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Analysis of performance deterioration of a micro gas turbine and the use of neural network for predicting deteriorated component characteristics †

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Abstract

Deteriorated performance data of a micro gas turbine were generated and the artificial neural network was applied to predict the deteriorated component characteristics. A program to simulate operation of a micro gas turbine was set up and deterioration of each component (compressor, turbine and recuperator) was modeled by changes in the component characteristic parameters such as compressor and turbine efficiency, their flow capacities and recuperator effectiveness and pressure drop. Single and double faults (degradation of single and two parameters) were simulated. The neural network was trained with a majority of the generated deterioration data. Then, the remaining data were used to check the predictability of the neural network. Given measurable performance parameters as inputs to the neural network, characteristic parameters of each component were predicted and compared with original data. The neural network produced sufficiently accurate prediction. Using a smaller number of input parameters decreased prediction accuracy. However, an acceptable accuracy was observed even without information on several input parameters.

Keywords: Micro gas turbine; Performance deterioration; Characteristic parameters; Performance parameters; Diagnosis; Neural network

1. Introduction

Micro gas turbines are attractive power sources for the distributed generation system considering its technical maturity, environmental friendliness and high heat recovery capacity. Design practice of micro gas turbines is different from that of conventional large gas turbines in some aspects. Turbine inlet temperature and pressure ratio are much lower than those of large gas turbines. Considering the low pressure ratio as well as the small volumetric flow due to small power rating, a single stage radial compressor and turbine are usually used. Another feature of micro gas turbine design is use of a recuperator to avoid efficiency penalty that would be inevitable in designing a simple gas turbine cycle with low pressure ratio and turbine inlet temperature.

In addition to increasing design performance, prediction and prevention of the performance degradation through an appropriate diagnosis is as important as in conventional gas turbines. Even with the several unique design features mentioned in the previous paragraph, the performance deterioration mechanism of a micro gas turbine is expected to be similar to that of conventional gas turbines. The performance deterioration of industrial gas turbines is well documented in a reference [1]. Most of the diagnosis methods such as model-based analysis methods and artificial intelligence methods [2] are applicable to micro gas turbines. A few studies have been reported on the subject of performance tests and basic diagnostics of

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small gas turbines [3-5].

Various physical problems cause changes in the characteristic parameters (component efficiency and flow capacity) of each component of the gas turbine, which results in changes in measurable performance parameters (temperatures, pressures, power, etc). Comparison of estimated characteristic parameters for any operating condition with reference data provides information on the healthiness of each component. Thus, the most important process of performance diagnosis is to predict the component characteristic parameters for a given set of measured performance parameters. The other important thing in developing a diagnosis system of an engine is preparation of the deterioration database linking the deteriorated characteristic parameters and the corresponding performance parameters.

Diagnosis methods of a gas turbine engine can be classified into either model-based methods or artificial intelligence methods. A typical example of the latter is the artificial neural network. Since the neural network is not based on analysis but on a database, its prediction process is rapid and accurate if the prediction is tried within the scope of a trained database. In particular, it is quite useful when the problem is highly non-linear and a functional relation between inputs and outputs is not easy to set up. Since physical problems of gas turbines have these characteristics, efforts to apply neural network to the fault detection and diagnosis of aero and industrial gas turbines have been increased during past decade [6-12].

In this study, a program to simulate operation of a micro gas turbine was constructed. Then, models to simulate the deterioration of each component of were made and the program was run to obtain the performance parameters for each deteriorated characteristic parameter. This process generated a database for deteriorated operation. Then, the database was applied to train a neural network. After having been trained, the neural network predicted the characteristic parameters for given sets of performance parameters.

2. Deteriorated performance data

2.1 Off-design modeling

The object of this study is a 30 kW class commercial micro gas turbine, which adopts a single stage centrifugal compressor and a single stage radial turbine and an annular recuperator wrapped around the core parts. The engine was tested with detailed measurements and reference component characteristic parameters were obtained [5]. Fig. 1 is a schematic of the engine with measuring locations. Details of the test and procedure of obtaining component characteristic parameters can be referred to the literature [5]. Table 1 exemplifies performance data for a full load condition.

Table 1. An example of full load performance data.

