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Defect diagnostics of gas turbine engine using hybrid SVM-ANN with module system in off-design condition†

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Abstract

A hybrid method of an artificial neural network (ANN) and a support vector machine (SVM) has been used for a health monitoring algorithm of a gas turbine engine. The method has the advantage of reducing learning data and converging time without any loss of estimation accuracy, because the SVM classifies the defect location and reduces the learning data range. In off-design condition, however, the operation region of the engine becomes wide and the nonlinearity of learning data increases considerably. Therefore, an improved hybrid method with the module system and the advanced SVM has been suggested to solve the problems. The module system divides the whole operating region into reasonably small-sized sections, and the advanced SVM has two steps of the classification. The proposed algorithm has been proven to reliably and effectively diagnose the simultaneous defects of the triple components as well as the defects of the single and dual components of the gas turbine engine in off-design condition.

Keywords: Defect diagnostics; Gas turbine engine; Hybrid method; Module system; Off-design condition

1. Introduction

The gas turbine engine as a system integration of various techniques has been used in many fields such as aerospace engineering, mechanical engineering, electronic and electrical engineering. The manufacture and the maintenance of the gas turbine engine are very important for safe operations. Recently, researches on the diagnosis system of the gas turbine engine have been highly active in order to increase the economical efficiency in the maintenance. The defect diagnosis system generally measures the performance parameters such as pressures and temperatures across each component, analyzes a certain tendency, and determines whether the engine is healthy or not[1-5]. The early detection and prediction of engine malfunction have many benefits such as preventive maintenance and the reduction of maintenance cost and time. It can also increase stability and reliability of the engine operations.

Generally, the artificial neural network (ANN), the generic algorithm (GA) and the support vector machine (SVM) have been used to develop the defect diagnosis system.[1, 6] The ANN algorithm is able to predict the characteristics of uncertain groups based on the specific information.[7, 8] The GA is a way of solving problems by mimicking the same processes as nature uses. It uses the combination of selection, recombination and mutation to evolve solutions of problems. The SVM, which is able to classify and analyze the pattern with fewer data, is a functional and efficient method[9].

The ANN algorithm has been widely used to solve the pattern recognition problem of the defect diagnostic system. However, this tool has many weak points; it's too difficult to know the ending time of learning. The most serious problem is the possibility of falling in the local minima. Because of these weak points, it

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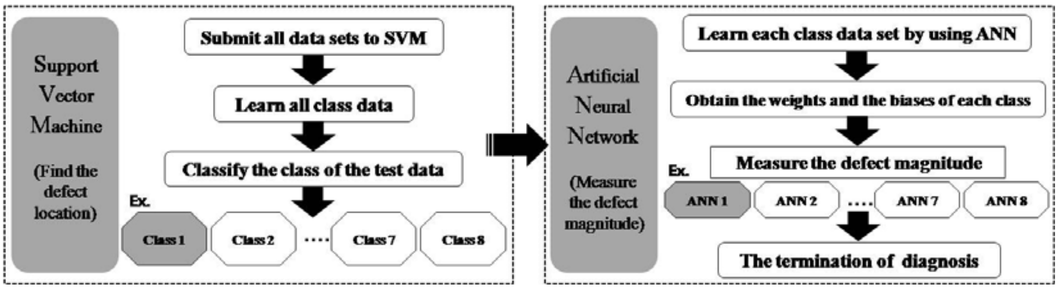

Fig. 1. Structure of hybrid method.

becomes very difficult to obtain good convergence ratio and high accuracy[10]. To solve these problems, the hybrid SVM-ANN method has been suggested[11, 12]. The SVM has been applied as a sorter of the defect location accompanied with an enormous amount of data, and the ANN algorithm has been used to estimate the defect magnitude. This hybrid method has advantages of the reduction of learning data and converging time without any loss of estimation accuracy, because the SVM classifies the defect location and then reduces the learning data range. However, since the operation region of the engine becomes wide and the nonlinearity of learning data increases considerably in off-design condition, the detecting ability of the suggested hybrid method has been deteriorated in case of the multiple defects.

