Springer

Journal of Mechanical Science and Technology 23 (2009) 559~568

Journal of
Mechanical
Science and
Technology

www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-008-1119-9

# Defect diagnostics of SUAV gas turbine engine using hybrid SVM-artificial neural network method †

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(Manuscript Received August 11, 2008; Revised October 11, 2008; Accepted November 20, 2008)

**Abstract**

A hybrid method of an artificial neural network (ANN) combined with a support vector machine (SVM) has been developed for the defect diagnostic system applied to the SUAV gas turbine engine. This method has been suggested to overcome the demerits of the general ANN with the local minima problem and low classification accuracy in case of many nonlinear data. This hybrid approach takes advantage of the reduction of learning data and converging time without any loss of estimation accuracy because the SVM classifies the defect location and reduces the learning data range. The results of test data have shown that the hybrid method is more reliable and suitable algorithm than the general ANN for the defect diagnosis of the gas turbine engine.

*Keywords*: Defect Diagnostics; Hybrid method; Support vector machine; Artificial neural network; Gas turbine engine

## 1. Introduction

Recently, the development of a defect diagnostic system for an aircraft gas turbine engine has been of concern for induction of early repair prediction and economical efficiency as well as safe operation.[1-4] The defect diagnostic system of the gas turbine engine usually decides whether the engine is operating well or not after it generally measures major engine parameters and analyzes a certain tendency. The healthy state of the engine and the cost reduction of its maintenance and repair could be obtained with the confirmation or the early detection of defects.[1, 5, 6] Additionally, the increased stability, maneuverability, and reliability of an in-flight aircraft would be acquired with prevention of unexpected failure of the engine.[7, 8]

In order to develop the defect diagnostic system, ANN, GA, and SVM algorithms have been commonly used.[2, 5, 9-12] Among them, the ANN algorithm has been widely used to solve the pattern recognition problem for defect diagnostic systems.[5, 12, 13] The neural network algorithm is able to predict the characteristics of uncertain groups based on the specific information. However, this tool has a few weak points: it needs many data and it is too difficult to know the ending time of learning. Since the most serious problem is the possibility of falling in the local minima instead of the global minima, it becomes very difficult to obtain good convergence and high accuracy ratios.[2] To solve these problems, the ANN algorithm has been suggested to be combined with the SVM algorithm.[14, 15] The SVM is a functional and efficient algorithm that can carry out classifying analysis of acquired data and show more efficient classifying performance with fewer data.[16-18] While the SVM is applied as a sorter of the defect location accompanied by an enormous amount of data, the neural network algorithm can be only applied to estimate the seriousness of the defects. This hybrid approach takes advantage of the reduction of learning data and converging time without any loss of estimation accuracy because the SVM classifies the defect location and

† This paper was recommended for publication in revised form by Associate Editor Tong Seop Kim
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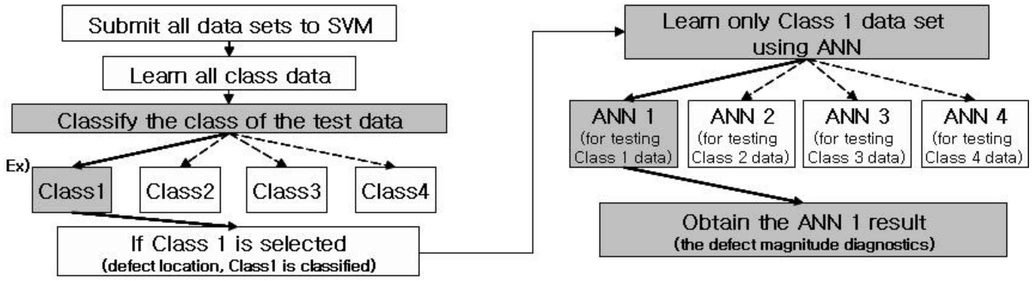



Fig. 1. The Hybrid method of SVM and ANN.

reduces the learning data range.

In this work, the proposed algorithm has diagnosed the defects for both single and dual components of an SUAV turbo-shaft engine through three cases: take-off, cruise, and high altitude conditions. Since the learning time of the hybrid method has been decreased notably for the generated map composed of weights and biases, it is helpful to obtain better accuracy and convergence. The results of test data have verified that the hybrid method is the more reliable and suitable algorithm in the defect diagnostics than the general ANN. It is also shown that the hybrid method can be a reliable diagnostic tool even in case of the off-design condition with increased operating data.

