Prognostics Health Management of Condition-Based Maintenance for Aircraft Engine Systems

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***Abstract*—Engine maintenance costs account for the largest part of the whole aircraft maintenance costs, for this reason, engine health management was presented. But almost all the researches are focused on diagnostics methods. In this paper, firstly, we analyzed the modes of engine faults, then discussed how to implement engine fault prediction and Remaining Useful Life (RUL) prediction, at last, we chose a SVM-based model to show how to predict wear trend (this belongs to the problem of fault prediction). Engine health management is also the premise of Condition Based Management (CBM) realization.**

Keywords-prognostics; engine systems; fault prediction; remaining useful life prediction; CBM

I. INTRODUCTION

Ensuring the flight safety is always a problem attached great importance of developed countries and airplanes. Around this issue, engine's condition monitoring and fault diagnosis technology keeps on developing from 1950s up to now, and has experienced a process from simple, junior, off-line diagnosis, single to complex, senior, real-time monitoring, integrated and intelligent.

In addition to the safety factor, reducing the aircraft life period cost becomes a goal almost all the airlines are pursuing. Therefore, the concept of health management is introduced into the design of aircraft. Health management is based on the diagnostic/prognostic information, available resources and use demands to make appropriate decisions on maintenance activities.

CBM (condition-based maintenance) is a series of maintenance processes and capabilities via the embedded sensors, portable external testing devices, measurement or other data collection tools to assess the real-time state of systems. CBM belongs to the category of predictive maintenance. This kind of maintenance strategy makes regularly (or continuously) condition monitoring and fault diagnosis on the main parts (or according to the needs) at run time to judge system's status, and then predicts the development trend of the system, and at last sets predictive maintenance plan in advance.

Implement the health management for aircraft is the only way to realize Condition-Based Maintenance (CBM). Engine health management (EHM) is mainly manifested in monitoring, detection, isolation, predictive trend analysis, engine demotion, fault and failure adaption, etc., and involves multiple disciplines such as material, structure and control. Managing engine health depends on the monitoring by airborne sensors, BIT and ground test equipment and the assessment of engine's key components or the whole system.

Currently, EHM is driven by various stat demotion thresholds and still has some conservative, which means we have not made full use of engine's life. Thus, engine health management system must have the predictive ability, and that is prognostics which is detecting the precursors of a failure, and predicting how much time remains before a likely failure [1]. Strictly speaking, prognostics also includes remaining useful life.

Prognostics is based on the past and present state to predict the future, from the known to the unknown. But it is also a relatively complex and difficult problem, especially for the engine's multi-factor and non-stationary and nonlinear dynamic process. Learning form the survey of IVHM prognostics methods made by Mark Schwabacher et al [1], the prognostics algorithms of aircraft engine system can be simply divided into the model-based methods and the data-driven methods. From the view of application, fault prognostics algorithms include three categories: methods based on insurance and warning devices, methods based on model and methods based on the fault warning monitoring and reasoning. RUL prognostics algorithms include: methods based on physical failure model and methods based on machine learning.

Figure1 shows the EHM prognostics algorithms.

In the algorithms of fault prediction, methods based on insurance and warning devices are realized by the built-in warning circuits. They need to be considered early in the process of system design, and just make prediction under the component level rather than the system level. In model-based methods, the models include physical models and mathematical models [2,3], by monitoring environment stress and working stress to calculate accumulative damage, the RUL will be deduced. For this kind of methods, the merit is the object's nature could be described and the fault could be predicted in real-time. But the premise is we know accurately about the mathematical model, if not, the prediction performance will be poor. An engine system is too complex for model-based methods, so that limits its application. Methods based on fault

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symptom monitoring and reasoning works via trends of measured state variables and fault symptom. Statistical models [4,5,6], neural networks[7,8,9], support vector machine[10,11] belong to this category, and these methods have a large space for development because of their outstanding intelligence.

In particular, many of the existing machine learning-based methods for RUL prediction have used artificial neural networks (NN) to model the system [7]. Nevertheless, NN are easy to fall into the local extremum which limits its development space in the aspects of RUL prediction.

