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Study on Gas Turbine Gas-Path Fault Diagnosis Method Based on Quadratic Entropy Feature Extraction

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ABSTRACT To avoid disrepair and over-repair and improve gas turbine reliability and availability, gas-path diagnosis is an effective technical means of disseminating early warning information for evolving or impending deterioration. Aiming at the problems of existing gas-path diagnosis methods (i.e., data-driven based gas-path diagnosis and a model-based gas-path diagnosis), this paper proposes a novel gas-path diagnosis method based on model-data hybrid drive, which is a forward solving mathematical process, to ensure real-time monitoring performance. Through case analysis, the proposed diagnostic method is not limited by the intrinsic nonlinear shape change of the characteristic maps of the actual component, which has good diagnostic applicability. And after the quadratic feature extraction of the two-dimensional entropy features (i.e., Shannon entropy and exponential entropy features), it is convenient to obtain visualized gas turbine gas-path diagnosis results for the operation and maintenance personnel. Moreover, although the extracted two-dimensional entropy values will change slightly when the operating conditions change, it can maintain good inter-class separation and intra-class aggregation performance.

INDEX TERMS Gas turbine, gas-path diagnosis, quadratic feature extraction, entropy, visualization.

I. INTRODUCTION

Gas turbines have been the core power equipment for energy efficient conversion and clean utilization in the 21st century. The gas turbine is an internal combustion heat engine that uses a continuous flow of gas as a working medium to drive the impeller to rotate at a high speed and convert the energy of the fuel into useful output power. Gas turbines are classified into aero engines, marine gas turbines, industrial gas turbines, heavy duty gas turbines, small gas turbines, and micro gas turbines depending on the application. In the second half of the 20th century, with the widespread use of gas turbines in the aerospace industry [1], due to its excellent performances such as fast start-stop, strong load-carrying capacity, high thermal efficiency and environmental protection, it is increasingly concerned by the shipbuilding industry, oil and gas pipeline transportation and industrial power plants [2]. As the power heart for the aviation industry, ship industry, industrial power station and other fields, safe and stable operation of gas turbines is the key. In the operation of the gas turbines, in addition to the harsh operating conditions of high temperature, high pressure, high rotational speed and high mechanical stress and thermal stress inside the unit, it may also suffer from surrounding polluted environmental condition, and its main components, such as compressors, combustion chambers and turbines, will produce a variety of performance degradation or damage with increasing operating time, and easily lead to various serious failures.

With the rapid development of gas turbine, the maintenance cost of gas turbine is increasing. It is reported that the operation & maintenance cost of the global industrial gas turbines exceeded \$18 billion in 2009 and is growing rapidly. In the cost of the life cycle of the F-class gas turbine power station, the operation and maintenance cost accounts for 15%-20%, of which the maintenance cost accounts for 10%-15% of the total cost. And with the advancement of

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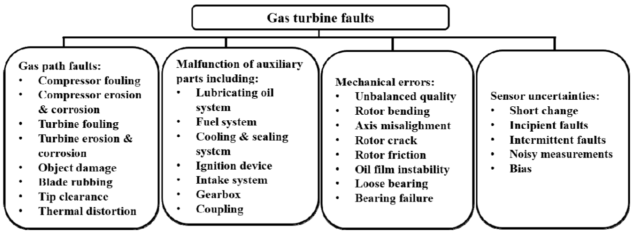
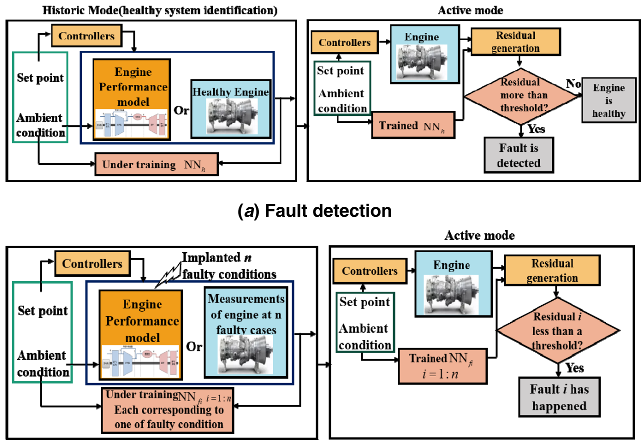


FIGURE 1. Gas turbine common faults [3].

technology, the proportion of infrastructure and fuel costs has gradually declined, and the proportion of maintenance costs has gradually increased. In gas turbine power plant equipment, the turbine, compressor, and combustion chamber have high failure rates, and the three components are the most troublesome components of heavy-duty gas turbines. At present, the world's major gas turbine manufacturers are developing next-generation gas turbines (H-class, G-class) with higher pressure ratio and gas entry temperature, and larger output power. At the same time, the working environment of heavy gas turbines is complex and the operating conditions are variable. The high parameters, complex environment and frequent changing conditions increase the risk of failure. Therefore, with the development of heavy-duty gas turbines, the reliability requirements are becoming higher and higher. At present, preventive maintenance is usually used in the daily maintenance strategy by gas turbine users, that is, it is usually determined whether minor inspection, hot gas path inspection and major overhaul are required according to the equivalent operating hours (EOH) indicated by the manufacturer. For downtime maintenance of units, both planned and unplanned, as well as ubiquitous disrepair (some components may fail prior to regular maintenance, causing the risk of abnormal equipment shutdown) and premature maintenance (Some components still have a certain remaining useful life during regular maintenance), which always means the high operating & maintenance costs. In order to improve the reliability and availability of the equipment, while maximizing the service life and reducing the operation & maintenance costs, the users need to adopt the corresponding maintenance strategy according to the actual performance and health status of the unit through monitoring, diagnosis and prognosis means, that is, condition-based maintenance, CBM.

