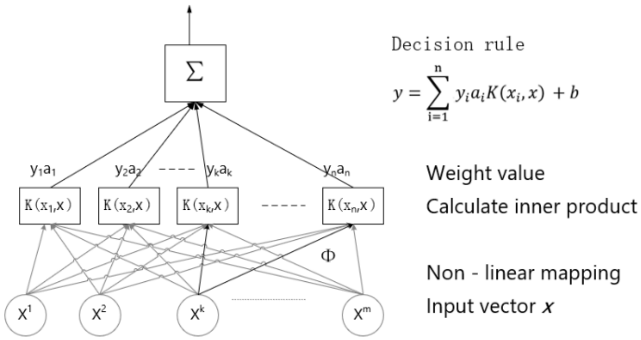

Fig. 1. Structural Network Diagram of Support Vector Machine [2]

Support vector machines are derived from statistical learning theory. This learning principle is to minimise structural risk, that is, the decision rules calculated from finite samples still have only small errors for independent test sets, which provides a framework for solving finite sample learning problems. Support vector machines offer two benefits for fault diagnosis: rapid diagnostic speed for high-dimensional samples and high diagnostic accuracy when there are few problem samples.

Pattern recognition using the SVM classification algorithm is data generation (converting the original information of the input pattern into a vector for computer processing), pattern analysis (processing data) and pattern classification (using the information obtained from pattern analysis, using the classification algorithm to train the computer and formulate the discrimination criteria). Shown in Figure 2, pattern recognition systems generally have a training phase and a testing phase; data processing uses appropriate feature extraction or feature selection methods to obtain features that can represent the input pattern, and the classifier uses the obtained features to divide the feature space to obtain the best classification surface [2].

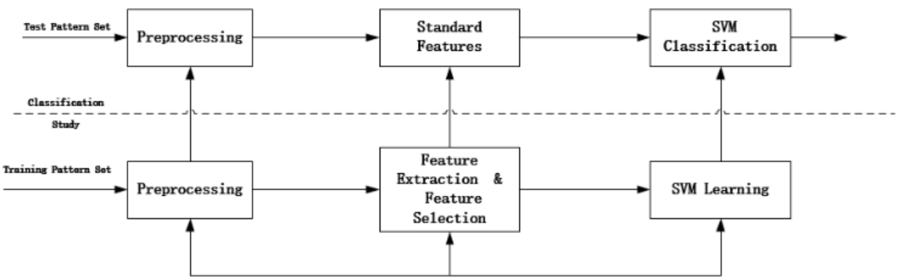

Fig. 2. General Process of SVM Pattern Recognition[2]

Application of Support Vector Machine Method. In practical applications, support vector machines can analyse engine performance trends, monitor engine health, and predict engine failure conditions based on the decoded information from the flight data recorder (including engine speed, temperature, pressure, fuel flow, engine vibration and other parameters at relevant locations) using gas path analysis methods.

The general framework of modelling based on SVM can be used to predict the metal content of lubricating oil and comprehensive performance parameters of aircraft engines. The amount of metal in lubricating oil and its consumption by aviation engines can provide an accurate indication of the state of the engine's bearings, accessories, and gears. Bearings, casings, or gears are seriously worn when lubricating oil consumption or the concentration of specific metals in lubricating oil is excessive. Monitoring lubricating oil consumption and the levels of magnesium, aluminium, iron, and copper in the oil, as well as their trends, can effectively track and forecast the wear and failure characteristics of engine transmission system components.

The flight parameter system of a certain type of aircraft records a large amount of data about lubricating oil [2]. The metal content in lubricating oil can be obtained through spectral analysis. Based on the historical data of lubricating oil metal content, a time series prediction model is established to predict and analyse the changing trend of metal content [2]. Conventional time series prediction methods are mainly based on autoregressive models. This model is very mature in theory, but its accuracy is not high, and its fault tolerance is poor, which makes it only suitable for short-term prediction [2]. Phase space theory is introduced into time series modelling. It is proposed to use the saturated embedding dimension of phase space or combine it with the FPE criterion to determine the number of input nodes of the time series model. One-step and multi-step time series prediction models based on SVM are established.

Statistical learning theory, represented by SVM, starts from the idea of controlling the complexity of learning machines and proposes the principle of structural risk minimisation, which enables learning machines to always use the function set with the lowest complexity within the allowable empirical risk range. In contrast to neural networks, statistical learning theory is built on a solid mathematical foundation and has a complete and complex theoretical system. Statistical learning theory is currently a rather established theory, but its application in engineering is still quite limited due to its lack of attention.