## 2. The hybrid method

### *2.1 Structure of the hybrid method*

Fig. 1 shows the hybrid method structure. The defect position has been detected by the SVM algorithm and the defect magnitude on the detected position has been estimated by the ANN separately. If the compressor defect group is supposed to be the class 1, and when a defect occurs in the compressor position, the SVM algorithm classifies and has the occurred defect belonging to class 1. The ANN, therefore, starts learning only classified data as the class 1 without all input data.

### *2.2 Support Vector Machine (SVM)*

The SVM presumes a hyper-plane which classifies learning data into two classes. There can exist many such planes, but only one plane is shown to maximize the margin among the classes.[16, 17] When two classes exist on the concerned domain, the optimal hyper-plane can be calculated in order that the margin becomes maximized.

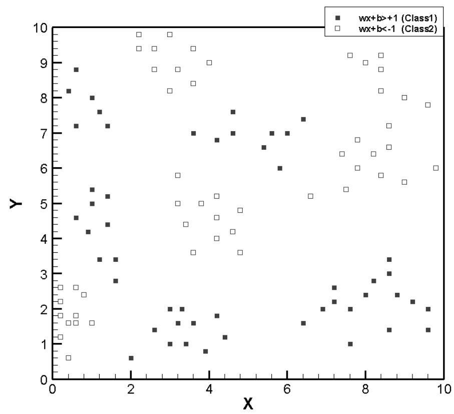



Fig. 2. Sample test data group of SVM.

The Lagrange function has been applied and solved by QP solver [19] in order to obtain the maximized margin, resulting in the hyper-plane equation, w, x+ b. The decision function with the hyper-plane equation has been used to classify the class belonging to optional vectors:

$$f(x,\alpha^*,b^*) = sign((w^*\cdot x)+b^*)$$
$$= sign\Big(\sum_{i\in SV}\alpha_i^* y_i (x_i\cdot x)+b^*\Big) \tag{1}$$

The SVM algorithm has been expanded to the multi-class SVM to classify the multiple groups,[20] such as the form of the "One vs. One" multi-class SVM suggested by Clarkson and Moreno.[21] For the verification of the SVM used in this study, arbitrary data sets have been classified. As shown in Fig. 2, sample data sets of two classes are selected randomly. Fig. 3 shows the classification of sample data by the hyper-plane. For example, if the test data, (4,2), (8,3), and (1,7) are located at XY-coordinates, they are in class 1 as shown in Figs. 2 and 3.

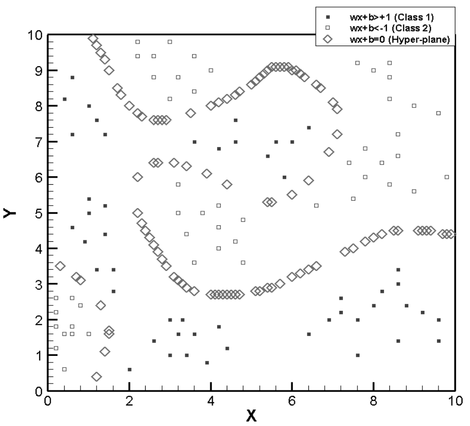



Fig. 3. Classified sample test data group by hyper plane.

Similarly, this method has also been applied for the defect diagnostics. The multi-class SVM has been used for 7-class cases considering multiple defects. Following the "one vs. one" method, one class is compared with other classes. The SVM needs labels, y=-1 or y=+1, for classified data. The sign of the label is decided by the order of comparison because the label means where the data are located. For instance, assuming that the test data belong to class 2, then the labels for them should be y= -1 because the comparison orders, class 1, 3, 4, 5, 6, and 7 versus class 2. To the contrary, the labels must be y= +1, when class 2(y=+1) compared with others(y=-1).

