Springer

Journal of Mechanical Science and Technology 22 (2008) 2489~2497

Journal of Mechanical Science and Technology

www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-008-0813-y

A study on separate learning algorithm using support vector machine for defect diagnostics of gas turbine engine †

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(Manuscript Received November 16, 2007; Revised June 20, 2008; Accepted August 12, 2008)

Abstract

A separate learning algorithm with support vector machine (SVM) has been studied for the development of a defect-diagnostic algorithm applied to the gas turbine engine. The system using only an artificial neural network (ANN) falls in a local minima and its classification accuracy rate becomes low in case it is learning nonlinear data. To make up for this risk, a separate learning algorithm combining ANN with SVM has been proposed. In the separate learning algorithm, a sequential ANN learns selectively after classification of defect patterns and discrimination of defect position using SVM, resulting in higher classification accuracy rate as well as the rapid convergence by decreasing the nonlinearity of the input data. The results have shown this suggested method has reliable and suitable estimation accuracy of the defect cases of the turbo-shaft engine.

Keywords: Artificial neural network; Hyper plane; Multi-layer perceptron; Separate learning; Support vector machine

1. Introduction

Recently, the development of a defect-diagnostic system for gas turbine engines has been in the spotlight to induce efficiency of early repair prediction and economical efficiency as well as safe operation [1-4]. The defect-diagnostic system of the gas turbine engine generally measures thermodynamic parameters such as pressures, temperatures across each components, RPM, and fuel mass flux of the engine, and analyzes a certain tendency, then decides whether the engine is working well or not. The confirmation or the early detection of defects if they exist, is able to maintain the healthy state of the engine and helps to reduce the cost of maintenance and repair [1, 5, 6], Also, it can increase stability, maneuverability, and reliability of an aircraft in flight as it prevents unexpected failure of the engine [7].

An artificial neural network (ANN) algorithm has been widely used to solve the pattern recognition problem for defect-diagnostic systems [5, 7-12]. The ANN algorithm is able to predict the characteristics of uncertain groups or features based on the specific information, using the Multi-layer perceptron (MLP) [9] of the error back propagation algorithm. However, this tool has many weak points: it needs many data, it's too hard to know the ending time of learning, and the most serious problem is the possibility of falling in the local minima instead of the global minima. Therefore, it becomes very difficult to obtain convergence and high accuracy ratio [2].

In this study, in order to solve these problems, a separate learning algorithm composed of support vector machine (SVM) [13-15] has been proposed to divide, analyze, and classify patterns qualitatively with ANN to track down an amount of defect quantitatively. The SVM has shown more efficient classifying performance with fewer data than MLP since it is a functional and efficient algorithm that can carry out classifying analysis of acquired data. To develop the algorithm for the defect-diagnostic system of the gas turbine engine, the original two-class SVM for the sepa-

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

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ration of the binary has been extended to multi-class SVM. The suggested method has been applied to find the defect positions of the turbo-shaft engine.

2. Artificial neural network

The organized neural network using the Multi-layer perceptron (MLP) as the most general form has been applied for the error back propagation algorithm. Fig. 1 shows the structure of MLP [2].

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 (O_{pk}) is computed in this process. Consequently, the error between the ANN output and desired output (d_{pk}) is as follows:

$$E = \sum_p E_p = \frac{1}{2}\sum_p \sum_{k=1}^{M-1} (d_{pk} - O_{pk})^2 \tag{1}$$

To make this error be the least change weights [11, 12] as:

$$W_{kj}(t+1) = W_{kj}(t) - \eta \frac{\partial E}{\partial W_{kj}} \tag{2}$$

This process is repeated until the error (E) satisfies the condition of convergence. The weights and biases as calculation results are stored to decide the state of new data. Fig. 2 shows the flow chart of this procedure.