The sections that follow are each devoted to one of the two parts (fault prediction and RUL prediction) described above. Section 2 analyzes the classification of engine faults briefly, not all. Section 3 focuses on the fault prediction methods, including the function of fault prediction in the design process of engine PHM system. Section 4 summarizes the current methods of engine RUL prediction, and still analyzes and presents its research direction. Section 5 is the conclusion.

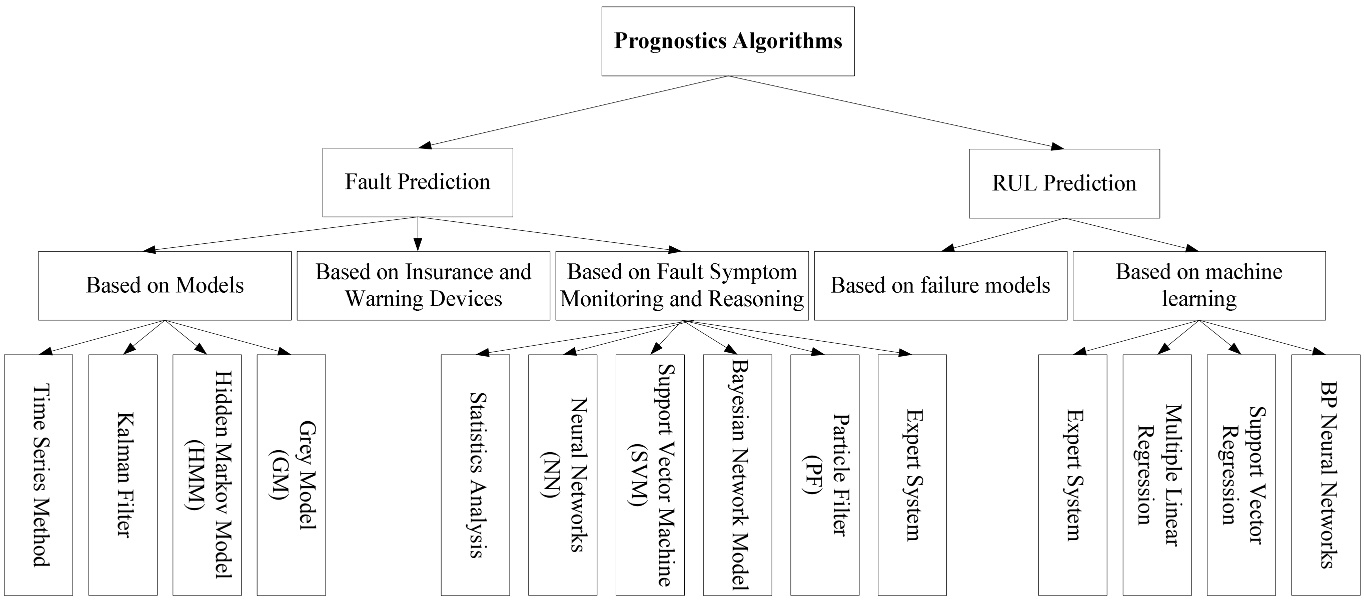


Figure 1 Taxonomy of EHM prognostics algorithms

II. Analysis on Engine Faults Classification

Aircraft engine is a complex thermal rotating machinery, under the high temperature and high pressure, high speed rotation and complex, changeful environment working condition, heavy load and harsh environment, various failure modes, multi-mode composite failure, large number of components, and for long life and other significant features, its security and maintenance support problem is very outstanding.

A typical turbine engine, for example, consists of inlet, fan, low pressure compressor, high pressure compressor, high pressure turbine, low pressure turbine, combustion chamber, transmission system, lubrication system, control system, etc.

In the process of the use of aircraft engine systems, common faults include: stable fault, gas path fault, vibration fault, wear fault, flameout fault, bearing fault, structure fatigue and control system fault.

During the use of aircraft engine, typical faults include: stability, gas line, vibration, wear, flameout, bearing, structure fatigue and control system faults.

Stable faults are an important kind of fault modes with great harmfulness and difficult to be detected out. Surge, for example, is devastating for engines; when it occurs, engine works discontinuously along with breath sounds and sharp vibration. Also engine speed will oscillate (or fall sharply), exhaust temperature will rise rapidly, and thrust force will decrease. If surge has not eliminated timely, it would cause the engine to stop or damage, even lead a serious accident.