### *2.3 Artificial Neural Network (ANN)*

The organized neural network using the Multi-layer perceptron [9] as the most general form has been applied for the error backpropagation algorithm. Information from the input-layer is multiplied by weights and biases before it is transferred to the hidden-layer. In a similar method, the calculated information of the hidden-layer is delivered to the output-layer. The ANN output is computed through this process. Consequently, in order to make the error between the ANN output and the desired output be the least, the weights and biases can be changed. This process is repeated until the error is satisfied with the condition of convergence. The weights and biases as calculation results are stored to decide the state of new data. Momentum theory [22] has been used to promote the convergence of the ANN and the sigmoid function [8,12] used to classify the nonlinear input pattern has been applied as below:

Table 1. Design point of the turbo-shaft engine.

| Variables | Values |
|---|---|
| Atmospheric condition | Sea-level Static Standard Condition |
| Mass flow rate (kg/s) | 2.008 |
| Fuel flow rate (kg/s) | 0.0402 |
| Compressor pressure ratio | 8.037 |
| TIT (K) | 1254 |
| Shaft horse power (hp) | 416 |
| SFC (kg/kW hr) | 0.3478 |
| Gas generator rotational Speed (100% RPM) | 54850 |
| Propeller rotational speed (100% RPM) | 6000 |

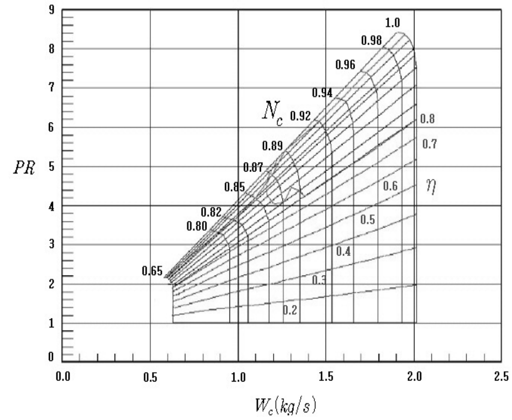



Fig. 4. Characteristic map of Centrifugal compressor map.

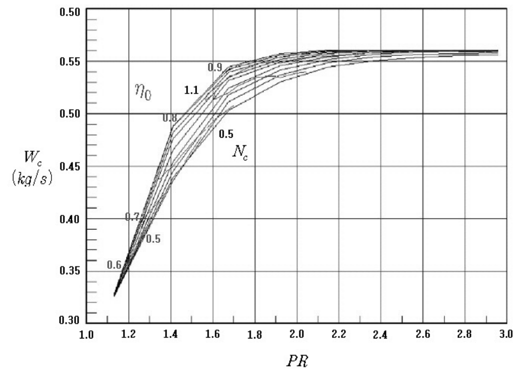



Fig. 5. Characteristic map of power turbine.

$$f(x) = \frac{1}{1+e^{-bx}} \tag{2}$$

The dimension of the output-layer has been only 1 in case of single defect cases for the ANN of the hybrid method because the defect position has been already classified by the SVM. Accordingly, the result of the ANN of the hybrid method has shown better accuracy. However, the dimension of the output layer for the ANN algorithm should increase to 3 if the considered defect components of the engine are 3. Then the estimation accuracy of the ANN may get worse since the number of the connected nodes and learning time are increased with the increased dimension of the output-layer.

## 3. Application to defect diagnostics of turbo-shaft engine

### *3.1 Engine selection and modeling*

In this paper, a turbo-shaft engine has been selected for study. On-design and off-design performance data of engine have been composed of the centrifugal compressor map and the turbine map provided by the GSP, and scaled for our own purposes. Fig. 4 and Fig. 5 show the characteristic maps of the centrifugal compressor and the turbine, respectively. Table 1 shows the design points of the turbo-shaft engine chosen for this study.

### *3.2 Applying the hybrid method to off-design condition*

The hybrid method has been applied for the off-design condition, especially altitude and velocity variations according to the fuel flow rates. The required number of the learning data sets for the hybrid method has been 28 for single defect cases and 148 for multiple defect cases, respectively. The altitude has been divided into 20 steps by increasing 240m from 240m to the maximum operating altitude 4,800m. Each altitude data set includes the learning data of velocity variations from Mach 0.2 to Mach 0.4. The data sets have been imposed between -1.0% and -5.0% of the defect range for each component. Even though the ANN learns according to altitude variations, if the defect position has not been classified by the SVM, it should learn 528 data sets (28 3 possibilities of single defect positions + 148 3 possibilities of multiple defect positions) including all the possible position data. In general, prediction accuracy of the ANN algorithm depends on the amount of learning data, and its total learning time also increases because of the possibility of non-convergence problems due to the increased size of data.[22, 24]