In this work, therefore, an improved hybrid method with the module system and the advanced SVM has been proposed and tested to overcome the problem. The method with the advanced SVM has effectively diagnosed the multiple defects in the whole off-design region, especially the triple defect case, as well as single defects of three major components, the compressor, the gas generator turbine, and the power turbine of the gas turbine engine. A module system has been applied to reduce the number of learning data and relieve the nonlinearity of input data. As a result, it has been shown that the real-time diagnosis using the improved hybrid method for both the single and multiple defects of the gas turbine engine in off-design conditions would be possible with reliable and suitable defect estimation accuracy.

2. The hybrid method

All input data have been classified into several classes by the SVM which finds the defect location. Each class represents the kind of defect such as single, dual and triple defects. The magnitude of classified data has been measured by the ANN algorithm.

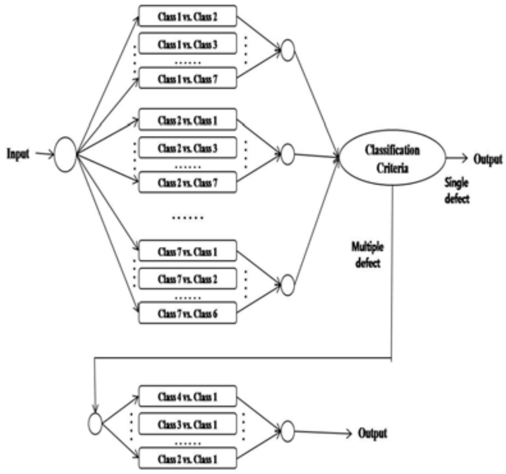

Fig. 2. Advanced support vector machine.

Fig. 1 shows the structure of the hybrid method divided into two parts, the SVM and the ANN. For example, suppose that class 1 is the compressor defect group and the defect occurred in the compressor; the SVM algorithm classifies and labels the input data into class 1[11, 12].

3. Improved method

3.1 Advanced support vector machine

The number of learning data in the triple defect case is at least six times more than that of the single and dual defect cases. When the SVM method diagnoses the defect locations of the triple defect case, the classification time considerably increases. The real-time estimation, therefore, becomes almost impossible. To reduce the running time in this case, an advanced SVM method with two step classifications has been proposed. At the first step, the "one vs. one" SVM classifies the defect position of the single defect and the multiple defects without distinguishment between the dual defects and the triple defects.[13, 14] At the next step, the multiple defects are classified into the dual defects and the triple defects by using the "one vs. one" SVM again. If the classified data has any defect at the last step, this state means the case of the triple defects. The structure of the advanced SVM method has been shown as Fig. 2.

3.2 The module system

The number of learning data is enormous and the nonlinearity of data also increases in case of off-design condition. Generally, the ANN learning data in the off-design region has been divided by the altitude. The divided data has been also split up by the fuel mass flow rate and the Mach number. Accordingly, the size of learning data becomes larger than that of sea-level condition, resulting in decreased convergence ratio. The overall behavior of the ANN method becomes poor. It is, therefore, necessary to reduce the size of learning data for the good convergence ratio without any loss of estimation accuracy. This can be solved by application of the module system. The data of all off-design regions are not supposed to be learned in the module system. The data only near the region where the defect is diagnosed by the advanced SVM are needed to be learned. That is, the whole operating region is divided into reasonable small-sized sections, the modules. To estimate the defect magnitude in the arbitrary operating point of the engine, the data of the specific module including the point have been used. Fig. 3 shows the structure of the module system.

4. Application

4.1 Engine Selection and Modeling

In this study, the improved algorithm has been applied to the turbo-shaft engine used in the smart UAV. On-design and off-design performance data of the engine have been generated by the gas turbine simulation program (GSP).[15] The characteristic maps of the centrifugal compressor and the turbine maps, which are provided by GSP, have been scaled for our own purposes.[12] The major components to estimate the engine state are the compressor, the gas-generator turbine and the power turbine, respectively. The defect positions are classified according to the components. Class 1 is the reference and normal state. Classes 2~4 represent the single defect state of each component. The dual defect states with two components are represented through class 5 to class 7. Finally, class 8 represents the triple defect state of all components. The classification is shown in Table 1.