Due to the surface’s corrosion, erosion, damage to seals, deviation of guide vanes, dirt retention, fatigue and foreign object damage, the structural size of engine changes and the performance of components declines, which could bring the so called gas line faults. Such as faults of compressor or fan, they will cause changes of the capacity of pressurization and adiabatic efficiency. For another example, turbine failure results in changes of the effective area of turbine stator and turbine expansion efficiency.

Vibration faults include the direction of the centroid offset, bend and misalign of rotor. Moreover, such as non-symmetric stiffness, instability sealing, oil film vibration, friction, looseness, cracked rotor, gear and rotation also can cause the vibration faults.

In all types of engine faults, wear is the main reason for early failure. Abnormal wear of bearings, gears and seals always become the reason that engine must be replaced because of stop-working. Engine wear faults happen at two places: 1) the oil lubrication components; 2) gas lines (e.g. blade erosion, wearing among power brakes, foreign object damage).

Bearing faults are one kind of the common faults of engine, especially spindle bearings, if there are problems, engine in-flight would shut down, even cause a serious accident. In turbine systems, rolling bearings are easy to fail. There are many fault modes of rolling bearings, and the basic forms are: wear failure, corrosion failure, fracture failure, indentation failure and scuffing failure.

Flameout faults come from the combustion chamber, the combustion instability, the flow in chamber, heart release and the change of outlet temperature are the main reasons causing the flameout.

Other faults like structure faults, control faults will not elaborate here.

III. AIRCRAFT ENGINE FAULT PROGNOSTICS

Engine fault prognostics is a more advanced maintenance support form than fault diagnosis, and it takes the current engine state as the starting point and combines with the known information (the structure properties, parameters, environmental conditions and historical data) to forecast, analyze and judge the future engine fault (with its nature, category, degree, cause and position). By fault prognostics, pre-eliminating the potential fault will be realized. This process can be descripted as a road map shown in figure 2.

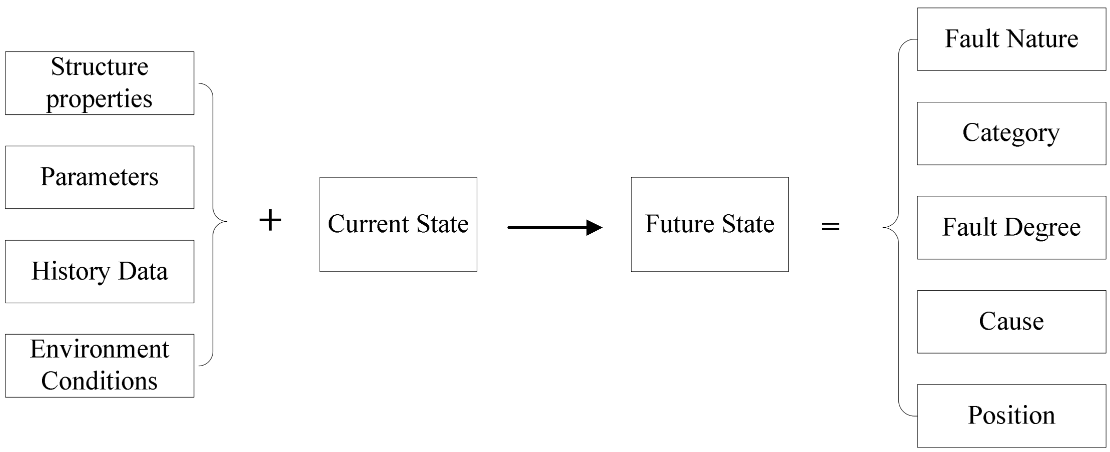


Figure 2 Engine fault prognostics road map

P-F curve is the theoretical basis of fault prognostics. This curve describes the process how the system state changes, and it is shown in figure 3. Here, point S is when the fault begins to occur, point P represents a potential fault, and in point F, the function fault happens. The time period T is the called P-F interval, which is the time course of a fault from will be happen to has been happened.