2.2 Artificial Neural Network Method

Artificial neural network (ANN) is a relatively advanced information processing method that plays an important role in aircraft fault diagnosis. It can use stored historical data to analyse the status and track faults. Its distributed ability to store information, parallel processing ability, and self-learning, self-organisation, and self-adaptation provide strong support for information processing in complex systems [2,3]. Since it is difficult to establish a system model for the relevant processing and calculation of fault diagnosis by analytical models, our demand for knowledge-based fault diagnosis methods is becoming more and more important and practical.

Neural networks are the most widely used data mining technique in engines, primarily for monitoring the status of engine dynamic processes, diagnosing and monitoring gas path faults, diagnosing and predicting engine faults based on oil analysis, and analysing and predicting engine reliability. The nonlinear mapping characteristics, parallel processing, and global collective action of neural networks, especially their high self-organisation and self-learning capabilities, make them an effective method for fault diagnosis and have been successfully applied in practical systems.

Basic principles of artificial neural network methods. An artificial neural network (ANN) is a mathematical model or computational model based on biological neural networks. It consists of a group of interconnected artificial neurons, uses a connectionist approach to process information, and relies on the dynamic response of the network state to external input information to process information. It is often used for classification, clustering, prediction, and pattern recognition. From a more practical point of view, neural networks are nonlinear statistical data analysis tools. They can be used to model complex relationships between inputs and outputs, or to find patterns in data. Since neural networks are best at identifying patterns or trends in data, they are very suitable for prediction or forecasting.

The neural network models in engine PHM mainly include back propagation (BP) network, radial basis function (RBF) network, probabilistic neural network (PNN), self-organising map model, fuzzy neural network, etc.

This fault diagnosis prediction is based on a self-organising map (SOM). An SOM is an artificial neural network that is trained to generate a discrete representation of the input space, called a map. Any input may affect multiple parts of the aircraft. The SOM separates the input into different parts, providing an output for each part.

Figure 3 shows the general principle of an artificial neural network (ANN). If there is a problem with any part of the aircraft, it will be inspected, and the possible problem areas and their repair solutions will be evaluated based on the reference, and the results will be fed into the ANN. Various factors affecting aircraft performance, such as maintenance history, weather, climate, airport location, flight hours, and historical data of all these variables (updated according to the results of each evaluation), will be used as input. The ANN works on the basis that the high-dimensional data input is converted to a low dimension with the help of Self Self-Organising Map (SOM) technique. The data is then clustered with the help of Multi-Dimensional Scaling (MDS), in different categories in relevance to the other data inputs [4].

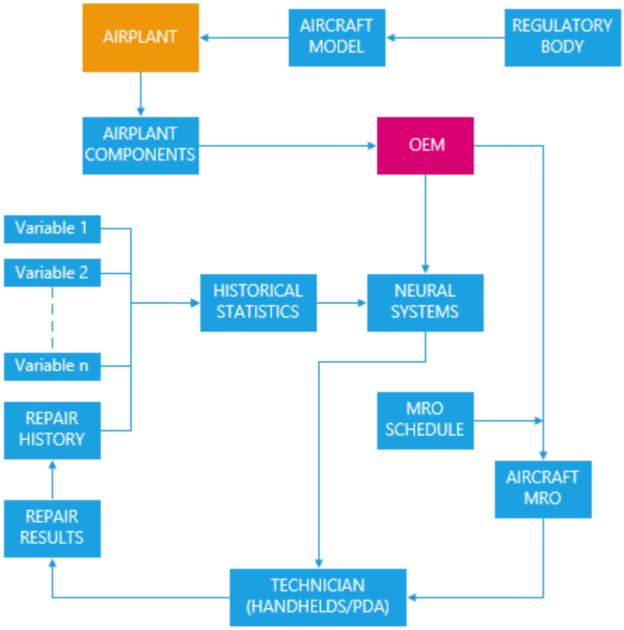

Fig. 3. Block Diagram of the Proposed System [3]

Applications of Artificial Neural Networks. Neural network has a great role in aircraft fault diagnosis. It uses historical data stored to analyse the condition and trace the fault. This neural network helps people grasp the current situation or problem better, which increases the system's overall efficiency. However, because neural networks are based on chance, they cannot be the deciding factor. Therefore, by providing the likelihood of harm, it aids man in identifying the issue and addressing it [3].

The system workflow is shown in Figure 4. MDS is a set of related statistical techniques, often used in information visualisation to explore similarities or differences between data [5]. Data clustering is a particular instance of sorting. It finds relationships and completes predictions by grouping like data together and keeping diverse data apart using the concepts of artificial neural networks. For high-performance aircraft systems, it is necessary to continuously evaluate the real-time status of the aircraft, but since operating conditions may be different, it is almost impossible to accurately predict component damage. Therefore, these conditions must be considered.