As the input data of the defect diagnostic algorithm, the temperatures across all components and the pressures across the compressor have been obtained by

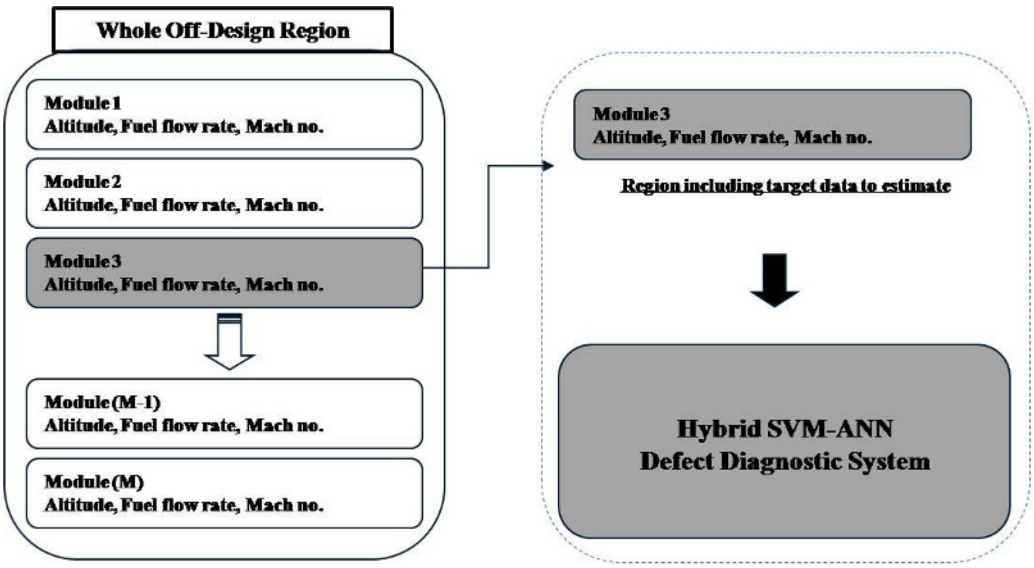

Fig. 3. Hybrid method with module system.

Table 1. Range of defect diagnostics.

Class no.	1	2	3	4	5	6	7	8
Defect no.	0	1			2			3
Compressor								
GG-Turbine								
P-Turbine								

Table 2. Input data and output data of hybrid method.

		Input	Output
Hybrid Method	Compressor	T_{t2}, T_{t3} P_{t2}, P_{t3}	η_c
	GG-Turbine	T_{t4}, T_{t7}	η_{ggt}
	P-Turbine	T_{t7}, T_{t8}	η_{pt}

GSP. The isentropic efficiency of each component as the output has been used to estimate whether the engine has any defect or not. Table 2 shows the input and output data of the engine.

4.2 Applying improved hybrid method in off-design condition

The improved hybrid method with the module system and the advanced SVM has been applied in off-design condition. For data learning, the section of data has been divided according to the variation of the altitude, the Mach number and the fuel flow rate. The altitude has been divided into 21 sections from sea level (0 m) to maximum operating altitude 4,800 m. Each altitude data includes the variation of the velocity and the fuel flow rate. The fuel flow rate and Mach number have been divided into 0.032kg/s and 0.038kg/s, and 0.1, 0.2 and 0.4, respectively. To simulate the engine with the defects, the forced defect representing the deterioration of engine performance has been imposed to learning data. The forced defect has been expressed by the minus percentage of isentropic efficiency. The defect rate of isentropic efficiency varies from 0.0 to -5.0%. For each altitude and Mach number, the fuel flow rate must be different in all cases. If the same fuel flow rate is used in all cases, the fuel lean or rich combustion appears in a certain altitude. Table 3 shows these input data for learning in off-design condition.

The test data of the simulated engine for the reliability confirmation of the improved algorithm has been obtained by GSP. The test data have been selected arbitrarily among continuous learning data, and the amount of performance deterioration has been randomly determined as shown in Table 4.

Table 3. Input data for learning on off-design.

Defect Location	Alt. (m)	Mach no.	Fuel flow rate (kg/s)	Forced defect magnitude (%)
Compressor(C)	0, 240, ~ 4,800	0.0, ~ 0.5	0.030, ~ 0.038	-0.5, -1.0, ~ -5.0
GG Turbine(GGT)				
P-turbine (PT)				
C+GGT				
C+PT				
GGT+PT				
All components				

Table 4. Test data.