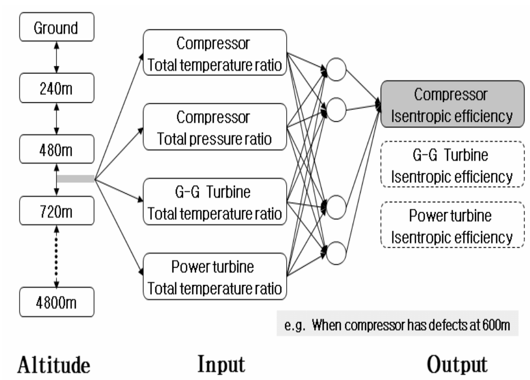



Fig. 6. Application of hybrid method in off-design condition.

Fig. 6 shows the application of the hybrid method in off-design condition. If a single defect occurs in the compressor, for example, the defect position is indicated by the SVM. The ANN does not have to use all information data to estimate the defect magnitude. It only needs 28 learning data sets. For the case of multiple defects, the ANN learns only 148 data sets in a similar manner. In contrast, the general ANN, if used independently, needs 528 learning data sets for both single and multiple defect conditions. The hybrid method, therefore, needs much fewer learning data sets.

### *3.3 Process of defect diagnostics*

Three locations of the compressor, the G-G turbine and the power turbine have been selected for the defect position. The single and dual defect cases of the components have been investigated. As shown in Table 2, the input data for the hybrid method and the ANN are total temperature ratio and total pressure ratio of the compressor, total temperature ratio of the G-G turbine, and total temperature ratio of the power turbine according to variations of altitude, velocity and fuel flow rates. The output data of the ANN algorithm are isentropic efficiencies of the components.

To check the capability and reliability, the hybrid method has been applied to the various off-design performance conditions of which the number of required data has been more than 20 times to that of the sea-level static condition. The learning for the defect diagnostics has been considered in off-design condition of variations of altitudes and Mach numbers as shown in Table 3.

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

<table>
<tr><th colspan="3"></th><th>Input Data</th><th>Output Data</th></tr>
<tr><td rowspan="3">Training Sets</td><td rowspan="2">Hybrid Method</td><td>SVM</td><td rowspan="3">$T_{t3}/T_{t2}$<br>$P_{t3}/P_{t2}$<br>$T_{t4}/T_{t7}$<br>$T_{t7}/T_{t8}$</td><td>Y= 1 (Subjective value) or Y= -1 (Objective value)</td></tr>
<tr><td>ANN</td><td rowspan="2">Deteriorated isentropic efficiency</td></tr>
<tr><td colspan="2">General ANN</td></tr>
</table>

Table 3. Input variables to learn.

<table>
<tr><th></th><th>Altitude</th><th>Velocity</th><th>Input defect magnitude</th></tr>
<tr><td>Compressor</td><td rowspan="6">240m,<br>480m,<br>720m,<br>~<br>4560m,<br>4800m</td><td rowspan="6">M 0.2,<br>~<br>M 0.4</td><td rowspan="6">-0.5%,<br>-1%,<br>-2%,<br>~<br>-5%</td></tr>
<tr><td>G-G turbine</td></tr>
<tr><td>Power turbine</td></tr>
<tr><td>Comp + G-Turbine</td></tr>
<tr><td>Comp + P-Turbine</td></tr>
<tr><td>G-Turbine + P-Turbine</td></tr>
</table>

Table 4. Test data selection in 3 cases.