Momentum theory [16] has been used to promote convergence of MLP. In order to convert the net values from each MLP node into the non-linear function values, the sigmoid function and tangent sigmoid function [8, 12] have been applied, resulting in the enhanced classification of the non-linear input patterns.

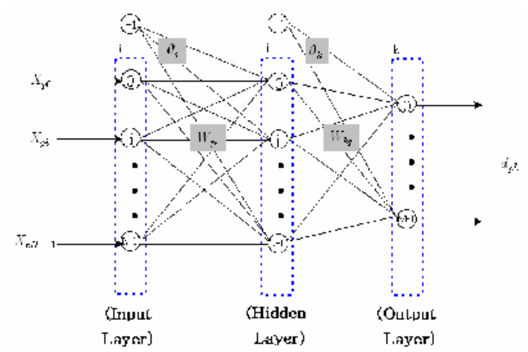

Fig. 1. Structure of MLP Model.

$$f(x) = \frac{1}{1+e^{-bx}} \tag{3}$$

$$f(x) = \frac{1-e^{-bx}}{1+e^{-bx}} \tag{4}$$

3. Support vector machine

3.1 Realization process of SVM

The purpose of SVM presumes the hyper-plane that classifies learning data in two classes [13, 14]. There exist as many such planes as can be, but only one plane called the optimal hyper-plane is shown to maximize the margin among the classes as shown in Fig. 3 [13].

The optimal hyper-plane is calculated only if next two conditions are satisfied:

1) When two classes are on the inside of boundary line,

2) When the margin has maximum value.

The first condition can be written in two equations [13]:

$$\begin{gathered} Minimize\ \frac{\|w\|}{2} \simeq \frac{\|w\|^2}{2} = \frac{(w \cdot w)}{2} \\ subject\ to\ \ y_i((w \cdot x_i) + b) \geq 1\ for\ \forall i \end{gathered} \tag{5}$$

And the second condition with Lagrange Function

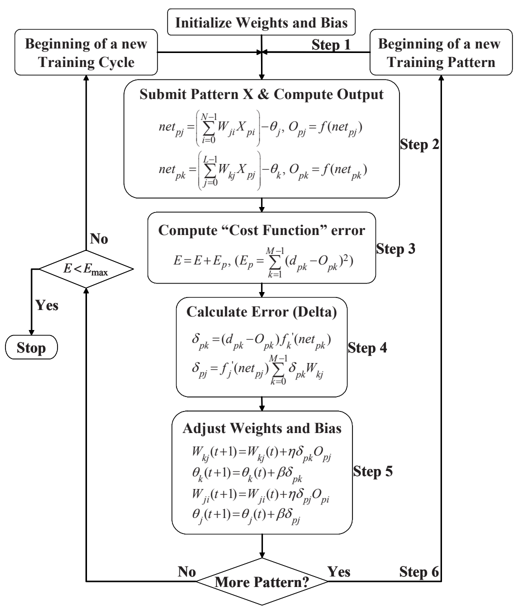

Fig. 2. Process of MLP learning.

to be solved will be Eq. (6). The QP solver has been used to get Lagrange multiplier [17].

$$\textit{Maximize}\;\; Q(\alpha)=\sum_{i=1}^{N}\alpha_i-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j (x_i\cdot x_j)$$
$$\textit{subject to}\;\; \sum_{i=1}^{N}\alpha_i y_i=0,\;\; \alpha_i\geq 0 \; for\; \forall i \tag{6}$$

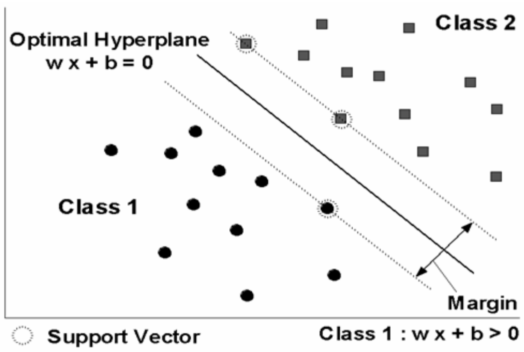

Fig. 3. Optimal hyper-plane and support vector.