In order to prevent the function fault generated, repair time must be before point F. Meanwhile, the timing also should be after point P for making full use of the effective life, such as the point M in figure 3. This is the CBM's basic idea.

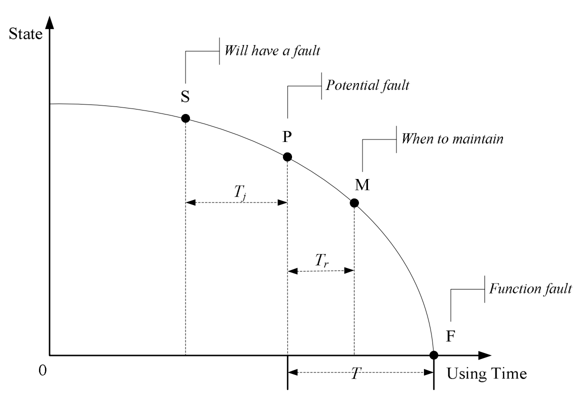


Figure 3 P-F curve

The general process of engine fault prognostics design is shown as figure 4.

A. *Determine the demand*

According to the length of time, engine fault prediction can be divided into short-term and long-term prediction, different prognostics methods play different roles on these two different prediction categories. Here three examples are given, methods based on the time series model are suitable for short-term prediction with uniform series changes rather than long-term conditions. If the history data come from a long-term time period and are regular, methods based on the fault monitoring and reasoning can be used to predict for a long time. Assuming a variable is changed as a law of exponential function, of course predicting this variable with grey model must be wise; just for a short-term task, not the long-term one. So it is necessary for prognostics to determine the demand, if wanting to get sufficiently accurate and ideal results.

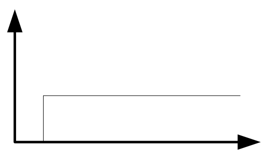
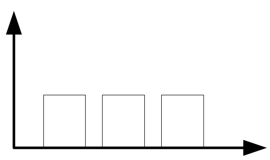
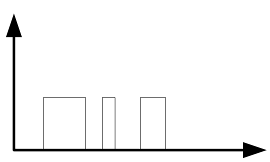
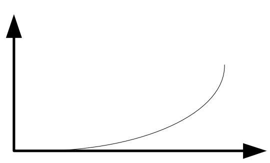
B. *Classify the fault mode*

From the view of time history of fault production, there are two different kinds of fault modes, one is paroxysmal and the other is progressive. The paroxysmal mode is produced by the external force impact on the system without any obvious symptom, and surely difficult to be monitored; that is to say, this kind of faults exhibit strong randomicity. On the contrary, the progressive mode is easier to be monitored and could make early prediction on it; generally, this kind of faults due to the system deterioration and occur in the later period of system's all life.

Fault modes have a variety of forms, table 1 presents the common ones. Binary faults refer to the simple fault or not fault case, which are not hard to be detected but predicted. Intermittent repeated faults could be isolated by some means such as reasoning or advanced time feature sets combination, however, this kind of faults are binary in essence so that also not fit for prediction. For intermittent pseudo random faults, it is not only unable to be isolated, but also hard to be predicted. Fortunately, the perfect degradation faults that can be detected and predicted by the use of system model and time correlation tracking parameter methods, simultaneously this kind of faults are most suitable for prediction.

In correspondence with the engine faults classification descripted in Section 2, table 1 created as follows:

TABLE I. COMMON FORMS OF FAULT MODES

Fault modes	**Fault mode forms**	**Corresponding to engine faults**
Binary faults		Stable faults ● surge Gas line faults ● foreign object damage ● damage of seals Bearing faults ● fracture ● rotor axle suspension ▯
Intermittent repeated faults		Vibration faults ● rotor direction of the centroid offset ● rotor bend ● rotor misalign ▯
Intermittent pseudo random faults		Control faults Structure faults Flameout faults ● flame instability ● flow in chamber ▯
Perfect degradation faults		Bearing faults ● wear failure ● corrosion failure Gas line faults ● dirt retention ● corrosion failure Wearing faults ▯

C. *Analyze supporting data*

Supporting data refer to forecasting objects' (engines') structure faults, parameters, environment conditions and history data. Different data support different prediction methods: methods based on insurance and warning devices needs the structure faults, parameters and environment conditions; methods based on models need objects' (engines') physical models or mathematical models, such as working mechanism, failure mechanism and degradation models; methods based on fault symptom monitoring and reasoning need history data, observation sequence, state sequence, topology and components' prior probability / conditional probability.