Gas turbine common faults are seen in fig.1.

Fig.1 shows that gas turbine faults are usually divided into two categories: one is related to mechanical properties, but has no coupling relationship with aerodynamics and thermodynamics, such as shaft misalignment, rotor dynamic imbalance, bearing defects, oil film instability [4]. For such faults, many technical means, such as vibration analysis, oil chip analysis, acoustic analysis, thermal imaging, load analysis, metal temperature, stress analysis, etc., can be used to diagnose. The other category is related to aerodynamics/thermodynamics, such as compressor and turbine fouling, compressor and turbine erosion/corrosion, thermal distortion, object damage, etc.. For such failures, gas path



(*a*) Fault detection

(*b*) Fault isolation

FIGURE 2. Artificial neural network for (*a*) fault detection and (*b*) fault isolation.

analysis (GPA) is an effective technical means of issuing early warning information for evolving or impending deterioration.

The goal of the paper is to introduce a novel gas-path fault diagnosis method based on quadratic entropy feature extraction. The remainder of the paper is organized as follows. In Sec.2, the problem of existing gas-path diagnosis methods are analyzed. The description of the proposed method is presented in Sec.3. And application and analysis of the proposed approach are discussed in Sec.4, followed by the conclusions in Sec.5.

II. PROBLEM DESCRIPTION OF GAS-PATH DIAGNOSIS

A. DATA-DRIVEN BASED GAS-PATH DIAGNOSIS

Gas turbine is an input-state-output strong nonlinear coupled thermodynamic system. The change of environmental conditions (such as atmospheric temperature, pressure, relative humidity) and operating conditions (such as operation in partial load, dynamic loading and unloading) will cause significant changes in the internal state (such as the performance parameters of each component) of the thermodynamic system. It poses a daunting challenge for how to diagnose and predict component performance degradation, aging, damage, and failure conditions in such highly nonlinear systems through effective methods.

Nowadays pattern recognition and machine learning based on data-driven artificial intelligence technology, such as neural network (NN) [5], Bayesian network [6], [7], fuzzy logic [8], [9], support vector basis and rough set theory [10], have been used for gas path diagnosis based on existing fault sample sets or maintenance experience, as shown in fig.2. However, for the types of faults not involved in the sample set, it is often difficult to obtain accurate diagnostic results by these methods.

For a newly commissioned gas turbine, it is difficult to establish a complete fault sample set covering all fault types in a short time due to the lack of calibrated component failure data. To accumulate rule base for the relationship between

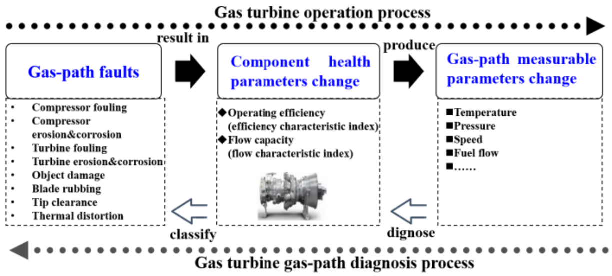


FIGURE 3. Thermodynami coupling relationship between component performance and gas-path measurable parameters.

failure modes and fault symptoms through the historical operation experience and on-site monitoring data is a difficult and time-consuming task. And it is not easy to quantitatively evaluate the severity of the fault. It restricts the application of data-driven artificial intelligence technology such as pattern recognition and machine learning.

B. MODEL-BASED GAS-PATH DIAGNOSIS

Gas turbine performance health conditions are usually expressed by the health parameters of the major components, such as the flow characteristic index (characterizing the flow capacity of the component) and the efficiency characteristic index (characterizing the operating efficiency of the component) of compressor and turbine and the efficiency characteristic index of combustion chamber [11], [12]. However, these vital health status information cannot be directly measured, so it is not easy to monitor and diagnose.

During the operation of a gas turbine, the component performance parameters (such as pressure ratio, mass flow rate, isentropic efficiency) will change when some components experience degradation or damage, and cause changes in the gas path measurable parameters (such as temperature, pressure, speed), as shown in fig.3.

In response to the above problems, the gas-path diagnosis method based on the thermodynamic model was proposed. The principle of the method is to use the gas path measurable parameters $\vec{z}$ (such as environmental parameters, operating control parameters and temperature and pressure at the inlet and outlet sections of each component) to obtain the component performance parameters $\vec{x}$ (such as mass flow rate, pressure ratio, expansion ratio, and isentropic efficiency) through thermodynamic coupling relationship. And the component health parameters $\vec{SF}$, which represent a shift of the component characteristic map due to degradation or damage, can be further obtained seen in fig.4.

The thermodynamic relationship between the gas path measurable parameters $\vec{z}$ of the gas turbine and the component performance parameters $\vec{x}$ can be expressed by Equation (1).

$$\vec{z} = f\left(\vec{x}, \vec{u}\right) + \vec{v} \tag{1}$$

where $\vec{u}$ is the ambient and operating condition vector; $\vec{v}$ is the sensor measurement noise vector.

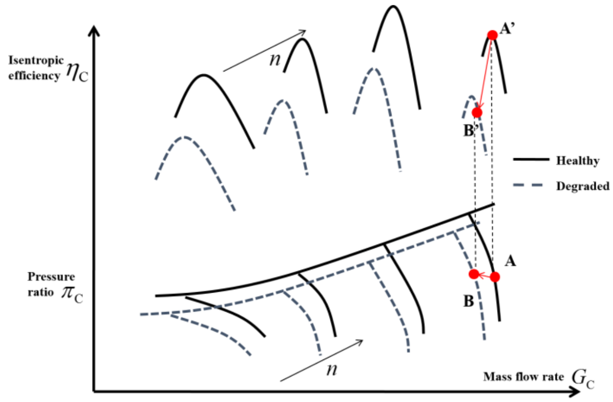


FIGURE 4. A shift of the characteristic curves on compressor map due to degradation or damage.