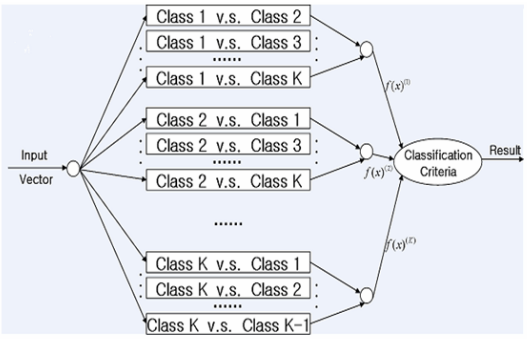

Fig. 4. Structure of "One VS One" Multi-Classes SVM Classifier.

With Eq. (5) and Eq. (6), the hyper-plane equation $w\cdot x+b$ has been obtained. The decision function to classify the class belonging to optional vectors is written as,

$$w=\sum_{i=1}^{N}\alpha_i y_i x_i=\sum_{i\in SV}\alpha_i y_i x_i \tag{7}$$

$$y_i\left(\sum_{i\in SV}\alpha_i y_i (x_i\cdot x)+b\right)=1 \tag{8}$$

$$\begin{aligned} f(x,\alpha^*,b^*) &= sign((w^*\cdot x)+b^*) \\ &= sign(\sum_{i\in SV}\alpha_i^* y_i (x_i\cdot x)+b^*) \end{aligned} \tag{9}$$

In order to raise classification accuracy for nonlinear input data, the Gaussian Kernel Function has been applied, being expanded to multi-class SVM for classification of the multiple groups [16]. Fig. 4 shows the form of "One vs. One" multi-class SVM suggested by Clarkson and Moreno [18, 19].

4. Separate learning algorithm

4.1 Necessity of separate learning algorithm

In this study, the separate learning algorithm has been suggested to improve classification accuracy and convergence of the MLP learning. The MLP has a problem of deterioration of convergence and reliability in case of increased data. Moreover, it brings about a decline of classification accuracy. To resolve these problems, this study suggests a method of separating learning data. That is, multi-class SVM has been used for the classification algorithm and then MLP manipu-

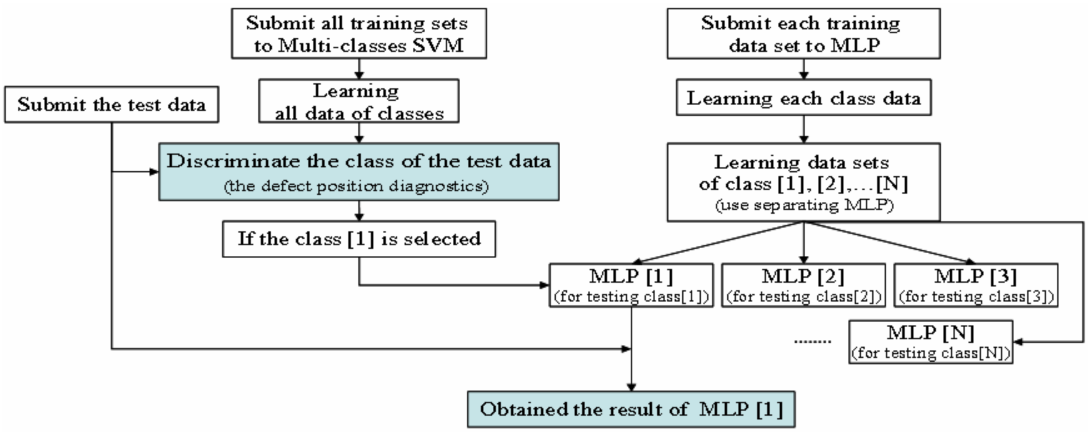

Fig. 5. Separate learning algorithm of MLP by multi-classes SVM classifier.

lates the separated data of the classified classes. The structure of the separate learning algorithm is shown in Fig. 5.