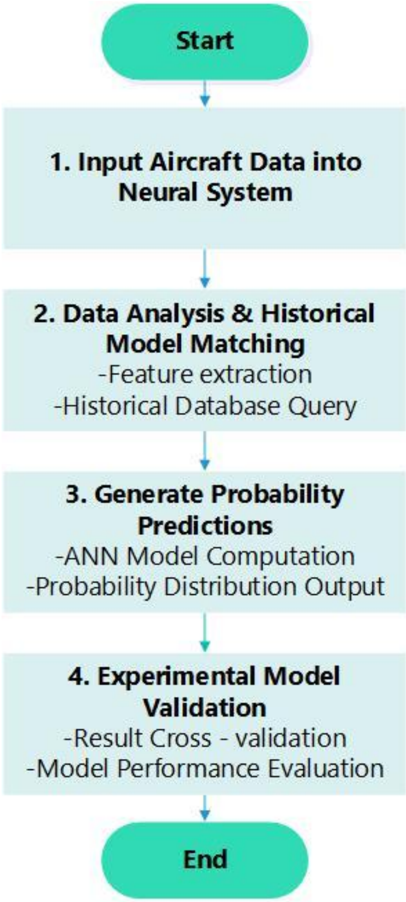

Fig. 4. ANN workflow (Picture credit: Original)

3 Comparative Analysis of Aircraft Engine Fault Diagnosis Methods

In aircraft engine fault diagnosis, the sample size has the most important impact on the evaluation of the support vector machine (SVM) algorithm and the artificial neural network (ANN) algorithm. An appropriate sample size helps improve the algorithm's diagnostic accuracy and reliability, while an inappropriate sample size can lead to problems such as overfitting and poor generalisation. The following is a comparative analysis of the two methods based on sample size, their problems, and practical applications.

The support vector machine algorithm (SVM) originates from statistical learning theory and follows the principle of structural risk minimisation. It has advantages in small sample fault diagnosis scenarios. When the sample size is small, it can effectively avoid overfitting because its goal is to obtain the global optimal solution, rather than only reaching the optimal solution when the number of samples tends to infinity. SVM's theoretical benefits allow it to conduct relatively accurate analysis and prediction in real-world applications, such as predicting the metal content of aircraft engine lubricating fluid, even when sample numbers are restricted. The model may find it challenging to learn comprehensive fault characteristics if the number of samples is too limited, which could compromise the diagnostic accuracy by failing to adequately cover different engine failure scenarios. For some complex fault modes, if there is a lack of sufficient sample support, SVM may not be able to accurately identify and classify.

As the sample size increases, SVM can learn richer fault features, making the classification more stable and thus improving the reliability of diagnosis. However, too large a sample size will also bring new problems, such as significantly extended training time, greatly increased computational complexity, and a corresponding increase in the demand for hardware resources. Excessive sample sizes can also introduce noise data, which hinders the model's ability to learn and lowers diagnostic performance.

In addition, because the support vector machine was originally used for binary classification, it cannot be directly used for some multi-class algorithm problems [2]. This method introduces decision-making into the combination of support vector machines, so that the combined classification has a strict generalizability limit. As for its training method, its essence is also a one-to-one method, but in the test phase, its judgment path is searched according to the path of the graph. As a result, there are far fewer binary classifiers used in the training phase, and the same category may be categorised in multiple ways, giving the combined classifier some redundancy. This method is sensitive to the classification results of a single classifier, and a classifier error often leads to an error in the entire classification result.

Unlike neural networks, the statistical learning theory of support vector machines is based on a solid mathematical foundation, has a complete and complex theoretical system, and is relatively mature. However, due to the very brief duration of attention, there are relatively few applications in engineering.

Applications involving defect diagnosis require large sample sizes for artificial neural networks (ANN). Training sample sets with fewer samples frequently fall short of covering all potential input locations, leading to inadequate model learning, since ANNS must learn error modes and features through a large number of samples. In aircraft engine fault diagnosis, if the sample size is insufficient, ANN may not be able to accurately capture fault features, and misdiagnosis and missed diagnosis may occur. At the same time, the generalisation ability of ANN is difficult to guarantee under small sample sizes, and it is impossible to effectively judge the correctness of the network response to the newly input data, which further reduces the diagnostic performance.