D. *Select prediction algorithms*

For the various data and the engine's (here refers to engine's subsystems, components, etc.) properties, there are many fault prediction methods could works well. So when choosing which one to use, it is important to take these factors into consideration: prediction demand, characteristics, support data and other ones.

IV. ENGINE REMAINING USEFUL LIFE PREDICTION

Prediction of engine remaining useful life is an indispensable part of engine health management. On the one hand, predicting the replacing time of engines makes it possible to manage the whole engine fleet and maintenance plans/decisions. On the other hand, failure of some parts of an engine is very dangerous, and for this reason, there must have effective means to prevent the failure.

The conventional approach is to associate the RUL of an engine with its normal working hours, and then calculate the timing of replacing this engine. When repairing the engine, some components will be retired for some reason, and some other components may be thought will-be-failure by the analysis of statistical probability so that need to be replaced. Furthermore, for security reasons, standard of components' replacing generally is weighted, which means they are still before useless.

Obviously, the RUL of an engine depends not only on its working hours, but also gas line performance, lubrication oil condition, vibration and results of borescope. Thus, comprehensively thinking about the requirements of safety and economy, it is essential for engines to develop a more accurate RUL monitoring system. Studies on RUL prediction are much less than engine fault diagnosis/prognostics, and here are two causes: firstly, engine failure models or degradation mechanism models are complex to be built; secondly, there are a large number of factors impacting RUL.

V. A PREDICTION MODEL OF WEAR TREND BASED ON SUPPORT VECTOR MACHINE

In this paper, phase space reconstruction and support vector machine (SVM) was adopted on the analysis data of a certain type of aero-engine. By analyzing the concentration of Fe element, it is able to deduce where the Fe element was appeared and make sure the severity of wear, thus assess the engine's work situation, which provides scientific basis for maintenance decision.

A. Data

Data comes from oil spectral analysis of a certain type of aircraft engine from one to another oil change, and sorted by time (88). Figure 5 shows them.

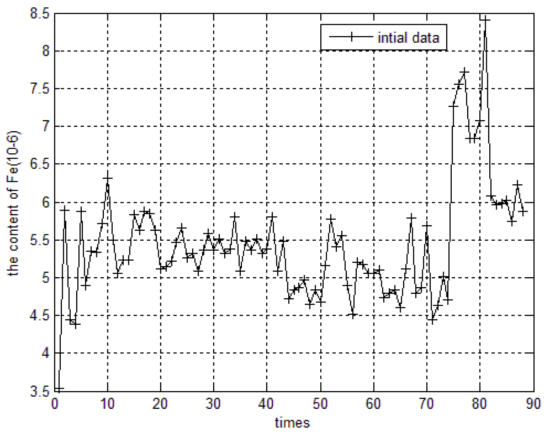


Figure 4 training and test data curve

B. Modeling

Here RBF function is chosen as SVM kernel function, loss function is ε-insensitive loss function. Modeling SVM prediction model need to determine three parameters:

(m, C, γ), where, m is the embedding dimension, C is the penalty factor, γ is the parameter of RBF kernel function.

Training data are from 1 to 62; test data are the left 63 to 88.

Order ε=0.001, log2C=0, log2γ=0, the trend of MSE-m of the SVM model is shown in figure 7. Obviously, m=5 is the best choice.

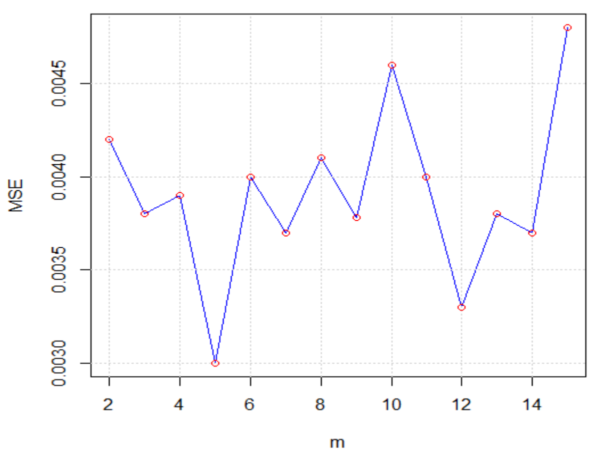


Figure 5 the trend of *MSE-m*

When m=5, select C=128, γ=16 through the cross-validation. Namely: (m, C, γ) = (5, 128, 16).