<table>
<tr><th>Case condition</th><th>Altitude [m]</th><th>Velocity [Mach No.]</th><th>Fuel flow rate [kg/s]</th></tr>
<tr><td>Take off</td><td>0</td><td>0</td><td>0.0402</td></tr>
<tr><td>Cruise</td><td>3,000</td><td>M 0.34</td><td>0.038</td></tr>
<tr><td>High altitude</td><td>4,200</td><td>M 0.3</td><td>0.032</td></tr>
<tr><td></td><td colspan="2">Defect [%]</td><td>Test data No.</td></tr>
<tr><td>Compressor</td><td colspan="2" rowspan="6">-1%<br>~<br>-5%<br>(Random defect magnitude)</td><td>8 sets</td></tr>
<tr><td>G-G turbine</td><td>8 sets</td></tr>
<tr><td>Power turbine</td><td>8 sets</td></tr>
<tr><td>Comp + G-Turbine</td><td>64 sets</td></tr>
<tr><td>Comp + P-Turbine</td><td>64 sets</td></tr>
<tr><td>G-Turbine + P-Turbine</td><td>64 sets</td></tr>
</table>

Table 4 shows test data for three cases: take-off, cruise, and high altitude conditions. The sea-level static condition is quite important to manage the engine on the ground. The cruise condition has been selected by the objective mission of the SUAV model. The high altitude condition has been chosen around 4800 m, which is the maximum operating altitude of the engine.

The single and dual component defect cases have used 8 sets and 64 sets, respectively. These test data have been applied to both the hybrid method and the ANN. The fuel flow rate of take-off condition has been 0.0402 kg/s. In case of cruise condition, the altitude, the velocity, and the fuel flow rate have been 3,000m, Mach 0.34, and 0.038 kg/s, respectively. The last test case is the high altitude condition: The altitude, the velocity, and the fuel flow rate have been 4,200m, Mach 0.3, and 0.032 kg/s, respectively. The defect location has total six cases including three single defect positions and three dual defect positions.

Table 5. Comparison average learning time of hybrid method and general ANN.

<table>
<tr><th rowspan="2">Case Condition</th><th colspan="2">Hybrid method</th><th colspan="2">General ANN</th></tr>
<tr><th>Single defect</th><th>Multiple defects</th><th>Single defect</th><th>Multiple defects</th></tr>
<tr><td>Take off</td><td>0.8 s</td><td>18.8 s</td><td colspan="2">122.1 s</td></tr>
<tr><td>Cruise</td><td>4.5 s</td><td>87.4 s</td><td colspan="2">312.1 s</td></tr>
<tr><td>High altitude</td><td>4.2 s</td><td>89.6 s</td><td colspan="2">245.6 s</td></tr>
</table>

Table 5 shows the average learning time of the hybrid method and the general ANN. For cruise condition, the average learning time of the hybrid method has been 4.5 seconds for single defect and 87.4 seconds for multiple defects, respectively. On the other hand, the general ANN has estimated up to 312.1 seconds. The results of the general ANN have not been separated into single and multiple defects. The general ANN should learn all the learning data because the defect position has not been identified. That is why the learning time of ANN is much longer than that of the hybrid method. The ANN algorithm has the characteristic that it has good convergence performance only in case the learning time is short. The ANN algorithm should have sufficient weights and biases in order to determine the defect magnitude accurately before the engine operates in off-design condition. The ANN may have reliable accuracy and high convergence rate only with a sufficient and well organized map of weights and biases.

## 4. Decision of defect position

The examples shown in Figs. 2 and 3 are two-dimensional data. The input data of this study are, however, four-dimensional data as shown in Table 2. The algorithm of 2-D classification has been expanded for 4-D data. The array of input data has been changed and the multi-class SVM has been executed. The multi-class SVM has shown good classification perform-

Table 6. Dividing classes according to defect position.

| Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| | Normal | Abnormal (Single defect) | | | Abnormal (Multiple defects) | | |
| Compressor | - | O | - | - | O | O | - |
| G-G Turbine | - | - | O | - | O | - | O |
| Power turbine | - | - | - | O | - | O | O |

Table 7. SVM classification results of test data.

| Defect Position | Test data | Classification accuracy | Average convergence time |
|---|---|---|---|
| Compressor | Take off | 100 % | 36.7 s |
| G-G turbine | | | |
| Power turbine | Cruise | 100 % | 36.2 s |
| Comp + G-Turbine | | | |
| Comp + P-Turbine | High altitude | 100 % | 37.1 s |
| G-Turbine + P-Turbine | | | |

ance irrespective of the dimension of the input data.

Table 6 shows seven states of engine conditions, existing in both normal and abnormal states: class 1 for the normal data group, class 2 for the compressor defect data group, class 3 for the G-G turbine defect data group, class 4 for the power turbine defect data group, class 5 for the compressor and G-G turbine defect data group, class 6 for the compressor and power turbine defect data group, and class 7 for the G-G turbine and power turbine defect data group.