Performing Taylor expansion of Equation (1) in the vicinity of the benchmark operating point as follows.

$$\vec{z} = \vec{z_0} + \frac{\delta f\left(\vec{x}, \vec{u}\right)}{\delta \vec{x}}|_0\left(\vec{x} - \vec{x_0}\right) + \frac{\delta f\left(\vec{x}, \vec{u}\right)}{\delta \vec{u}}|_0\left(\vec{u} - \vec{u_0}\right) + HOT \tag{2}$$

After omitting the second-order and higher-order items *HOT*, we can obtain:

$$\Delta\vec{z} = H \cdot \Delta\vec{x} + H' \cdot \Delta\vec{u} \tag{3}$$

where $H = \frac{\delta f(\vec{x}, \vec{u})}{\delta \vec{x}}|_0$ is the influence coefficient matrix (*ICM*) and $H' = \frac{\delta f(\vec{x}, \vec{u})}{\delta \vec{u}}|_0$.

It is assumed that the environmental conditions and operating conditions are maintained at the benchmark operating point (such as on-design conditions), namely $\Delta\vec{u} = 0$. The Equation (3) can be further simplified as follows:

$$\Delta\vec{z} = H \cdot \Delta\vec{x} \tag{4}$$

$$\Delta\vec{x} = H^{-1} \cdot \Delta\vec{z} \tag{5}$$

where H^{-1} is the failure coefficient matrix (*FCM*).

Therefore, the gas turbine gas path diagnosis is an inverse mathematical process, seen in fig.5, to detect and identify the degraded components and quantify performance degradation/damage.

The gas-path diagnosis method based on the thermodynamic model is characterized in that it does not need to accumulate component fault sample sets. The method can be divided into linear method [13], [14] and nonlinear method [15] according to the thermodynamic model used. Among them, the nonlinear method is the mainstream trend of current research. With the continuous development of thermodynamic modeling method, the modeling efficiency and model precision have been greatly improved. The nonlinear gas path diagnosis method based on thermodynamic model will be an important development direction in the field of gas turbine fault diagnosis and prognosis. At present, the solution algorithms of nonlinear gas path diagnosis methods are mainly based on local optimization algorithms (such as

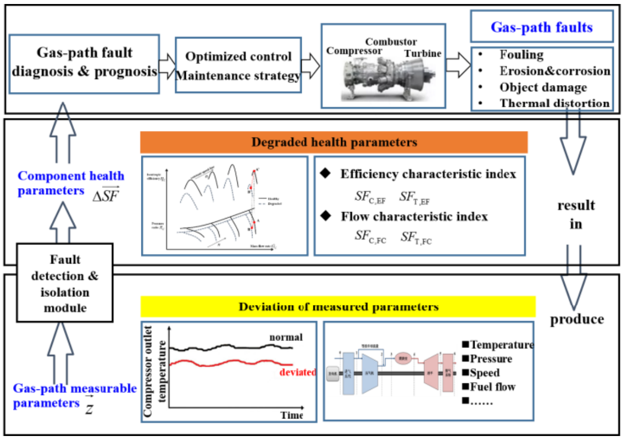


FIGURE 5. Gas turbine gas-path diagnostic process.

Newton-Raphson [16] and Kalman filter [17]) or global optimization algorithms (such as genetic algorithms (GA) [18], particle swarm optimization (PSO) [11]). There has been considerable development in solving the inherent problem of low diagnostic reliability caused by linearization of thermodynamic system and the problem that the diagnostic accuracy is sensitive to sensor measurement noise and bias [19], measurement parameter selection [20], operating conditions and environmental conditions. However, the calculation process of the currently widely used nonlinear gas-path diagnostic method is usually based on this assumption that "When the level of degradation is small, it is always assumed that the characteristic maps of the degraded components (i.e., compressors, combustors and turbines) will keep more or less the same shape as their original ones, based on the fact that the geometries of gas-path components do not change significantly after degradation." That is, in essence, component degradation or damage is characterized by an external linear shift of its characteristic maps. However, when the level of component degradation or damage gradually becomes large, the actual component characteristic maps will inevitably undergo an inherent nonlinear shape change. In this phase, the diagnostic error will inevitably increase with the augment of the level of component degradation or damage using traditional GPA method. The reliability and accuracy of existing gas path diagnostic methods have certain requirements on the degree of component degradation or damage. Therefore, it is especially important to study a gas path diagnosis method that can fully consider the intrinsic nonlinearity of the characteristic map shape when the component is degraded or damaged.

III. THE PROPOSED METHOD

Aiming at above problems, this paper proposes a novel gas path diagnosis method based on model-data hybrid drive, which is a forward solving mathematical process, seen in fig.6.

The proposed diagnostic method does not depend on the fault sample set, nor is it limited by the intrinsic nonlinear shape change of the characteristic maps of the actual component, which has good diagnostic applicability. In order to effectively identify the degraded component, it is first necessary to analyze the sensitivity of the gas-path measurable parameters to the component health parameters, so as to select the sensitive characteristic parameters for fading pattern recognition. From the sensitivity analysis of the gas-path measurement parameters to the component health parameters, the more sensitive gas-path parameters can be retained for secondary feature extraction, to obtain visualized gas turbine gas path diagnosis results for the operation and maintenance personnel.

