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Gas Turbine Fault Diagnosis based on Support Vector Machine

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Abstract: Support Vector Machines (SVMs), a new generation learning system based on recent advances in statistical learning theory. This algorithm can be well applied to the structural risk minimization principle of statistical learning theory. Its greatest advantage for fault diagnosis is that it is suitable for small-sample learning problems. In this paper, a large number of fault data of gas turbine units in actual operation has collated and sorted out. the fault and corresponding fault phenomena are tabulated. After that, the historical development and basic principle of SVM are introduced. The fault diagnosis of gas turbine is realized by scikit-learn and The core code of fault diagnosis using SVM method is given. Examples shows that the method is effective under the condition of restricted samples.
Keywords: Support Vector Machines , Gas Turbine, Fault Diagnosis, Scikit-learn.

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1. INTRODUCTION

With the increasing use of gas turbines in various fields in recent years, the importance has become higher and higher, attracting many research institutions or scholars to invest in research related topics. The independent research and development capabilities of related technologies at home and abroad have been improved year by year, and new methods have emerged in an endless stream. Some of the fault diagnosis systems that have been formed have achieved considerable results in practical engineering applications.

In engineering practice, most fault diagnosis and condition monitoring technologies can easily extract fault characteristics for relatively single and simple faults, and the accuracy of fault diagnosis is relatively high. However, for faults with complex feature representations, it is difficult to identify the fault features atypically, and the fault diagnosis results are often quite different from the actual faults. It is likely to cause misdiagnosis, delay the troubleshooting time, cause the vicious development of the fault, and ultimately cause the enterprise to suffer. Huge economic and social losses[1].

Support Vector Machine (SVM) is a machine learning method based on statistical learning theory. It can well apply the principle of structural risk minimization and solve small sample and nonlinear problems in machine learning. The biggest advantage of SVM is that it is suitable for small sample decision-making. Its learning method can maximize the classification information in the sample on the basis of limited information[2-3].

2. GAS TURBINE FAULTS AND PHENOMENA CHARACTERISTICS

The structure of the gas turbine system is complex, and the working environment of some system components and its harshness make the gas turbine faults various in various forms, and the causes of the various faults are also different. Therefore, in order to use the machine learning-based method to diagnose the gas turbine, a large amount of gas turbine fault data must be used in the preliminary work as the basis for analysis and training. This paper synthesizes a large amount of literature and summarizes related materials[4-9]. See Tables 1 and Tables 2, which are the main faults and phenomena of common gas turbines.

Table 1 Gas turbine fault type

label	fault type	label	fault type	label	fault type
0	Nozzle Blockage	9	Anti-asthmatic deflation valve failure	18	Rotor blade failure
1	Blockage of Fuel Pipeline	10	Oil system	19	Great environmental change
2	Burning component damage	11	Installation and processing error	20	Intake passage failure
3	Flow distributor failure	12	IGV connecting rod is loose	21	Shaft misalignment
4	Thermocouple failure	13	Hydraulic cylinder failure	22	Fuel regulation servo valve failure
5	IBH control valve failure	14	Compressor blade fouling	23	Compressor impeller structure
6	Transition section failure	15	Seal damage	24	Signal interference
7	Natural gas temperament changes greatly	16	Compressor stator blade wear	25	Failure of Combustion Chamber Bypass Valve
8	Gas switching blow-off valve failure	17	Exhaust passage failure	26	Blockage of Swirl Blade in Combustion Chamber

3. SUPPORT VECTOR MACHINE

3.1 SVM theory

Statistical learning theory began in the 1960s, In 1971, Vapnik and Chervonenkis proposed an important theoretical basis of SVM - VC dimension theory. In 1982, Vapnik further proposed the epoch-making principle of structural risk minimization. In 1995, the famous statistician Vladimir led his team to develop a new machine learning method based on the theoretical basis of mathematical statistics - support vector machine[4][10][11].

Table 2 Gas turbine fault characteristics

index	characteristics	index	characteristics	index	characteristics
0	Increased dispersion of exhaust temperature	11	Thermocouple temperature fluctuation during load increase	22	Bearing wall temperature anomaly
1	Combustion instability	12	NOx emissions increase	23	Generator Short Circuit Trip
2	IGV Fault Alarm	13	Turbine exhaust temperature dispersion is relatively large	24	Compressor exhaust pressure lost
3	Compressor surge	14	IBH feedback deviation is large	25	Compressor flow change
4	Low Pressure Shaft Locking Jump	15	Stable at full load	26	Increase with increasing speed
5	High fluctuation of combustion chamber pressure	16	Lower frequency fluctuation is larger	27	IGV moves slowly when speeding up
6	High Temperature Between Turbine Wheels	17	Burning noise is strong	28	Lower speed
7	ACC signal abnormality	18	Gas Pressure Fluctuation	29	The compressor cannot be driven
8	Pressure fluctuation under high load	19	Failure to switch combustion mode	30	Tripping under normal conditions
9	Increase with load	20	Slow opening of control valve	31	TCS alarm
10	Stable after load reduction	21	Make an abnormal sound		

SVM evolved from the linearly separable optimal classification surface. The optimal classification surface is to require the classification line to not only correctly separate the two categories (training error rate is 0), but also to maximize the classification interval. The SVM considers finding a hyper-plane that satisfies the classification requirements, and makes the points in the training set as far as possible from the classification surface, that is, finding a classification surface to maximize the margins on both sides[12].

3.2 Fault Diagnosis of SVM Gas Turbine

The data in Table 1 and Table 2 are preprocessed and classified using scikit-learns SVM classifier[13-14]. The main codes of the calculation process are as follows:

```
X_feature=np.load("fault diagnosis file')
y = list(fault_dict.values())#feature dict
X_test = np.array([x x x x]) # test sample
model=OneVsRestClassifier(svm.SVC(kernel='linear',probability=True))
clt = model.fit(X_feature, y)
xmax =np.argmax(clt.predict_proba(X_test))
print(list(fault_dict.keys())[list(fault_dict.values()).index(xmax)])
```

Three samples were tested at the same time. The results are shown in Table 3 below.

Table 3 The predicted results of SVM are compared with the actual results.

Sample number	Predicted result	Maximum probability	Actual fault
1	Flow Distributor Failure	0.05856388	Flow Distributor Failure
2	Great changes in natural gas temperament	0.04388121	Great changes in natural gas temperament
3	Intake passage failure	0.057006	Intake passage failure

According to the above test results, it can be seen that the prediction result obtained by the SVM algorithm is consistent with the actual situation.

4. CONCLUSION

This paper briefly introduces the fault diagnosis and SVM algorithm of gas turbine. Collect a large number of fault data of gas turbine units in actual engineering applications, and collect the fault forms of all collected gas turbine units in actual application and their corresponding performance forms. Then use the SVM algorithm to build a diagnostic model, and train the sample space data with the corresponding tag pair model. In the training model, the randomly selected sample points are tested. Compared with the actual results, it can be seen that the SVM has a good ability to identify gas turbine fault diagnosis. The performance in the test is excellent and the results are satisfactory.

In summary, the SVM method based on machine learning, in a small sample, is fast and computationally small, and can be applied to online real-time monitoring and fault diagnosis requirements in the future.

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