Test data				
Test no.	Altitude (m)	Forced defect magnitude (%)		
		comp	GG-T	P-T
1	210	-1.3	-2.6	-3.9
2	450	-2.3	-3.6	-4.9
3	690	-3.3	-4.6	-1.9
4	930	-4.3	-1.6	-2.9
5	1000	-1.3	-2.6	-3.9
6	1230	-2.3	-3.6	-4.9
7	1470	-3.3	-4.6	-1.9
8	1710	-4.3	-1.6	-2.9
9	1950	-1.3	-2.6	-3.9
10	2190	-2.3	-3.6	-4.9
11	2430	-3.3	-4.6	-1.9
12	2670	-4.3	-1.6	-2.9
13	2910	-1.3	-2.6	-3.9
14	3150	-2.3	-3.6	-4.9
15	3390	-3.3	-4.6	-1.9
16	3630	-4.3	-1.6	-2.9
17	3870	-1.3	-2.6	-3.9
18	4110	-2.3	-3.6	-4.9
19	4350	-3.3	-4.6	-1.9
20	4590	-4.3	-1.6	-2.9

5. Results

5.1 Decision of defect position

The SVM has been used to detect the single or dual defects in off-design condition. All data have been classified 100% as shown in Table 5.

The average convergence time of defect predictions has been about 36 seconds for the cases of the single and dual defects. However, the convergence time of the triple defect case has been about 1,400 seconds. The advanced SVM has been used to solve this problem. It has classified 100% and shown an improved convergence time of about 36 seconds as shown in Table 5. The possibility of real-time diagnosis has been revealed with this method.

5.2 Estimate of defect magnitude

The defect magnitude of the data groups has been estimated by the ANN with the module system after the advanced SVM classification. The estimation has been performed by using weights and biases to complete the learning procedure. All kinds of defect cases such as the single, the dual and the triple defects, have been diagnosed in this application. The RMS defect error rate calculated at each altitude has been used to estimate the algorithm reliability, which means the percentage of the difference between the real defect and the calculated defect values. [11, 12] For each test data, the relative error rate between the real and calculated defect magnitudes also has been used in order to express the calculation accuracy. The defect magnitudes of the single or the multiple defects have been imposed according to the values in Table 4, which shows there are total 20 sets of the test data number.

Figs. 4, 5 and 6 show the efficiencies and the relative error rates of the single defect cases. The square symbol filled with black means the efficiency by the

Table 5. SVM classification results.

Defect position	Classification Accuracy	General	Advanced
		Average convergence time	
C	100 %	36 s	36 s
GGT	100 %		
PT	100 %		
C+GGT	100 %		
C+PT	100 %		
GT+PT	100 %		
C+GT+PT	100 %	1400 s	36 s

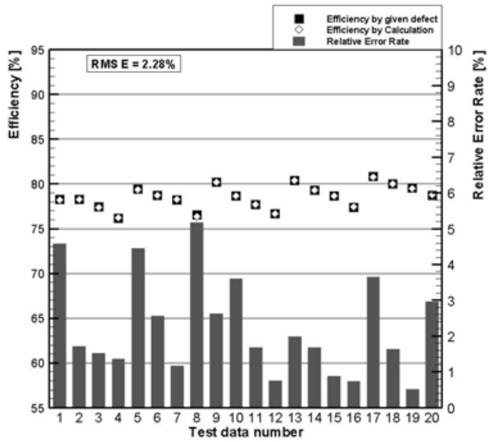

Fig. 4. Estimate efficiencies and relative error rate of compressor.

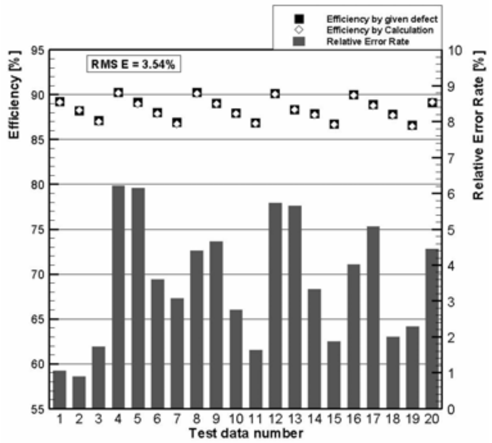

Fig. 5. Estimate efficiencies and relative error rate of gas generator turbine.