Ambient temperature (K)	291.0
Pressure ratio	3.59
Air flow rate (kg/s)	0.283
Compressor efficiency (%)	75.6
Turbine efficiency (%)	87.5
Recuperator effectiveness (%)	85.0
Turbine inlet temperature (K)	1115.5
Turbine exit temperature (K)	862.8
Exhaust gas temperature (K)	534.9
Fuel flow rate (kg/s)	0.00217
Electric power (kW)	27.53
Thermal efficiency (%)	25.68

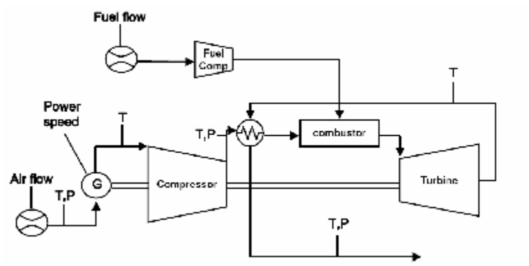

Fig. 1. Schematic of the micro gas turbine with measuring locations.

As it is hard to obtain deteriorated engine performance by degrading each component artificially, deterioration data were generated by simulation. In order for a simulation program to generate the deteriorated data accurately, it should be able to predict the normal (non-deteriorated) operation of the micro gas turbine first. To simulate engine operation, component characteristics (compressor, turbine and recuperator) are needed. A compressor map was generated based on the measured mass flow, pressure ratio and efficiency data. Since the engine operates with varying shaft speed, only a single operating point exists per speed. Therefore, performance curves (flow capacity vs pressure ratio and flow capacity vs efficiency) were generated by using an existing performance map of a compressor with a similar design point. Fig. 2 exemplifies the compressor map with a running line. Tur-

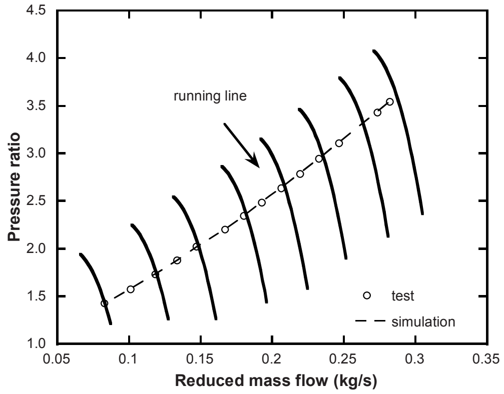

Fig. 2. Compressor map with an example of the engine running line.

bine characteristic was modeled by the following Stodola equation because it represents the variation of turbine flow capacity sufficiently well [5].

$$\frac{\dot{m}_{in}\sqrt{T_{in}}/P_{in}}{(\dot{m}_{out}\sqrt{T_{out}}/P_{out})_{ref}} = \frac{\sqrt{1-(P_{out}/P_{in})^2}}{\sqrt{1-(P_{out}/P_{in})_{ref}^{\ 2}}} \tag{1}$$

The variation of recuperator effectiveness was modeled by the following correlation which had regenerated the observed effectiveness behavior of the engine well enough [13].

$$\frac{\varepsilon_{rec}}{\varepsilon_{rec,ref}} = \left(\frac{\dot{m}_{air}}{\dot{m}_{air,ref}}\right)^{-0.021} \tag{2}$$

These component models were incorporated into process simulation software [14] to simulate operating behavior of the engine. A wide range of off-design operation has been simulated and compared with test data, and good agreement was observed [13]. The good agreement between tested and simulated operation line in Fig. 2 is an example. Accordingly, the off-design models are quite appropriate in simulating the operation of the micro gas turbine. Therefore, the components models were used as reference characteristics and the off-design analysis program was adopted to simulate the deteriorated operation in the next section.

2.2 Generation of deterioration data

Deterioration of gas turbine performance is caused by a performance decrease of each component, which is represented (or sensed) by variations of its characteristic parameters from the reference values. Several studies summarized and reported causes and effects regarding the gas turbine performance degradation [1, 15, 16]. Main causes of performance deterioration are fouling, erosion, corrosion and foreign object damage. Due to these problems, efficiencies and flow capacities of each component change, which leads to engine performance deterioration. In addition to compressor and turbine degradation, recuperator deterioration is added in micro gas turbines. Problems of the compressor and turbine usually result in reductions of flow capacity and efficiency. In a turbine, however, erosion may increase the flow capacity. Recuperator degradation (usually due to fouling) will cause a decrease of effectiveness and an increase of pressure loss, i.e., an increase of the back pressure. Modification of the following component characteristics, given as either a curve or an equation, simulates deterioration of each engine component.