Total temperature ratio and total pressure ratio from sensed parameters of each engine component are compared with the normal state. The defect location can be finally identified when there exists any defect. The optional defects have been given to components for the take-off condition, the cruise condition, and a high altitude of 4,200m condition, respectively. All test data have been classified 100% as shown in Table 7. The average convergence time per the case of each defect prediction has been 36.7 seconds. It is confirmed that the suggested multi-class SVM algorithm has high classification accuracy without any failure even for the 20 times as much of data sets compared with those of the sea-level static condition.

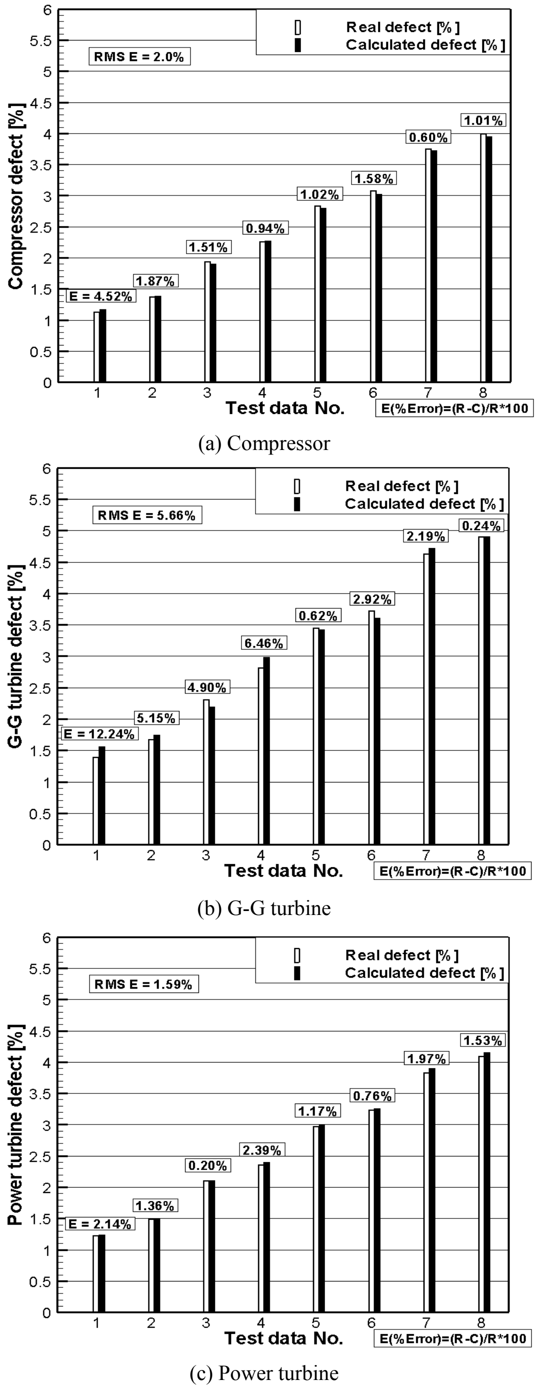



Fig. 7. RMS defect error rate of single defect in cruise condition

## 5. Estimation of defect magnitude

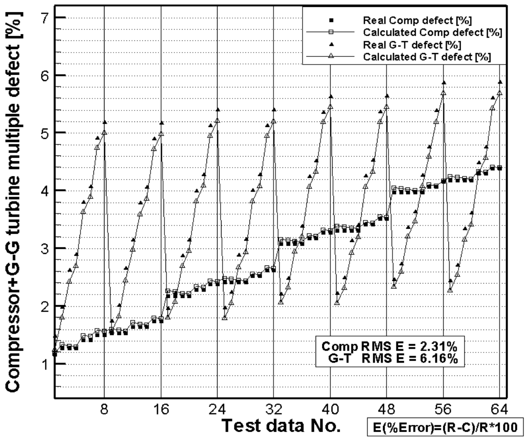
The defect data group classified by the SVM has to be evaluated by the ANN for the determination of the defect magnitude. The advantage of the hybrid algorithm is that the parameters acquired at any altitude and velocity can be processed in real time to estimate the defect seriousness with high accuracy because the map of weights and biases has been obtained sufficiently according to the variations of the altitude, the velocity and the fuel flow rate.