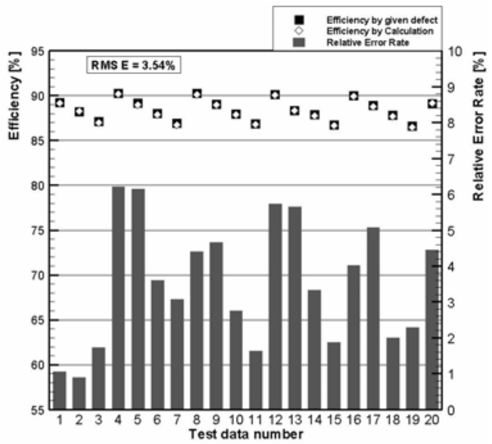

Fig. 6. Estimate efficiencies and relative error rate of Power Turbine.

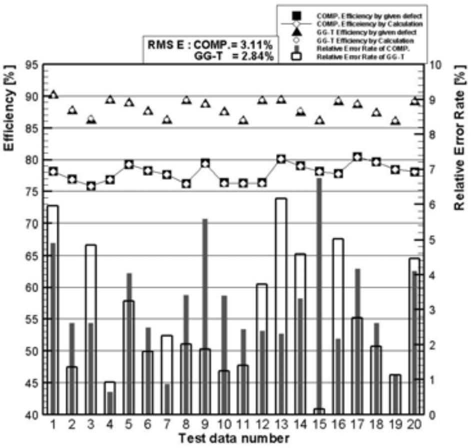

Fig. 7. Estimate efficiencies and relative error rate of compressor and GG-Turbine.

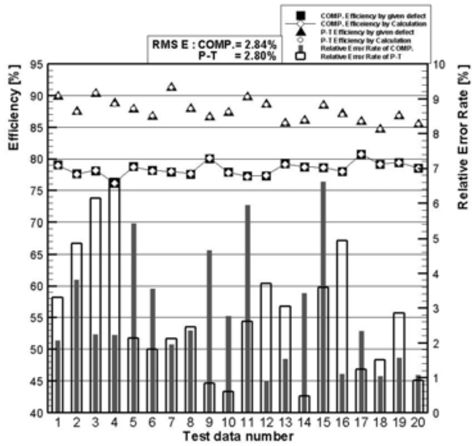

Fig. 8. Estimate efficiencies and relative error rate of compressor and power turbine.

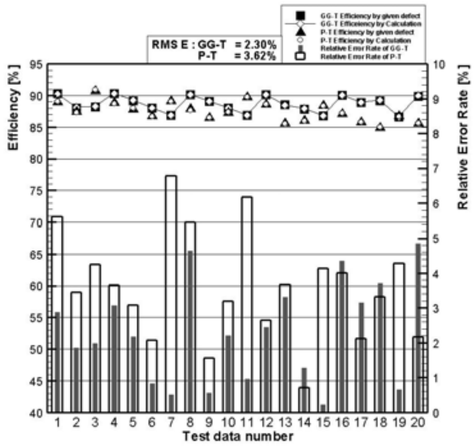

Fig. 9. Estimate efficiencies and relative error rate of GG-turbine and power turbine.

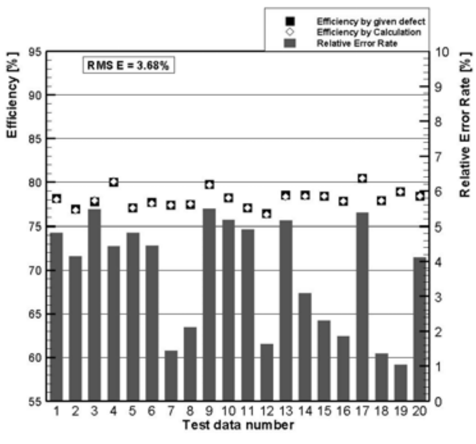

Fig. 10. Estimate efficiencies and relative error rate of Compressor in triple defect case.

imposed defect while the diamond symbol reveals the calculated efficiency (the left-hand side of the y-axis).