Compressor flow capacity: $$\Gamma_c = \left.\frac{\dot{m}\sqrt{T}}{P}\right)_{c,in} \tag{3}$$

Compressor efficiency: $$\eta_c = \frac{h_{out,s} - h_{in}}{h_{out} - h_{in}} \tag{4}$$

Turbine flow capacity: $$\Gamma_t = \left.\frac{\dot{m}\sqrt{T}}{P}\right)_{t,in} \tag{5}$$

Turbine efficiency: $$\eta_c = \frac{h_{in} - h_{out}}{h_{in} - h_{out,s}} \tag{6}$$

Recuperator effectiveness: $$\varepsilon_{recc} = \frac{T_{air,out} - T_{air,in}}{T_{gas,in} - T_{air,in}} \tag{7}$$

Back pressure: $$\Delta P_b = (P_{gas,out} - P_{amb}) \tag{8}$$

A decrease of Γ_c by a prescribed percentage for all pressure ratios on the compressor map simulated the compressor flow capacity reduction. Compressor efficiency reduction was also simulated by a similar correction of the reference efficiency. Fig. 3 shows the method of compressor map correction schematically. A decrease of the turbine flow capacity (Γ_t) and efficiency was simulated similarly by reducing the flow parameter given by Eq. (1) and the reference efficiency. The recuperator performance deterioration was simulated by a decrease of the effectiveness and an increase of the back pressure loss. These corrections for component deteriorations can be expressed

Table 2. Fault cases.

	Fault number																										
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
Compressor flow capacity reduction	○							○	○	○	○	○	○														
Compressor efficiency reduction		○						○						○	○	○	○	○									
Turbine flow capacity reduction			○						○					○					○	○	○						
Turbine flow capacity increase				○						○					○							○	○	○			
Turbine efficiency reduction					○						○					○			○			○			○	○	
Recuperator effectiveness reduction						○						○					○			○			○		○		○
Back pressure loss increase							○						○					○			○			○		○	○

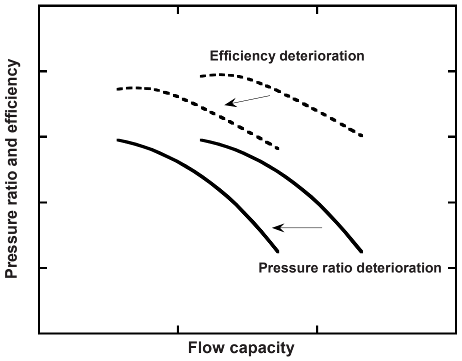

Fig. 3. An example of correcting compressor characteristics to simulate deterioration.

as follows:

$$\Gamma_c = c_1 \cdot \Gamma_{c,ref} \tag{9}$$

$$\eta_c(\Gamma_c) = c_2 \cdot \eta_{c,ref}\left(\Gamma_{c,ref}\right) \tag{10}$$

$$\Gamma_t = c_3 \cdot \Gamma_{t,ref} \tag{11}$$

$$\eta_t(\Gamma_t) = c_4 \cdot \eta_{t,ref}\left(\Gamma_{t,ref}\right) \tag{12}$$

$$\varepsilon_{rec} = c_5 \cdot \varepsilon_{rec,ref} \tag{13}$$

$$\Delta P_b = c_6 \cdot \Delta P_{b,ref} \tag{14}$$

where the coefficients c_1 to c_6 were adopted to generate arbitrary deteriorations. The values of the coefficients vary from 1.0 to 0.97 with a decrement 0.005, corresponding to zero to 3% reduction of each characteristic parameter. In case of the turbine flow capacity, zero to 3% increase of the flow capacity characteristic curve is also simulated to consider the erosion effect. Table 2 lists all the cases of simulated faults. Seven single faults (fault set number 1 to 7) and twenty double faults (fault set number 8 to 27) were simulated. The analysis was applied to full load (full speed) conditions of four different ambient temperatures between 291 to 301 K. Since the turbine inlet temperature had been estimated to be almost same for all full load conditions in the engine test, it was kept constant during the simulation. The simulation generated more than 3,000 fault data points.