4.2 Defect diagnostics of gas turbine engine

Fig. 6 indicates the selected turbo-shaft engine model used in this study. On-design and off-design performance data of the engine have been generated by a gas-turbine simulation program (GSP) [20]. The characteristic maps of the engine are composed of the centrifugal compressor map and the turbine map which are provided by GSP and scaled for our own purposes. Table 1 shows the design points of the corresponding turbo-shaft engine, which are supplied by the Smart UAV Development Center.

The parameters used in the separate learning algorithm for health monitoring are composed of deteriorating rates of adiabatic efficiencies of the compressor, the compressor-turbine, and the power turbine, respectively. Sensed parameters are the compressor pressure ratio (P_{t3} / P_{t2}), the compressor temperature ratio (T_{t3} / T_{t2}), the power turbine temperature ratio (T_{t7} / T_{t9}), and the shaft horsepower (SHP), respectively.

Table 2 shows four normal and abnormal states of engine conditions used in this model. Table 3 shows the 34 intentionally-generated sets of learning data in terms of deteriorated rate of efficiency for each component of the engine model.

5. Results of deffect diagnostics

5.1 Decision of defect location by Multi-Class SVM

Based on the learning results of multi-class SVM, 30 sets of new data have been tested to classify and decide where the defect is located. Test data and classification rates have been shown in Table 4, in which

Table 1. Range of defect diagnostics.

Variable	Value
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

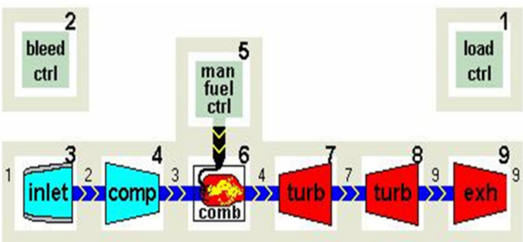

Fig. 6. Turbo-Shaft Engine Model using GSP Program.

Table 2. Range of defect diagnostics.

	Class 1	Class 2	Class 3	Class 4
State Position	Normal State	Abnormal State (Single Defect)		
Compressor	-	O	-	-
Compressor Turbine	-	-	O	-
Power Turbine	-	-	-	O

Table 3. Learning data sets for Multi-Class SVM.

	Defect input for training	Each training set number	Total training set number
Normal state	0%	1 Set	34 Sets
Compressor	-0.5%, -1~-10%	11 Sets	
Compressor Turbine	-0.5%, -1~-10%	11 Sets	
Power Turbine	-0.5%, -1~-10%	11 Sets	

Table 4. Testing data set and classification rate.

	Defect input for test	Testing set number	Classification rate
Compressor	-0.3%, -0.6%, -0.9%, -9.3%, -9.6%, -9.9%	30 Sets	100 %
Compressor Turbine		30 Sets	100 %
Power Turbine		30 Sets	100 %

Table 5. Training sets for MLP learning.

	Input Data	Output Data
Training sets	P_{t3}/P_{t2} , T_{t3}/T_{t2} T_{t7}/T_{t9} , SHP	Deteriorated isentropic efficiency

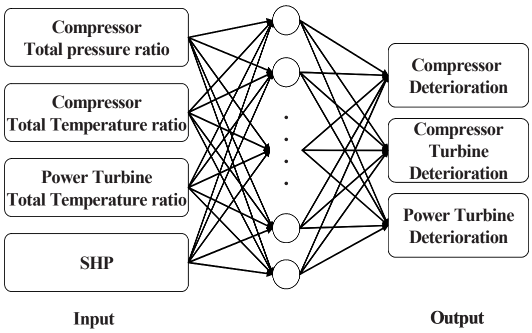

Fig. 7. Standard MLP structure for defect diagnostics.

it is confirmed that the multi-class SVM has 100% classification accuracy within 2 seconds of total learning time.