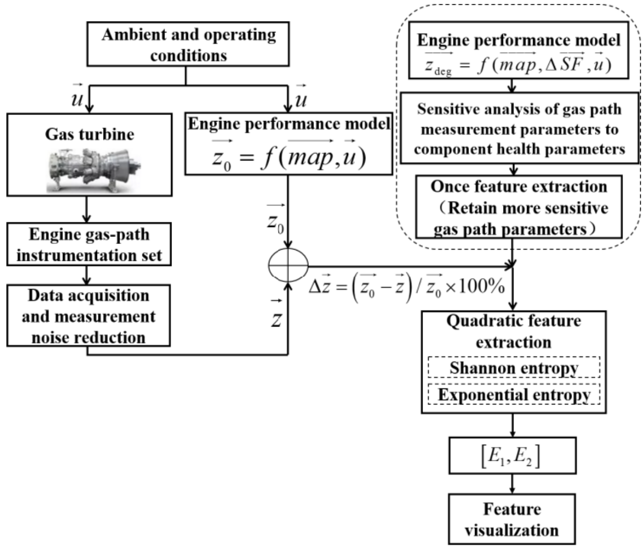


FIGURE 6. Gas turbine gas-path fault diagnosis based on quadratic entropy feature extraction.

A. QUADRATIC ENTROPY FEATURE EXTRACTION

In a system composed of a large number of atoms, molecules, etc., particles appear in various sorting ways. Wherein the degree of irregular arrangement between the particles can be expressed by entropy to indicate the degree of disorder of the system. The degree of irregular arrangement between particles can be expressed in terms of entropy to indicate the degree of disorder of the system. That is, the more disordered the particle arrangement in the system, the larger the entropy value of the system; the more ordered the particle arrangement in the system, the smaller the entropy value of the system. According to the principle of entropy increase, for an isolated closed system, the entropy value always changes in the direction of increasing, that is, the system always proceeds from the ordered to the disordered direction. In addition, there is a complementary relationship between information and entropy. It can be said that information is negative entropy, which is also the meaning of the existence of a negative sign in the definition of entropy. The relationship between information and entropy can be summarized as follows: the higher the order degree of a system, the smaller its entropy value, but the greater the amount of information the system contains; on the contrary, the higher the degree of disorder

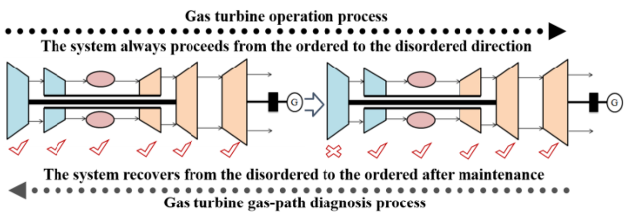


FIGURE 7. The system always proceeds from the ordered to the disordered direction.

of the system, the higher its entropy value, the smaller the amount of information the system contains.

With the rapid development of information theory, it is possible to use the information theory method to extract the secondary features of gas turbine gas path measurable signals. Entropy is a characteristic index used to measure the uncertainty of the signal distribution state and the complexity of the signal. Therefore, the information contained in the signal can be quantitatively described by the entropy. It also provides a theoretical basis for the quantitative description of the characteristics of the gas path measurable signal by entropy, as shown in fig.7.

Let the event set be X, and use the n-dimensional probability vector $\overrightarrow{P} = [P_1, P_2, \ldots, P_n]$ to represent the probability set of each event, and satisfy:

$$0 \le P_i \le 1 \tag{6}$$

And

$$\sum_{i=1}^{n} P_i = 1 \tag{7}$$

Then, the entropy E can be defined as:

$$E\left(\overrightarrow{P}\right) = E\left([P_1, P_2, \ldots, P_n]\right) = -\sum_{i=1}^{n} P_i \log_e P_i \tag{8}$$

Therefore, the entropy E can be regarded as a function of the n-dimensional probability vector $\overrightarrow{P}$.

On the basis of the definition of Shannon entropy, the definition of exponential entropy is introduced. By constructing the two-dimensional entropy features, a better quadratic feature extraction is obtained for the measurable gas-path signals.

Assume that the probability of an event is P_i, and the amount of information can be defined as:

$$\Delta I\left(P_i\right) = e^{1-P_i} \tag{9}$$

According to the basic definition of entropy, exponential entropy E can be defined as:

$$E = \sum_{i=1}^{n} P_i e^{1-P_i} \tag{10}$$

From the Equations (9) and (10), it is clear that compared with the traditional definition of the amount of information $\Delta I\left(P_i\right) = \log\left(1/P_i\right)$, $\Delta I\left(P_i\right) = e^{1-P_i}$ has the same meaning.

And the domain of $\Delta I\left(P_i\right)$ is $[0, 1]$, and $\Delta I\left(P_i\right)$ is a monotonically decreasing function, and its value range is $[1, e]$, where entropy E takes the maximum if and only if the probabilities of all events are equal.

Then, the quadratic entropy feature extraction of the gas turbine gas-path measurable parameters can be performed, and the specific steps are as follows:

Step 1: The sensitivity analysis of the measurable gas-path parameters to the component health parameters is carried out by implanting different faults in the gas turbine thermodynamic model (by setting different component health parameters), and the more sensitive gas-path parameters are retained as a feature vector $\Delta\overrightarrow{z}$, as shown in the fig.6.

Step 2: The feature vector $\Delta\overrightarrow{z}$ can be used as a certain signal sequence to perform Fast Fourier Transformation (FFT), namely:

$$F(k) = \sum_{i=1}^{m} \Delta z(i) \exp\left(-j\frac{2\pi}{m}ik\right), \quad k = 1, 2, \ldots, m \tag{11}$$

where m is the number of parameters in the feature vector $\Delta\overrightarrow{z}$.