Figs. 4 to 6 show variations of power, thermal efficiency and exhaust gas temperature for five fault cases (2, 5, 8, 19 and 27 of Table 2). The degree of deterioration means the degree of correcting each characteristic parameter to simulate the specific deterioration. For example, 3.0% means a case with the coefficient of 0.97 in Eqs. (9) to (14). All of the results seem physically reasonable. For example, a decrease of compressor efficiency (fault case 2) causes a reduction in the net power production. The resulting increase of the compressor discharge temperature (CDT) makes the combustor inlet temperature (recuperator exit air temperature) higher than the nominal value, which reduces the required fuel supply to the combustor. Thus, the degree of reduction in thermal efficiency is slightly less than that of the power. The higher air side inlet temperature at the recuperator causes an increase of the gas side exit temperature, i.e., exhaust gas temperature (EGT) of Fig. 6. Additional flow capacity reduction of the compressor (fault case 8 - reduction of both the efficiency and

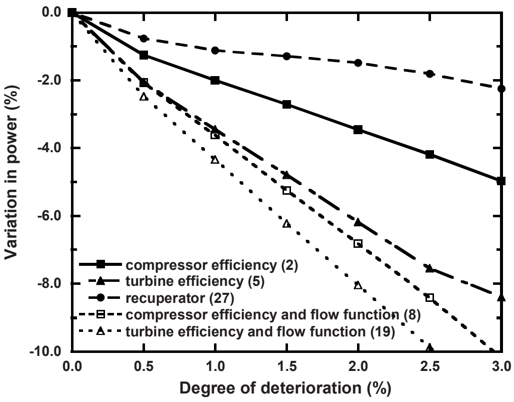

Fig. 4. Variation in power due to component deteriorations.

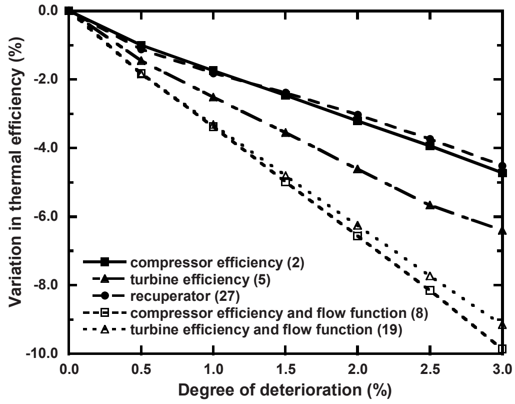

Fig. 5. Variation in thermal efficiency due to component deteriorations.

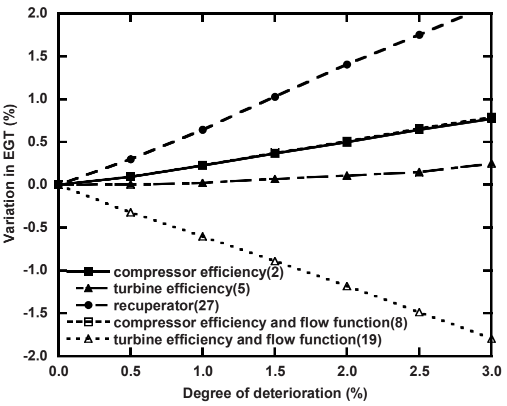

Fig. 6. Variation in exhaust gas temperature due to component deteriorations.

flow capacity) worsens the engine performance. The reduced compressor mass flow causes a decrease in the compressor discharge pressure, i.e., a lower pressure ratio, which increases the turbine exit temperature (TET).

A decrease of turbine efficiency (fault case 5) increases the turbine exit temperature, which in turn makes the combustor inlet temperature (air side exit temperature at the recuperator) higher. Thus, thermal efficiency does not decrease as much as power does due to a reduced requirement of fuel supply. In case of mixed reductions of turbine efficiency and flow capacity (fault case 19), both the power and thermal efficiency reduce further. Deterioration of the recuperator (case 27) causes a moderate power reduction due to increased back pressure loss. The reduced recuperator effectiveness makes the exhaust gas temperature higher and the combustor inlet temperature lower. Thus, the decrease of thermal efficiency is greater than that of power. All of the other simulated results, not shown here, are also physically sound. Consequently, the generated fault data are evaluated to be quite reasonable and practical.