5.2 Decision of Defect Magnitude by MLP

The quantitative defect diagnostic results by using MLP have been carried out in two different cases for comparison. The first case involves using MLP without the separate learning algorithm and the second case using the separate learning algorithm. Table 5 shows the input and output data for the learning procedure of MLP.

5.3 Standard MLP without Separate Learning Algorithm

Fig. 7 shows the structure of MLP for learning all 34 data without separate learning algorithm. All data of the compressor, the compressor turbine, and the power turbine are needed because the defect location is not known. If a defect is found in one of the parts during the learning period, defects of the rest are set to be zero.

The MLP structure is composed of 4 input-layer nodes, 5 hidden-layer nodes, and 3 output-layer nodes. The maximum errors (E_{max}) for convergence are set to be 10^{-5} and 10^{-6}, respectively.

Figs. 8-10 show the results of defect estimation after learning 4-5-3 structure of MLP using the 90 test data. The detection characteristics of exact defect estimation of the defected component without any remarkable error on the un-defected components have been revealed. For 10^{-5} tolerance, the mean errors between the real defect and the calculated one are about 0.7 % for the compressor, about 0.54 % for the compressor-turbine, and about 0.09 % for the power turbine, respectively, with 37.0 seconds of total learning time.

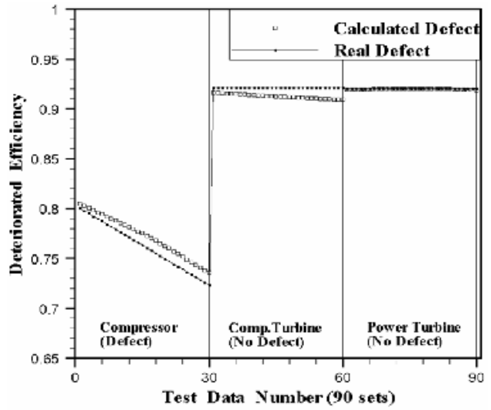

Fig. 8. Result of standard MLP for compressor defect.

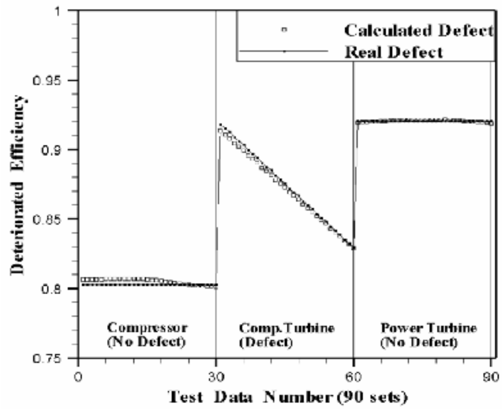

Fig. 9. Result of standard MLP for compressor turbine defect.

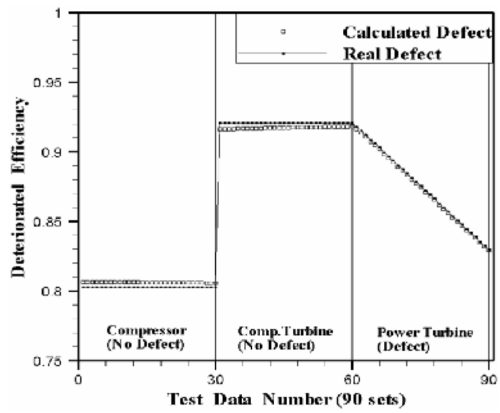

Fig. 10. Result of standard MLP for power turbine defect.