C. Results

As the results presented in figure 7, with the increase of the length of the prediction, this model still maintain a high precision.

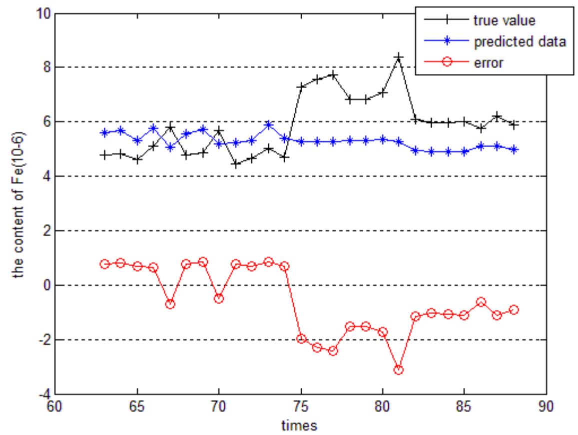


Figure 6 the results from the prediction model

VI. CONCLUSION

In this paper we have reviewed the application of condition based maintenance in the engine system, and respectively from two parts (the fault prediction and RUL prediction) to we placed great emphasis on the realization of engine prognostics health management. From the process of engine fault prognostics design to the algorithm selection, this paper presented a complete description of the process of the EHM implementation. Finally, based on support vector machine (SVM), we made a wear trend prediction for an aircraft engine system, which got the conclusion: it is theoretically achievable to develop the real engine prognostics system. Then we also need to study further such as how to make the scientific maintenance decision by using the data from prognostics, and combining with the sensor network to implement CBM on engine systems.

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REFERENCES

[1] Schwabacher M, Goebel K. A survey of artificial intelligence for prognostics[C]//Aaai fall symposium. 2007: 107-114.

[2] Goebel K, Qiu H, Eklund N, et al. Modeling Propagation of Gas Path Damage[C]//Aerospace Conference, 2007 IEEE. IEEE, 2007: 1-8

[3] Chatterjee S, Litt J. Online model parameter estimation of jet engine degradation for autonomous propulsion control[C]//Proceedings of the AIAA Guidance, Navigation, and Control Conference and Exhibit. 2003.

[4] Yan J, Koc M, Lee J. A prognostic algorithm for machine performance assessment and its application[J]. Production Planning & Control, 2004, 15(8): 796-801.

[5] Jardine A K S, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance[J]. Mechanical systems and signal processing, 2006, 20(7): 1483-1510.

[6] Wu W, Hu J, Zhang J. Prognostics of machine health condition using an improved ARIMA-based prediction method[C]//Industrial Electronics and Applications, 2007. ICIEA 2007. 2nd IEEE Conference on. Ieee, 2007: 1062-1067.

[7] Heimes F O. Recurrent neural networks for remaining useful life estimation[C] //Prognostics and Health Management, 2008. PHM 2008. International Conference on. IEEE, 2008: 1-6.

[8] Brotherton T, Jahns G, Jacobs J, et al. Prognosis of faults in gas turbine engines[C]//Aerospace Conference Proceedings, 2000 IEEE. IEEE, 2000, 6: 163-171.

[9] Bishop C M. Neural networks for pattern recognition[J]. 1995.

[10] He F, Shi W. WPT-SVMs based approach for fault detection of valves in reciprocating pumps[C]//American Control Conference, 2002. Proceedings of the 2002. IEEE, 2002, 6: 4566-4570.

[11] Brotherton T, Volponi A, Luppold R, et al. eSTORM: Enhanced self tuning on-board real-time engine model[R]. INTELLIGENT AUTOMATION CORP POWAY CA, 2003.