A sufficient sample size can enable ANN to learn more comprehensive and accurate fault modes, give full play to its self-learning, self-organisation, and self-adaptation capabilities, and significantly improve the accuracy and reliability of fault diagnosis. When processing high-dimensional data, a large sample size helps ANNS to mine intricate correlations in the data and better cope with complicated challenges in engine defect detection. However, too large a sample size will also bring many problems. If the sample size increases but the quality is uneven, it will also affect the model performance and lead to a decrease in diagnostic accuracy.

For artificial neural networks, their application in fault diagnosis also has the following problems. The selection of training samples and the comprehensive use of samples from different sources, as well as the reliance on models and measurement noise, may cause misdiagnosis and missed diagnosis [6]. In addition, due to the incompleteness of system samples (currently, there are only a few sample data points for some aircraft engine failures), it is difficult to achieve a certain degree of accuracy in a complex system. Secondly, the network itself may also have certain defects [7]. For example, some networks themselves have problems such as difficulty in determining the initial value of weights, difficulty in selecting the number of hidden layer nodes, and the existence of local minima. Moreover, the learning unit of the artificial neural network cannot control its learning ability during the learning process, so this learning ability may be magnified to infinity, which is prone to over-learning [2].

After comparison, it can be concluded that when the sample size is small, the support vector machine (SVM) is usually higher than the artificial neural network (ANN) in diagnostic accuracy; but when the sample size is sufficient, if the ANN can be reasonably trained and optimized, it can obtain better diagnostic results with its strong learning ability [8]. In actual aircraft engine fault diagnosis, the algorithm should be selected comprehensively based on factors such as data availability, computing resources, and diagnostic task requirements. SVM should be prioritised if the sample size is small; ANN can be tried if the sample size is large enough and computational resources permit, and its performance can be enhanced by model optimisation, appropriate sample screening, and other techniques [9,10].

4 Conclusion

At present, support vector machines (SVM) and artificial neural networks (ANN) are leading methods and technologies in aircraft engine diagnosis and monitoring. Models and theories based on basic disciplines such as mathematics and statistics have greatly promoted the development of the modern aerospace industry. Accurately anticipating and diagnosing engine problems is particularly challenging because of the intricacy of aircraft engine operations and the unpredictability of aircraft obsolescence. In practical applications, attention should be paid to the stability of diagnostic accuracy, which will undoubtedly become one of the challenges for aircraft engine fault diagnosis in the future. Due to the large demand for experiments on engine fault diagnosis systems, high failure costs, and precise data and condition control, the development of experiments on this technology is limited to a certain extent. To mitigate the combinatorial explosion problem in classification space, future complex systems may use several neural network topologies to decrease pattern-matching searches for classification. As an alternative, system optimisation can be accomplished by improving training speeds through network structure simplification and algorithm refinement.

References

1. Link, C.J., Jack, D.M.: Aircraft Engine Controls: Design, System Analysis, and Health Monitoring (AIAA, Reston, VA, 2009)
2. Li, Y., Yu, X.: Intelligent Diagnosis, Modeling and Prediction Methods for Aero Engines (National Defense Industry Press, 2013)
3. Paul, S., Kapoor, K., Jasani, D., et al.: Application of artificial neural networks in aircraft maintenance, repair and overhaul solutions, Total Eng. Anal. Manuf. Technol., 2008, pp. 1–6
4. Hornik, K., Stinchcombe, M., White, H.: Multilayer feedforward neural networks are universal approximators, Neural Netw., 2(5), 359–366(1989)
5. Kruskal, J.B.: Multidimensional Scaling (Springer, 1978)
6. Zhang, S., Kang, Y.: Application of data mining technology in aero-engine PHM, J. Proj. Rockets Missiles Guid., 28(5), 124–127(2008)
7. Wang, H., Li, D., Li, D., et al.: Remaining useful life prediction of aircraft turbofan engine based on random forest feature selection and multi-layer perceptron, Appl. Sci., 13(2), 1015(2023)
8. Zhao, Y., Lin, B., Chen, Y.: An aero-engine fault diagnosis method based on adaptive neural networks, Aerosp. Syst. Sci. Technol., 10(3), 65–71(2022)
9. Cao, M., Huang, J., Zhou, J., et al.: Current situation, challenges and opportunities of fault diagnosis and health management of civil aviation engines I: Fault diagnosis and prediction of airway, mechanical and FADEC systems, Acta Aeronaut. Sin., 43(9), 2115–2127(2022)
10. Lu, N., Chen, C., Jiang, B., Xing, Y.: Latest progress on maintenance strategy of complex systems: From condition-based maintenance to predictive maintenance, Acta Autom. Sin., 47(1), 1–14(2021)