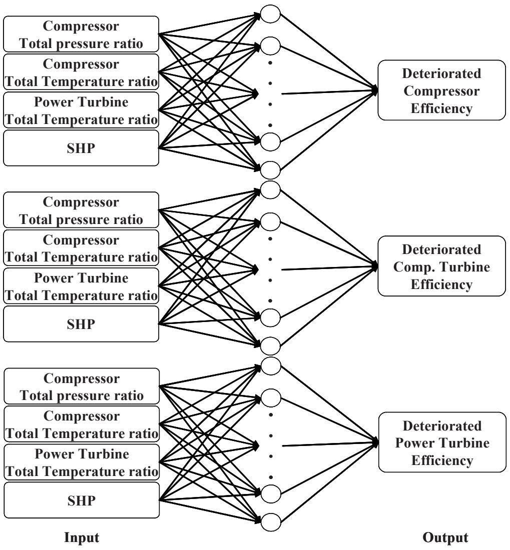

Fig. 11. Proposed MLP Structure for Single Defect Diagnostics.

For 10^{-6} tolerance, the standard MLP has not been converged.

5.4 MLP with separate learning algorithm

5.4.1 Defect estimation at sea level static condition

Fig. 11 is the structure of MLP for the separate learning algorithm. It is different from the standard MLP algorithm because it learns independently a single defect which has been known after being classified and identified by multi-class SVM.

The MLP learns independently three times. The output-layer has only one node since it does not need the data without any defect. The proposed MLP is composed of 4-15-1 structures and the maximum errors (E_{max}) for convergence are set to be 10^{-5} and 10^{-6}, respectively. Since MLP learns independently, one of the advantages of the separate learning algorithm is that the amount of required learning data can be reduced and the learning rate can be consequently increased.

Figs. 12-14 show the results of predicting a single defect at sea-level static condition after learning procedure using 4-5-1 structure of the proposed MLP with 11 learning data and 30 test data, compared to those obtained by the standard MLP without separate learning algorithm. The MLP using separate learning algorithm (SLA) has been verified to converge for both 10^{-5} and 10^{-6} tolerances with much less learning time and better accuracy. Table 6 summarizes the comparison of the results between the standard MLP and the MLP using SLA with different tolerances.

Table 6. Mean error results compared to MLP and separate learning algorithm.

	$E_{max} = 10^{-5}$		$E_{max} = 10^{-6}$	
	Standard MLP	MLP using SLA	Standard MLP	MLP using SLA
Compressor	0.694%	0.132%	-	0.054%
Comp. Turbine	0.544%	0.118%	-	0.032%
Power Turbine	0.087%	0.119%	-	0.037%
Learning Time	37.4sec	4.2sec	-	5.8sec
Convergence	Yes	Yes	No	Yes

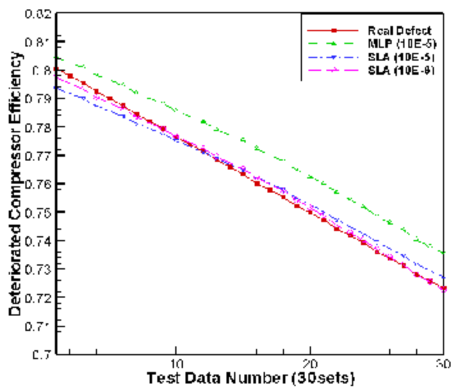

Fig. 12. Results of MLP with separate learning algorithm for compressor defect diagnostics.

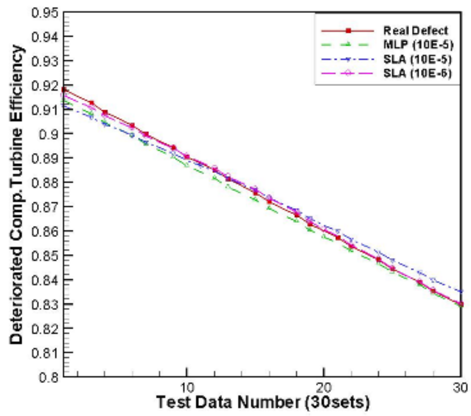

Fig. 13. Results of MLP with separate learning algorithm for compressor turbine defect diagnostics.