3. Neural network

3.1 Methodology

Artificial neural network is a mathematical or computational model mimicking biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. More practically, neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data through training. Therefore, they are quite useful in solving problems where the system is non-linear and a functional relation between inputs and outputs is hard to describe. Performance diagnosis of the gas turbine is a good example of such problems. Accordingly, the effort to try out neural networks in performance diagnosis of gas turbines has been increased recently.

Peformance diagnosis of a gas turbine engine is a process to predict the component operating state represented by characteristics parameters (effciency and flow capacity) for a given (usually measured) set of performance parameters (temperture, pressure, etc.). Detailed setup of a complete diagnosis system depends on user's purpose, but performance diagnosis usually means a comparison of the predicted or estimated characteristic parameters with those at healthy operating conditions, resulting in a judgment of healthiness of a component and its degree of deterioration. In this work, the usefulness of the artificial neural network in predicting characterisitc parameters for deteriorated operation is examined. This is a primary step in developing a diagnosis program. A sucessful validation of the methodology in this work may present useful information in developing a full diagnosticprogram.

Table 3 summarizes input and output data used in the neural network system of this work. Both the input and output data are the simulated data obtained in section 2. The input data are measurable parameters (usually performance parameters) and the output data are component characteristic parameters that should be estimated by using the measured parameters. A commercial program [17] was used for the neural network simulation. Fig. 7 shows the structure of the neural network when all of the nine inputs of Table 3 are used. When different numbers of input data are used, different numbers of nodes of input and hidden layers were used. The quick propagation method was adopted to train the network and a logarithmic transfer function was used. A manual randomization range of ± 0.3 is given to select the initial value randomly. The number of iterations during training was 100,000. To deal with overtraining, a method called 'retain and restore best network control' was used. A copy of the network with the lowest validation error achieved during one of the previous iterations was retained and restored after network training was completed.

Table 3. Data classification for the neural network prediction.

Input data	Output data
Compressor inlet temperature Compressor inlet pressure Compressor discharge temperature Compressor discharge pressure Fuel mass flow Turbine exit temperature Exhaust gas temperature Exhaust gas pressure Power	Compressor efficiency Air flow Turbine efficiency Recuperator effectiveness Turbine exit pressure

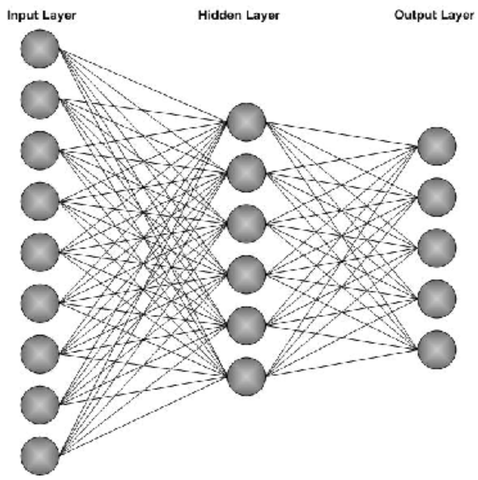

Fig. 7. An example of the neural network structure.

Application of the neural network consisted of two steps: training and prediction. In the training phase, the neural network was trained with 80% of the generated deterioration data. In the prediction phase, the accuracy of the trained neural network was validated with the remaining 20% data. For each fault case, deteioration data were randomly divided into the two data categories (data for training and data for prediction). Deviation of the predicted result of the neural network from the original value was evaluated and the root mean square deviation for each fault case was defined as follows to check the predictability of the network.

$$\delta_i = \frac{X_{i,N} - X_{i,O}}{X_{i,O}}, \quad RMS = \sqrt{\frac{\sum_{i=1}^{N} \delta_i^2}{N}} \tag{15}$$

3.2 Results

Several neural networks with different structures, depending on the number of input parameters used, were applied. First, the neural network architecture of Fig. 7 (9-6-5: numbers of nodes of input, hidden and output layers are 9, 6 and 5, respectively) was used. In this situation, it was assumed that all of the nine input data of Table 3 are available as measured data. In general, the neural network regenerates the original

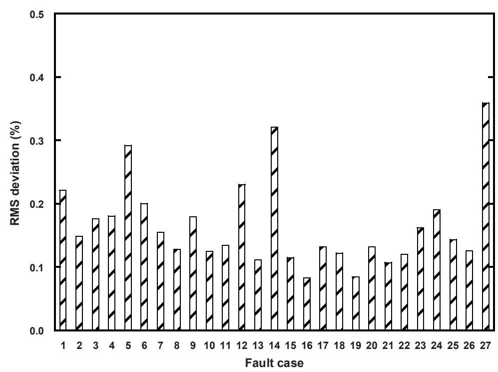

Fig. 8. RMS deviations of neural network prediction when all input data are used.