Step 3: After the signal spectrum is obtained, the energy of each point can be calculated:

$$En_k = \left|F(k)\right|^2, \quad k = 1, 2, \ldots, m \tag{12}$$

Calculate the total energy value of each point:

$$En = \sum_{k=1}^{m} En_k \tag{13}$$

Calculate the energy probability ratio of each point to the total energy:

$$P_k = \frac{En_k}{En} = \frac{En_k}{\sum_{k=1}^{m} En_k} \tag{14}$$

Step 4: Then, Shannon entropy E_1 and exponential entropy E_2 can be respectively calculated.

$$E_1 = -\sum_{k=1}^{m} P_k \log_e P_k \tag{15}$$

$$E_2 = \sum_{k=1}^{m} P_k e^{1-P_k} \tag{16}$$

At this time, the two-dimensional entropy feature vector $[E_1, E_2]$ extracted by quadratic feature extraction can be obtained, and through two-dimensional graphic visualization, it can be used as the dominant feature vector to identify whether the main gas-path components of gas turbine have performance degradation, damage or fault.

B. THE DIAGNOSTIC PROCESS

The overall process of gas-path fault diagnosis based on quadratic entropy feature extraction is shown in fig.6.

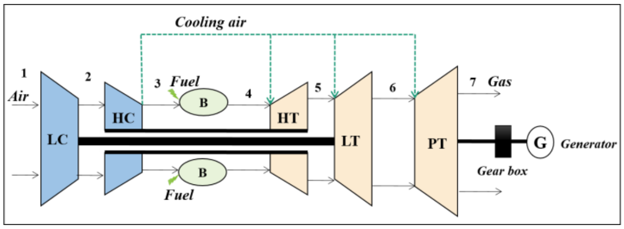


FIGURE 8. The illustration of the three-shaft gas turbine.

The specific diagnostic steps are as follows:

① Establish a full nonlinear component-level thermodynamic model of the target gas turbine that fully reflects the characteristics of each component based on gas-path measurements when the engine is clean or healthy. At this stage, adaptation methods [21] need to be used, in order that the thermodynamic results of engine performance model well matches with the actual gas-path measurements;

② The sensitivity analysis of the measurable gas-path parameters to the component health parameters is carried out by implanting different component faults in the gas turbine thermodynamic model (by setting different component health parameters), and the more sensitive gas-path parameters are retained as a feature vector;

③ The gas-path measurements of the target gas turbine are collected in real time, and taken as the gas-path parameters to be diagnosed after noise reduction processing. And it is arranged as a form of relative deviation $\Delta\overrightarrow{z} = (\overrightarrow{z_0} - \overrightarrow{z})/\overrightarrow{z_0}$ of the gas-path measurement parameters from the target gas turbine with respect to those from the engine performance model, and the advantage of this treatment is to eliminate the negative influence on the diagnostic results due to changes in environmental conditions and operating conditions;

④ The two-dimensional entropy features $[E_1, E_2]$ are further extracted by inputting the feature vector $\Delta\overrightarrow{z}$ into Shannon entropy and exponential entropy feature extraction algorithm. A component that has undergone performance degradation, damage, or failure can be detected by the inter-class separation and intra-class aggregation of each feature point on the two-dimensional feature scatter plot.

IV. APPLICATION AND ANALYSIS

A. THE TARGET GAS TURBINE

The target engine chosen for demonstration of effectiveness of the proposed approach is a three-shaft gas turbine used in marine integrated power system and its configuration is shown in fig.8.

Note: The three-shaft gas turbine contains two compressors (i.e., LC and HC), a combustor (B), three turbines (i.e., HT, LT and PT), and the generator is connected to PT by a reduction gear box. 1-2 is a compression process of air in the low-pressure compressor (LC); 2-3 is a compression process of air in the high-pressure compressor (HC); 3-4 is a combustion process of compressed air and oil fuel in the combustor (B); 4-5 is a expansion process of high temperature and pressure gas in the high-pressure turbine (HT); 5-6 is a expansion process of gas in the low-pressure turbine (LT); 6-7 is a expansion process of gas in the power turbine (PT).

LC consumes the power output of LT by a shaft to condense air from intake duct, and HC consumes the power output by a shaft to further condense air from LC. Then the high pressure air enters B together with fuel supply and the combustion product enters HT, LT and PT, to drive turbines to produce power. Eventually the power output of PT drive the generator to produce electric power output. The cooling air extracted from HC flows to the hot gas-path component to cool the front vanes and blades of HT, LT, and PT meantime. When the gas turbine runs at a certain operating condition, the PT rotational speed and generator electric power output as the key control parameter are kept constant.

TABLE 1. Gas turbine gas-path instrumentation set.

Parameter	Symbol	Unit
Ambient Pressure	p_0	MPa
Ambient Temperature	T_0	K
Relative humidity	ϕ	%
LC inlet pressure	p_1	MPa
LC inlet temperature	T_1	K
Fuel flow rate	G_f	kg/s
LC outlet pressure	p_2	MPa
LC outlet temperature	T_2	K
HC outlet pressure	p_3	MPa
HC outlet temperature	T_3	K
HT outlet pressure	p_5	MPa
HT outlet temperature	T_5	K
LT outlet pressure	p_6	MPa
LT outlet temperature	T_6	K
PT outlet pressure	p_7	MPa
PT outlet temperature	T_7	K
LT shaft rotational speed	n_1	r/min
HT shaft rotational speed	n_2	r/min
PT shaft rotational speed	n_3	r/min
Generator power output	N_e	kW

The engine gas-path instrumentation set for the gas-path analysis of the engine is shown in Table 1.