The relative error rate of each test case is expressed by the bar graph (the right-hand side of the y-axis). The x-axis represents the test data number. In the single defect diagnoses, the RMS defect error rates of each component have been shown about 2.3%, 3.5%, and 2.9% for the compressor, the G-G turbine, and the power turbine, respectively.

The efficiencies and the relative error rates of the dual defect cases are shown in Figs. 7, 8 and 9, which show the multiple defects of the compressor and G-G turbine, the compressor and power turbine, the G-G turbine and power turbine, respectively. In a similar manner as the single defect, the triangle and square symbols filled with black represent the real efficiency. The hollowed diamond and circle mean the calculated efficiency. From the dual defect diagnoses, the RMS defect error rates have been revealed as about 3.1% and 2.8%, 2.8% and 2.8%, and 2.3% and 3.6% for the compressor and G-G turbine, the compressor and power turbine, G-G turbine and power turbine, respectively.

Figs. 10, 11 and 12 show the triple defect cases. The triple defect case has been the representative result by the improved hybrid method with the module system and the advanced SVM. Similar to the above, the RMS defect error rates have appeared as 3.7%, 1.3%, and 2.8% for the compressor, the G-G turbine, the power turbine, respectively. The results in all figures have shown that the RMS error rates of all cases have less than 5% difference between the imposed and calculated defect magnitudes.

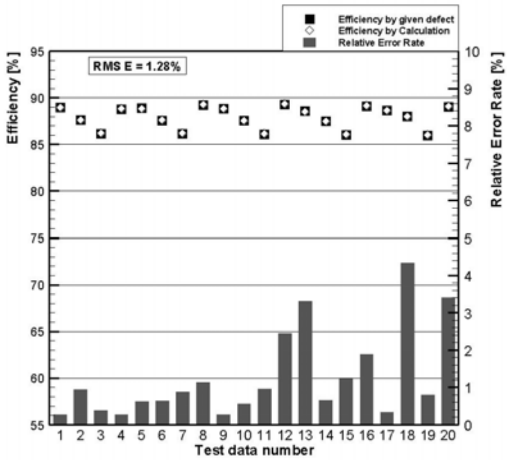

Fig. 11. Estimate efficiencies and relative error rate of GG-turbine in triple defect case.

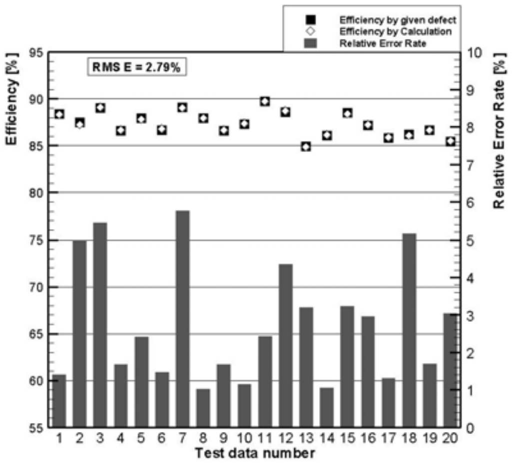

Fig. 12. Estimate efficiencies and relative error rate of Power turbine in triple defect case.

In Table 6, for example, the defect mean error rates of the non-module learning and the module learning of the hybrid method have been compared at 1,000m. For the single defect cases, the defect error rates have decreased from 12.6% to 4.5% for the compressor, from 16.5% to 6.7% for the G-G turbine, and from 20.2% to 2.1% for the power-turbine, respectively. The defect error rates for the dual defect cases have been reduced from 37.6% and 9.1% to 4.0% and 3.3% for the compressor and G-G turbine, from 31.9% and 44.3% to 8.5% and 2.2% for the compressor and power turbine, and from 17.8% and 33.3% to 2.2% and 3.1% for the G-G turbine and power turbine, respectively. Also, for the triple defect case, the defect error rates have decreased from 39.9%, 9.1% and

Table 6. Comparison of defect mean error rates between non-module and module learning of hybrid method.