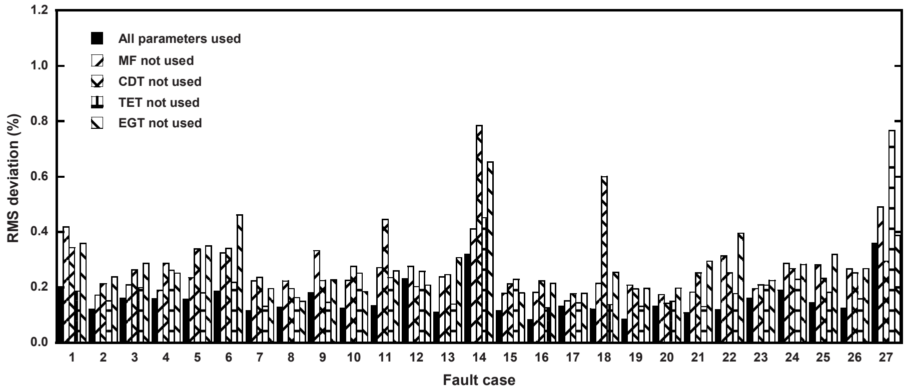

Fig. 9. Deviations of neural network prediction when one input parameter is not used.

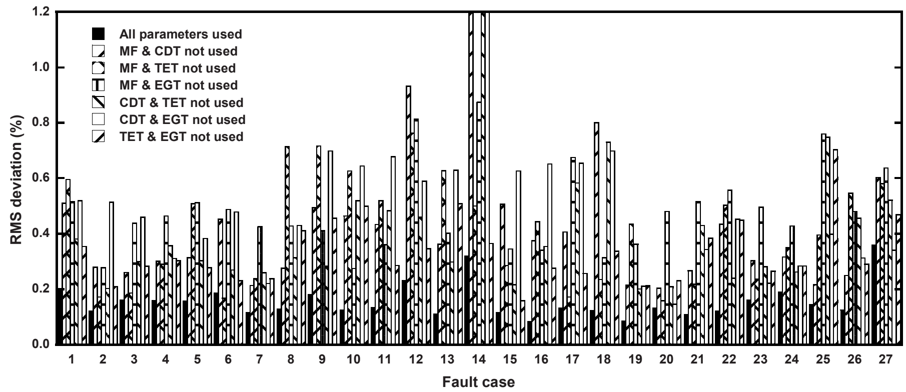

Fig. 10. Deviations of neural network prediction when two input parameters are not used.

data very well. As shown in Fig. 8, the RMS deviations of all 27 fault cases are sufficiently less than 0.2% except for a couple of cases. The greatest RMS deviation is less than 0.4%. There is no sensible difference between deviations for single and double faults. Accordingly, it can be concluded that the neural network was well structured and trained, and its accuracy is sufficiently good.

As mentioned above, the reference results of Fig. 8 were obtained assuming that all of the nine input data were provided. In reality, however, some of the data may not be available because they are not measured. For example, fuel mass flow (MF), compressor discharge temperature (CDT) and exhaust gas temperature (EGT) were not measurable in the original commercial version of the micro gas turbine used in this study. They were measured with additionally equipped sensors [5]. Therefore, it would be useful to check if the neural network can predict the characteristic parameters sufficiently well even without information of some input parameters. Consequently, predictions were also performed with reduced numbers of input data. It was assumed that some of selected four parameters (MF, CDT, EGT and TET) were not available (not measured onsite) as inputs. In these situations, the number of input nodes was reduced to fit the number of input data. The number of nodes of the hidden layer was also reduced. Architectures of 8-6-5, 7-5-5, 6-5-5, 5-4-5 were used for situations where the number of input parameters unused are one, two, three and four, respectively. Each network was trained and applied to prediction independently with different structures.