The test data have been selected as the defect value of three cases - take-off, cruise, and high altitude conditions - as shown in Table. 4. Fig. 7 shows the comparison of the defect estimation with RMS error in case of the single defect in cruise condition. Equation (3) presents RMS defect error rate, which can be calculated by the difference between the real and the calculated defects.

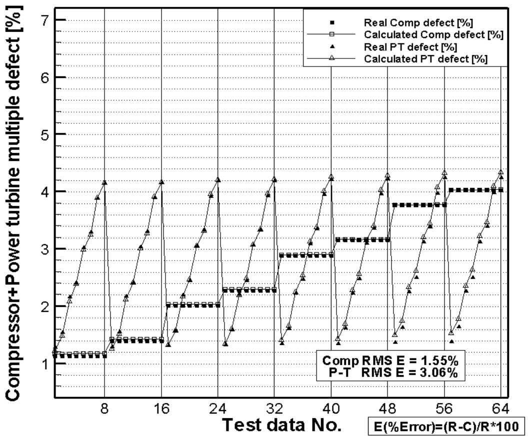
$$RMS\ defect\ error\ rate[\%] = \sqrt{\sum_{i=1}^{N} \left(\frac{D_{real} - D_{cal}}{D_{real}} \times 100\%\right)_i^2 / N} \quad (3)$$

The test data number on the horizontal-axis has been increased according to the given defect magnitude. The defect magnitude has been represented on the vertical-axis. In Fig. 7(a) for the compressor defect, in case of test data No. 1 with the given defect -1.128 % (shown in blank rod), the compared error is about 4.5% with the calculated defect -1.179% (shown in stuff rod). The errors of other test data No. have been shown in similar manner. The RMS error rate of the compressor defect shown in Fig. 7(a) is about 2.0%. Figs. 7(b) and 7(c) show the results of the G-G turbine and the power turbine in the same way. The RMS defect error rates for the G-G turbine and the power turbine are about 5.7 % and 1.6 %, respectively. The errors of the G-G turbine are higher than other components, which is a general trend caused by characteristics of each component.

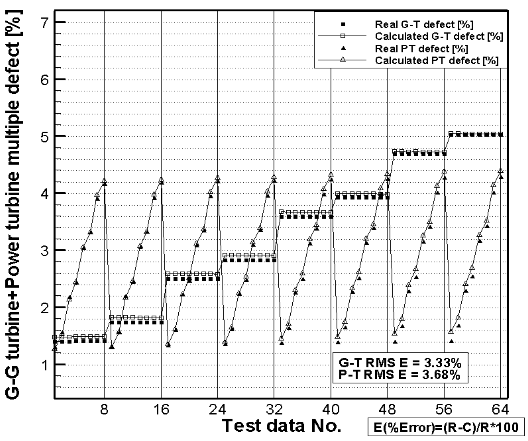
Fig. 8 shows a comparison of the RMS defect error rates of dual defects in cruise condition. The total test data number is 64 because the number of test data for dual defects is a square of the single defect number. In Fig. 8a, for example, for the compressor of the test data No.1 with -1.3 % of defect, the G-G turbine defects have eight sets of test data numbers between -1.3% and -5%. The given and calculated defects of the compressor and the G-G turbine have been shown as a square (■, □) and a triangle (▲, △), respectively. Similar to the same calculation of the single defect case, the RMS defect error rates of Comp +




(a) Compressor + G-G turbine




(b) Compressor + power turbine




(c) G-G turbine + power turbine

Fig. 8. RMS defect error rate of multiple defects in cruise condition.