<table>
<tr><td rowspan="2"></td><td colspan="6">Defect mean error rate (%)</td></tr>
<tr><td colspan="3">Learning of all data For 1,000m</td><td colspan="3">Learning of one module for 1000m</td></tr>
<tr><td>C</td><td colspan="3">12.55</td><td colspan="3">4.47</td></tr>
<tr><td>GG-T</td><td colspan="3">16.54</td><td colspan="3">6.16</td></tr>
<tr><td>P-T</td><td colspan="3">20.21</td><td colspan="3">2.05</td></tr>
<tr><td>C/ GG-T</td><td colspan="2">37.61</td><td>9.08</td><td>4.04</td><td colspan="2">3.25</td></tr>
<tr><td>C/ P-T</td><td colspan="2">31.91</td><td>44.27</td><td>8.48</td><td colspan="2">2.16</td></tr>
<tr><td>GG-T/ P-T</td><td colspan="2">17.82</td><td>33.29</td><td>2.19</td><td colspan="2">3.09</td></tr>
<tr><td rowspan="2">All component</td><td>C</td><td>GG-T</td><td>P-T</td><td>C</td><td>GG-T</td><td>P-T</td></tr>
<tr><td>39.92</td><td>9.06</td><td>107.49</td><td>7.24</td><td>0.79</td><td>2.83</td></tr>
</table>

107.5% to 7.2%, 0.8%, 2.8% for the compressor, the G-G turbine, and the power turbine, respectively. The results show that the estimated accuracy of the hybrid method with the module system has been far better than that of the hybrid method without the module system. It is also shown that the suggested method would be reliable and effective for the multiple defect diagnosis of the gas turbine engine in off-design condition.

6. Conclusion

A hybrid method of the artificial neural network (ANN) and the support vector machine (SVM) has been used for engine health monitoring. The method has the advantage of a reduction of learning data and converging time without any loss of estimation accuracy, because the SVM classifies the defect location and can reduce the learning data range. The general ANN has been used only for the estimation the defect magnitude with the reduced data range. The augmented learning data due to the off-design condition, however, increase the non-linearity of the input data and the convergence time of the ANN algorithm. In this study, therefore, an improved hybrid method with module system and advanced SVM has been proposed for the multiple defect diagnosis of the gas-turbine engine in off-design condition.

The advanced SVM as a classifier for the detection of the defect locations, which has one more step of the classification compared to the general SVM, has been used to find the locations of the multiple defects as well as the single defects. A module system has been suggested to reduce the non-linearity and solve the increased convergence time problem. The learning data of the whole off-design region have been divided into appropriate-sized sections, the modules. To estimate the defect magnitude in the arbitrary operating point of the engine, the learning data of the specific module including the point have been used. In the developed hybrid technique for the multiple defect diagnosis, the higher classification accuracy by decrease of the nonlinearity of the input data has been observed, and the error rate has decreased, compared with the existing hybrid method. Overall, the proposed algorithm, the improved hybrid method with the module system and the advanced SVM, has shown good performance in diagnosis of the defects of triple components as well as those of the single and dual components of the gas turbine engine in off-design condition. The real-time diagnoses for the single and multiple defects in the whole off-design region have been expected with reliable and suitable accuracy of the defect estimation.

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Nomenclature

ANN	:	Artificial Neural Network
b	:	Standard vector of hyper-plane
D	:	Defect magnitude
d	:	Desired output
E	:	Cost Function error value
GA	:	Genetic Algorithm
GG-T	:	Gas generator turbine
HPC	:	High-pressure compressor
HPT	:	High-pressure turbine
LPC	:	Low-pressure compressor
MLP	:	Multi layer perceptron
N	:	Data set number
O	:	Objective output
P-T	:	Power turbine
P	:	Total pressure
Q	:	Lagrange objective function
SFC	:	Specific fuel consumption
SVM	:	Support Vector Machine
T	:	Total temperature
w	:	Direction vector of hyper-plane
W	:	Intensity
y	:	Labels
α	:	Lagrange Multiplier

Subscripts

cal	:	Calculated defect
kj	:	*kj*th connection of neuron
pk	:	*k*th row
real	:	Real defect
t2	:	Compressor inlet
t3	:	Combustor inlet
t4	:	GG-turbine inlet
t7	:	Power turbine inlet
t9	:	Power turbine outlet

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