Results of predictions with one parameter excluded from the input data are shown in Fig. 9. For comparison, results of predictions using all input data (Fig. 8) are also shown as dark bars. In general, excluding one parameter reduces accuracy. However, RMS deviations of almost all instances remain under 0.5%. Only

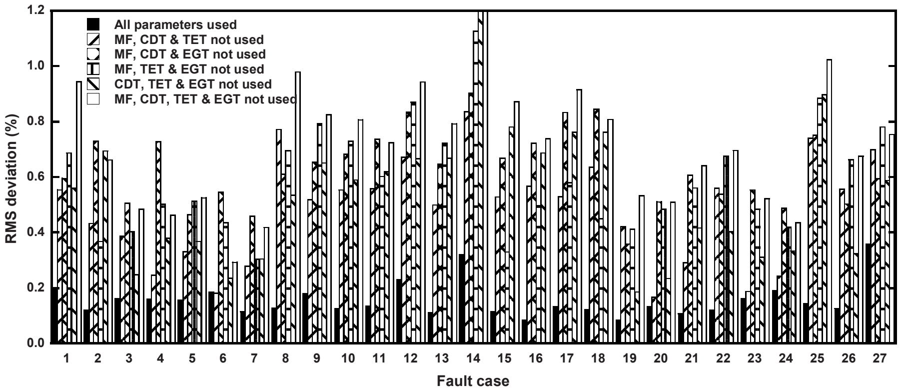

Fig. 11. Deviations of neural network prediction when three or four input parameters are not used.

4 out of 108 instances show RMS deviations over 0.5%. There are no special correlations between the excluded parameters and the fault cases, which seems to result from the randomness of the neural network. In particular, fuel flow is not usually measured in micro gas turbines, and thus cannot be used as an input parameter in engine diagnosis. Excluding fuel flow may give a slightly higher inaccuracy. However, it is not greater than the inaccuracies due to excluding other parameters. This seems to be a great advantage of the neural network method. Consequently, the neural network seems to produce satisfactory results even without using one of the input data. Results of predictions with two parameters excluded from the input data are shown in Fig. 10. All six combinations among four parameters were analyzed. Inaccuracies further increase from the previous analysis. About 22% instances produce deviations over 0.5%. The worst instance (case 14) reaches about 1.5%. However, most deviations are much less than 1%. Again, there are no noticeable correlations between the excluded parameters and their effects on special fault cases are observed. Results of predictions with three as well as four (all) parameters excluded from the input data are shown in Fig. 11. Naturally, the overall inaccuracy increases again. Now, about 55% and 75% instances result in deviations over 0.5% for the predictions without using three and four parameters, respectively. The worst instance (case 14) reaches about 1.5% again; however, almost all instances produce RMS deviations less than 1%.

4. Conclusions

Component deterioration of a micro gas turbine was simulated, and deteriorated component characteristics were predicted by using an artificial neural network. Results are summarized as follows.

(1) Based on performance test results, component characteristic parameters for normal (healthy) operation were estimated. A simulation program for off-design operation of the micro gas turbine was constructed. Deteriorated engine data were generated considering changes in characteristic parameters such as efficiency and flow capacity of the compressor and the turbine, and effectiveness and pressure drop of the recuperator. Seven single faults and twenty double faults were simulated. The simulation provided physically reasonable deterioration data.

(2) The majority of the deterioration data were applied to train an artificial neural network and the remaining data were used to check its predictability. If all of the input parameters were used, the RMS deviations of the predicted characteristic parameters from the original values were less than 0.2% for most cases. The effect of excluding some parameters from the input data on the accuracy of the prediction was also analyzed. This simulates conditions where some of the performance parameters (temperatures and flow rate) are not measured onsite. Excluding one parameter produces RMS deviations far less than 0.5% on the average. Increasing the number of unused parameters increases the prediction error. However, even if two parameters are excluded, 80% instances produce RMS deviations less than 0.5%. Excluding three or four input parameters worsens the prediction accuracy further but the deviation hardly exceeds 1%.

(4) This work validated the usefulness of the neural network as a tool to predict deteriorated characteristic parameters. The network can predict component

characteristic parameters with an acceptable accuracy even without information on a couple of temperatures and fuel flow. Additional information on those parameters would make the neural network produce sufficiently high accuracy.