Table 8. RMS defect error rate of multiple defects in cruise condition.

| | RMS defect error rate [%] | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Hybrid method | | | | | | General ANN | | | | | |
| | Take off condition | | Cruise condition | | High altitude condition | | Take off condition | | Cruise Condition | | High altitude condition | |
| Compressor | 4.6 | | 2.0 | | 1.65 | | 11.94 | | 15.75 | | 5.90 | |
| G-G turbine | 1.07 | | 5.66 | | 2.02 | | 12.03 | | 12.95 | | 8.39 | |
| Power turbine | 5.20 | | 1.59 | | 4.12 | | 35.52 | | 36.17 | | 44.73 | |
| Comp + G-Turbine | 4.92 | 5.95 | 2.31 | 6.16 | 2.63 | 1.95 | 7.49 | 14.26 | 10.63 | 16.14 | 6.37 | 11.17 |
| Comp + P-Turbine | 2.07 | 3.31 | 1.55 | 3.06 | 1.05 | 1.51 | 12.87 | 38.33 | 13.47 | 40.72 | 4.27 | 51.22 |
| G-Turbine + P-Turbine | 2.90 | 5.61 | 3.33 | 3.68 | 3.73 | 3.33 | 7.12 | 19.73 | 10.32 | 22.05 | 5.16 | 39.21 |

GG-T, Comp + PT, and GG-T + PT cases have been about 2.3 % / 6.2 %, 1.6 % / 3.1 %, and 3.3 % / 3.7 %, respectively.

The defect estimation for the take-off and the high altitude conditions also has been calculated. The calculation results are summarized in Table 8 for both single and multiple defects of three cases: take-off, cruise, and high altitude conditions. The results of the hybrid method have been compared with those of the general ANN algorithm.

In case of cruise condition in Table 8, the RMS defect error rates of the hybrid method are about 2.0, 5.7, and 1.6 % for each single component defect, while those of the general ANN are 15.8, 13.0, and 36.2 %, respectively. In the multiple defects case of the compressor + power turbine, it is shown about 1.6 % / 3.1 % for the hybrid method and about 13.5% / 40.7 % for the general ANN, respectively. From the results shown in the table, it has been verified that the proposed hybrid method has better defect estimation accuracy than the general ANN for all tested conditions.

## 6. Conclusion

This study has proposed a hybrid method composed of the SVM and ANN algorithms for defect diagnosis of an SUAV gas turbine engine. The ANN learns selectively after classification of defect patterns and discrimination of defect position using the SVM, resulting in higher classification accuracy rate as well as the rapid convergence by decreasing the nonlinearity of the input data. By qualitative learning with the SVM, the location of defect parts can be classified perfectly. This hybrid method takes advantage of reduction of learning data and converging time without any loss of estimation accuracy, because the SVM classifies the defect location and reduces the data range. The proposed algorithm has diagnosed the defects for both single and dual components through three cases: take-off, cruise, and high altitude conditions. The hybrid method has notably decreased the learning time for the map generation composed of weights and biases, and it has been helpful in obtaining better accuracy and convergence in the defect diagnostics. The comparisons of the RMS error rates of the hybrid method have shown good results in three test cases. The results of test data have verified that the hybrid method is the more reliable and suitable algorithm in the defect diagnosis than the general ANN. It is also shown that the hybrid method can be a reliable diagnostic tool even in case of the off-design condition with increased operating data. The hybrid method with a proper extension might be, therefore, reliable and suitable for the defect diagnostics of the gas turbine engines.

## Acknowledgment

This study is a part of the results of the research work sponsored by the Smart UAV Development Center, Korea Aerospace Research Institute.

## Nomenclature

| | | |
|---|---|---|
| *ANN* | : | Artificial Neural Network |
| B | : | Standard vector of hyper-plane |
| $D_{cal}$ | : | Calculated defect magnitude |
| $D_{real}$ | : | Real defect magnitude |
| *GA* | : | Genetic Algorithm |
| *GG-T* | : | Gas Generator Turbine |

| | | |
|---|---|---|
| $N$ | : | Data set number |
| $P\text{-}T$ | : | Power Turbine |
| $P$ | : | Total pressure |
| $SFC$ | : | Specific Fuel Consumption |
| $SVM$ | : | Support Vector Machine |
| $T$ | : | Total temperature |
| $TIT$ | : | Turbine Inlet Temperature |
| $w$ | : | Direction vector of hyper-plane |
| $y$ | : | Labels |
| $\alpha$ | : | Lagrange Multiplier |

***Subscripts***

| | | |
|---|---|---|
| *cal* | : | Calculated defect |
| *real* | : | Real defect |
| *t2* | : | Compressor inlet |
| *t3* | : | Combustor inlet |
| *t4* | : | GG-turbine inlet |
| *t7* | : | Power turbine inlet |
| *t8* | : | Power turbine outlet |

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