The thermodynamic model of the target gas turbine is built by a mixed programming of VC++ and MATLAB, to combine the advantages of both. C++ code execution has good real-time performance, and therefore the thermodynamic property calculation program of the working fluid is established by VC++, and compiled into a dynamic link library file suitable for MATLAB call, called as a subroutine for the engine performance model; The M script file is easy to program, and therefore the full nonlinear component-level thermodynamic model of the target gas turbine is built using the M script file from MATLAB. The input conditions of the thermodynamic model are: environmental conditions (atmospheric temperature, pressure, relative humidity), generator output power (as operating conditions), fuel composition, fuel low heat value, and component health parameters (for clean or healthy engine, $\overrightarrow{SF} = 1$). The calculated output of the thermodynamic model is: fuel flow rate, rotational speed,

TABLE 2. The common degradations and the range of component degradations.

Fault Pattern	Health Parameter	Range (%)
Compressor(LC/HC) Fouling	Flow Capacity Index $\Delta SF_{\mathrm{C,FC}}$	-5 to -1
	Isentropic Efficiency Index $\Delta SF_{\mathrm{C,Eff}}$	-5 to -1
Combustion chamber (B) failure	Combustion Efficiency Index $\Delta SF_{\mathrm{B,Eff}}$	-5 to -1
Turbine(HT/LT/PT) Erosion	Flow Capacity Index $\Delta SF_{\mathrm{T,FC}}$	1 to 5
	Isentropic Efficiency Index $\Delta SF_{\mathrm{T,Eff}}$	-5 to -1

gas-path parameters (such as pressure, temperature) at the cross section of the inlet and outlet of various components.

B. SENSITIVE ANALYSIS

According to Diakunchak's experimental results [22], the common degradations and the range of component degradations considered in this study are seen in Table 2.

The sensitivity analysis of the measurable gas-path parameters to the component health parameters is carried out by implanting different faults in the gas turbine thermodynamic model (by setting different component health parameters, seen in Table 3), and the more sensitive gas-path parameters are retained as a feature vector $\Delta\vec{z}$, as shown in the Table 4.

It can be seen from Table 4 that the performance degradation of different gas-path component will result in various gas-path measurable parameter deviations. And under the same environmental conditions and operating conditions, all cases of gas-path component performance degradations result in an increase in fuel consumption, that is, the overall thermal efficiency of the engine is reduced. From the sensitivity analysis of the gas-path measurable parameters to the component health parameters in Table 4, it can be known that for the three-shaft gas turbine, the following gas-path measurable parameters $\Delta\vec{z}$ can be selected for further quadratic entropy feature.

$$\begin{aligned}\Delta\vec{z} &= \frac{(\vec{z}-\vec{z_0})}{\vec{z_0}} \times 100\% \\ &= [\ \Delta p_1, \Delta p_2, \Delta t_2, \Delta p_3, \Delta t_3, \Delta p_5, \Delta t_5, \Delta p_6, \Delta t_6, \\ &\quad \Delta p_7, \Delta t_7, \Delta n_1, \Delta n_2, \Delta G_f\ ]^T \end{aligned} \tag{17}$$

C. QUADRATIC ENTROPY FEATURE EXTRACTION

In this study, to test the effectiveness of the proposed method, two engine thermodynamic models are used, which are established in our previous works [19].

The engine thermodynamic model for this three-shaft marine gas turbine with implanted engine component degradations is regarded as the *target gas turbine engine*. The other engine thermodynamic model for this three-shaft marine gas turbine is referred to as the *engine performance model*.

TABLE 3. Implanted major gas-path component degradations (%).

Component	Symbols	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
		Implanted Degradation (%)					
LC	$\Delta SF_{\mathrm{LC,Eff}}$	-2	0	0	0	0	0
	$\Delta SF_{\mathrm{LC,FC}}$	-2	0	0	0	0	0
HC	$\Delta SF_{\mathrm{HC,Eff}}$	0	-2	0	0	0	0
	$\Delta SF_{\mathrm{HC,FC}}$	0	-2	0	0	0	0
B	$\Delta SF_{\mathrm{B,Eff}}$	0	0	-2	0	0	0
HT	$\Delta SF_{\mathrm{HT,Eff}}$	0	0	0	-2	0	0
	$\Delta SF_{\mathrm{HT,FC}}$	0	0	0	2	0	0
LT	$\Delta SF_{\mathrm{LT,Eff}}$	0	0	0	0	-2	0
	$\Delta SF_{\mathrm{LT,FC}}$	0	0	0	0	2	0
PT	$\Delta SF_{\mathrm{PT,Eff}}$	0	0	0	0	0	-2
	$\Delta SF_{\mathrm{PT,FC}}$	0	0	0	0	0	2

Therefore, the simulated engine performance with implanted engine component degradations is called "actual performance" and the diagnostic results by the proposed method based on gas-path measurable parameters is called "predicted performance".

As measurement noise is inevitable in actual gas-path measurements and can produce a side effect on diagnosis, measurement noise is introduced in the simulated gas-path measurements to make the analysis more realistic. The maximum measurement noise for different gas-path measurements is according to the information provided by Dyson and Doel [23], as shown in Table 5.

In order to reduce the side effect of measurement noise on diagnostic results, multiple gas-path measurement samples are collected in real time and a 30-point rolling average [16]

TABLE 4. Sensitivity analysis ($t_0 = 15°$, $p_0 = 1.013$ bar, $\phi = 60\%$ and $N_e = 24265$kW).