5.4.2 Defect estimation with altitude variation

As the number of data increases, the learning time increases with the possibility of non-convergence

Table 7. Extraction of Testing set and classification rate of Multi-Class SVM.

	Altitude	Defect input for testing	Testing set number	Classification rate for Testing
Compressor	1600ft, 3200ft ~ 14400ft, 16000ft	-0.3% ~ -9.9%	330 sets	100%
Compressor Turbine			330 sets	100%
Power Turbine			330 sets	100%

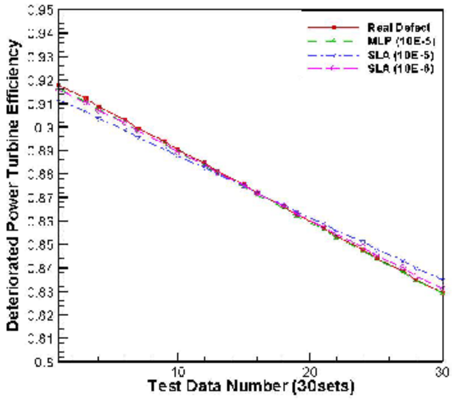

Fig. 14. Results of MLP with separate learning algorithm for power turbine defect diagnostics.

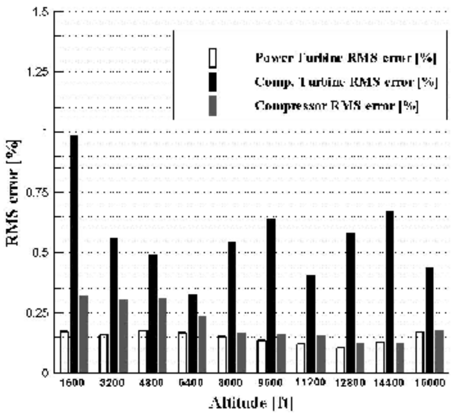

Fig. 15. RMS errors with altitude variations.

problem. In order to check the capability and reliability, the suggested separate learning algorithm has been applied to the various off-design performance conditions of which the number of required data is 10 times to those of the sea-level static condition. The required number of learning data sets is 330 of which 10 different altitudes by increasing 1600 ft up to 16000 ft, and 33 data sets of defect range between 0 and -9.9% for each component. The input data have been generated by GSP commercial engine simulation program. The rate of classification for each component has been shown in Table 7, in which it is confirmed that the suggested multi-class SVM algorithm has high classification accuracy without any failure even for the 10 times as much of data sets compared to those of the sea-level static condition. The total learning time, however, has been increased to 21.2 seconds.

Fig. 15 shows the RMS errors between the real defects and the calculated ones for each component with altitude variations. The maximum RMS error has been less than 1%, with about 0.18 % for the compressor, about 0.99 % for the compressor-turbine, and about 0.32 % for the power turbine, respectively

6. Conclusion

A separate learning algorithm using SVM has been suggested for classification and discrimination of the defect position in the gas turbine engine, before applying MLP for the quantitative defect diagnostics. As the algorithm development for the defect diagnostic system, the original two-class SVM for the separation of the binary has been extended to multi-class SVM. The suggested method has been applied to find the positions and the quantity of the defects of the turbo-shaft engine. Several features have been obtained as results:

(1) By qualitative learning with SVM, the locations of defect parts can be classified perfectly.

(2) A rapid convergence and higher classification as well as the quantitative estimation accuracy can be obtained by reducing the non-linearity of the input data because the suggested algorithm using SVM can discriminate the defect location in advance.

(3) The learning results of the separate learning algorithm show improved learning speed and decreased error compared to the standard MLP.

(4) The possibility of practical application of the suggested algorithm to the defect diagnostics of the gas turbine engine has been verified.

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
d_{pk}	=	Desired output of *k* row
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_{pk}	=	Objective output of *k*th row
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_{kj}	=	*kj*th connection intensity of neuron
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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