Parameter	Measurement Deviations(%)(relative to the measurements when the engine is healthy)					
	Case1	Case2	Case3	Case4	Case5	Case6
P_1	0.038	0.038	0.001	0.064	0.036	-0.105
t_1	0	0	0	0	0	0
P_2	-1.263	1.273	0.006	2.252	-6.084	3.575
t_2	0.852	0.843	0.004	1.487	-4.293	2.491
P_3	-0.468	-0.463	-0.010	-2.936	-0.647	2.638
t_3	0.903	0.894	-0.005	-1.338	-0.309	1.200
P_5	-0.376	-0.372	-0.001	-0.619	-2.434	2.271
t_5	1.292	1.279	-0.057	2.307	0.259	0.088
P_6	-0.326	-0.323	0.003	-0.550	-0.306	0.301
t_6	1.398	1.384	-0.041	2.407	1.329	-0.450
P_7	-0.048	-0.048	0.002	-0.081	-0.045	0.413
t_7	1.720	1.703	-0.021	2.914	1.614	0.414
n_1	0.606	-0.508	-0.015	-0.857	-0.658	1.589
n_2	0.699	-0.098	-0.023	-2.675	3.129	0.037
n_3	0	0	0	0	0	0
G_f	0.711	0.704	2.076	1.182	0.659	1.963

TABLE 5. Maximum measurement noise.

	Range	Typical Error
P	3~45 psia 8~460 psia	±0.5% ±0.5% or 0.125 psia whichever is greater
t	-65~290℃ 290~1000℃ 1000~1300℃	±3.3 ℃ $\pm\sqrt{2.5^2+(0.0075\cdot t)^2}$ $\pm\sqrt{3.5^2+(0.0075\cdot t)^2}$
G_f	Up to 5450 kg/hr Up to 12260 kg/hr	63.4 kg/hr 142.7 kg/hr

can be used to obtain an averaged measurement sample before the measurements are input to the diagnostic system. And then the averaged measurement samples can be taken as the gas-path parameters to be diagnosed after noise reduction processing. The mathematical expression for the rolling averaging is shown in Equation (18).

$$\overline{z_i} = \frac{1}{q}\sum_{i=1}^{q} z_i \tag{18}$$

where z_i is i_{th} gas-path measurement samples and P is the number of samples ($q = 30$ for 30-point rolling average).

In order to test the effectiveness of the proposed method, six case studies seen in Table 6 are used, and 11 equally spaced points at the range of component degradations considered for each case study under same operating condition are used, with the diagnostic results seen in fig.9.

From fig.9, we can see that the two-dimensional entropy features $[E_1, E_2]$ are further extracted by inputting the feature vector $\Delta\vec{z}$ into Shannon entropy and exponential entropy feature extraction algorithms. When operating condition varies within 50% to 100% rated load range, the diagnostic results are seen in fig.10.

From fig.10, it is interesting to see that, although the extracted two-dimensional entropy values will change slightly when the operating conditions change, it still has good inter-class separation and intra-class aggregation performance. A component that has undergone performance degradation, damage, or failure can be detected by the inter-class separation and intra-class aggregation of each feature point on the two-dimensional feature scatter plot. The operation and maintenance personnel can clearly and conveniently monitor

TABLE 6. Implanted major gas-path component degradations (%).

		Case1	Case2	Case3	Case4	Case5	Case 6
Component	Symbols	Implanted Degradation (%)					
LC	$\Delta SF_{LC,Eff}$	-5~-1	0	0	0	0	0
	$\Delta SF_{LC,FC}$	-5~-1	0	0	0	0	0
HC	$\Delta SF_{HC,Eff}$	0	-5~-1	0	0	0	0
	$\Delta SF_{HC,FC}$	0	-5~-1	0	0	0	0
B	$\Delta SF_{B,Eff}$	0	0	-5~-1	0	0	0
HT	$\Delta SF_{HT,Eff}$	0	0	0	-5~-1	0	0
	$\Delta SF_{HT,FC}$	0	0	0	1~5	0	0
LT	$\Delta SF_{LT,Eff}$	0	0	0	0	-5~-1	0
	$\Delta SF_{LT,FC}$	0	0	0	0	1~5	0
PT	$\Delta SF_{PT,Eff}$	0	0	0	0	0	-5~-1
	$\Delta SF_{PT,FC}$	0	0	0	0	0	1~5

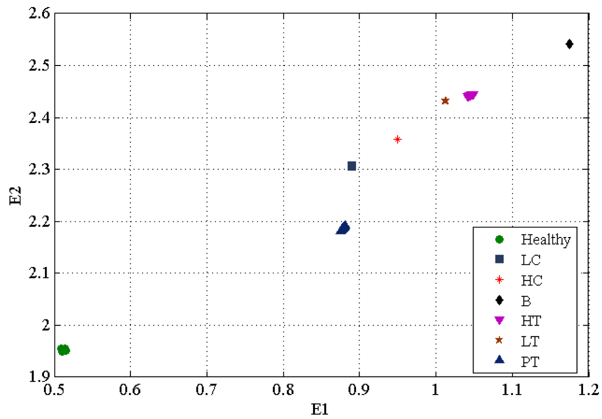


FIGURE 9. Gas turbine gas-path fault diagnosis results based on quadratic entropy feature extraction under same operating condition.

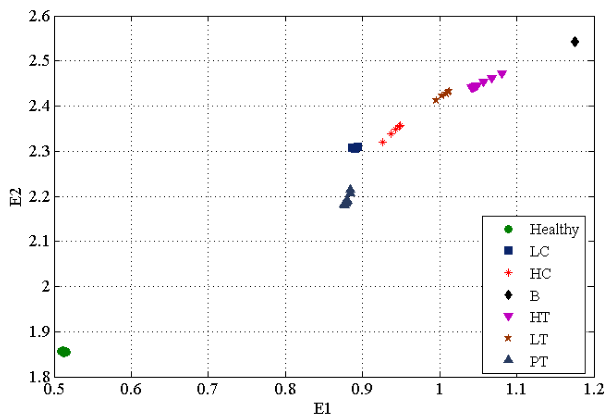
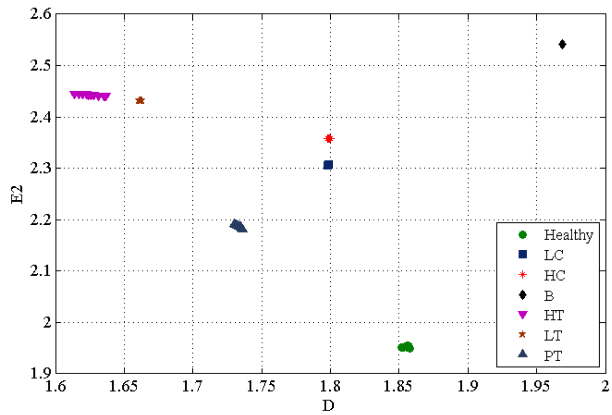
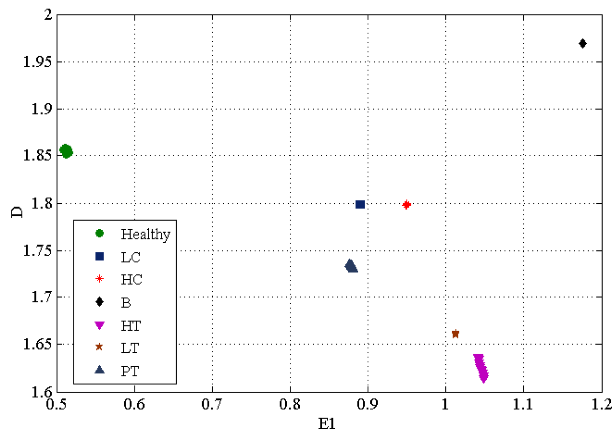


FIGURE 10. Gas turbine gas-path fault diagnosis results based on quadratic entropy feature extraction under different operating conditions.



(a) Gas turbine gas-path fault diagnosis based on exponential entropy feature and fractal box-counting dimension extraction



(b) Gas turbine gas-path fault diagnosis based on Shannon entropy feature and fractal box-countin• dimension feature extraction

FIGURE 11. Gas turbine gas-path fault diagnosis based on quadratic feature extraction.

the performance degradation of each main gas-path component of the gas turbine by the proposed method. When the main gas-path component experiences degradation, damage or failure, a certain degraded pattern will exhibit a significant intra-class aggregation degree on the two-dimensional feature scatter plot.

D. FURTHER DISCUSSION

In order to further test the effectiveness of the proposed framework of gas turbine gas-path fault diagnosis based on quadratic feature extraction, seen in fig.6, the fractal box-counting dimension characteristics (D) [24] is also used for quadratic feature extraction, with the diagnostic results seen in fig.11.

Fractal theory is one of the most important branches for contemporary nonlinear science, which is fit for processing all types of nonstationary and nonlinear phenomenon and may also be suitable for quadratic feature extraction. Fractal box-counting dimension algorithm has the virtue of simple calculation compared with other fractal dimension algorithms. From fig.11, it is interesting to see that the fractal box-counting dimension characteristics can be also used for quadratic feature extraction based on the proposed diagnostic framework. In the future research, the appropriate quadratic feature extraction algorithm can be selected according to the actual application conditions.

V. CONCLUSIONS

In this paper, a novel gas turbine gas path diagnostic framework based on model-data hybrid drive is proposed aiming at the problems of existing gas-path diagnosis methods. The related case studies have illustrated the following conclusions:

(1) The proposed diagnostic method is neither dependent on the fault sample set, nor limited by the intrinsic nonlinear shape change of the characteristic maps of the actual component, which has good diagnostic applicability.

(2) When the operating conditions change, although the extracted two-dimensional entropy values will change slightly, the diagnostic results still have good inter-class separation and intra-class aggregation performance.

(3) The fractal box-counting dimension characteristics can be also used for quadratic feature extraction based on the proposed diagnostic framework.

(4) This proposed visualization method for gas-path fault diagnosis of gas turbine based on quadratic feature extraction may make it simple for gas turbine users and operators to adopt gas-path analysis method to monitor the health status of gas turbine and bring convenience for life-cycle management.

SYMBOLS AND ABBREVIATIONS

EOH	Equivalent operating hours
CBM	Condition-based maintenance
GPA	Gas path analysis
NN	Neural network
$\overrightarrow{SF}$	Component health parameter vector
$\vec{z}$	Gas path measurement parameter vector
$\vec{x}$	Component performance parameter vector
$\vec{u}$	Ambient and operating condition vector
$\vec{v}$	Sensor measurement noise vector
HOT	Second-order and higher-order items
ICM	Influence coefficient matrix
FCM	Failure coefficient matrix
GA	Genetic algorithm
PSO	Particle swarm optimization
X	Event set
$\vec{P}$	Probability vector
E	Entropy
ΔI	Amount of information
FFT	Fast Fourier Transformation
En	Energy
LC	Low-pressure compressor
HC	High-pressure compressor
B	Combustor
HT	High-pressure turbine
LT	Low-pressure turbine

PT Power turbine
E1 Shannon entropy
E2 Exponential entropy
D Fractal box-counting dimension

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