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Nomenclature

$c_1, \ldots, c_6$	:	Coefficients
CDT	:	Compressor discharge temperature [K]
EGT	:	Exhaust gas temperature [K]
MF	:	Fuel mass flow rate [kg/s]
$\dot{m}$	:	Mass flow rate [kg/s]
h	:	Specific enthalpy [kJ/kg]
N	:	Number of data
P	:	Pressure [kPa]
ΔP_b	:	Back pressure loss [kPa]
RMS	:	Root mean square deviation
T	:	Temperature [K]
TET	:	Turbine exit temperature [K]
X	:	Characteristic parameter
δ	:	Deviation
ε_{rec}	:	Recuperator effectiveness
Γ	:	Flow capacity
η	:	Efficiency

Subscript

c	:	Compressor
i	:	Parameter index
in	:	Inlet
N	:	Neural network result
O	:	Original
out	:	Outlet
ref	:	Reference
s	:	Ssentropic
t	:	Turbine

References

[1] I. S. Diakunchak, Performance deterioration in industrial gas turbines, Journal of Engineering for Gas Turbines and Power, 114 (1992) 161-168.

[2] Y. G. Li, Performance analysis based gas turbine diagnostics: A review, Proc. of The IMechE, Part A – J. of Power and Energy, 216 (2002) 363-377.

[3] C. R. Davison and A. M. Birk, Steady state and transient modeling of a micro-turbine with comparison to operating engine, Proc. of ASME Turbo Expo, Amsterdam, The Netherlands, (2004) ASME paper GT2004-53378.

[4] J. Yin, M. S. Li and W. Huang, Performance analysis and diagnostics of a small gas turbine, Proc. of the Int. Gas Turbine Congress, Tokyo, Japan, (2003) IGTC2003Tokyo TS-006.

[5] J. J. Lee, J. E. Yoon, T. S. Kim, and J. L. Sohn, Performance test and component characteristics evaluation of a micro gas turbine, J. of Mechanical Science and Technology, 21 (1) (2007) 141-152.

[6] K. Kanelopoulos, A. Stamatis and K. Mathioudakis, Incorporating neural networks into gas turbine performance diagnostics, Proc. of ASME Turbo Expo, Orlando, USA, (1997) ASME Paper 97-GT-35.

[7] A. J. Volponi, H. R. DePold, R. Ganguli and C. Daguang, The use of Kalman Filter and neural networks methodologies in gas turbine performance diagnostics: A comparative study, Proc. of ASME Turbo Expo, Munich, Germany, (2000) ASME Paper 2000-GT-0547.

[8] C. Romessis, A. Stamatis, and K. Mathioudakis, A parametric investigation of the diagnostic ability of probabilistic neural networks on turbofan engines, Proc. of ASME Turbo Expo, New Orleans, USA, (2001) ASME Paper 2001-GT-0011.

[9] M. Ghoreyshi and R. Singh, Using neural network for diagnostics of an industrial gas turbine, Proc. of ASME Turbo Expo, Amsterdam, The Netherlands, (2004) ASME paper GT2004-53638.

[10] R. Bettocchi, M. Pinelli, P. R. Spina and M. Venturini, Artificial intelligence for the diagnostics of gas turbines. part I: neural network approach, Proc. of ASME Turbo Expo, Reno, USA, (2005) ASME Paper GT2005-68026.

[11] E. E. B. Gomes, D. Mc. Caffrey, M. J. M. Garces, A. L. Polizakis and P. Pilidis, Comparative analysis of microturbines performance deterioration and diagnostics, Proc. of ASME Turbo Expo, Barcelona, Spain, (2006) ASME paper GT2006-90304.

[12] R. M. Gustavo, B. Roberto, B. Cleverson and L. Isaias, Gas turbine fault detection and isolation using MLP artificial neural network, Proc. of ASME Turbo Expo, Montreal, Canada, (2007) ASME paper GT2007-27987.

[13] J. J. Lee, J. E. Yoon and T. S. Kim, Operation simulation of a microturbine based on test data, J. of Fluid Machinery (in Korean), 9 (6) (2006) 22-28.

[14] Aspen Technology, AspenOne HYSYS, ver. 2004. 02 (2004).
[15] R. Kurz and K. Brun, Degradation in gas turbine systems, Trans. ASME, Journal of Engineering for Gas Turbines and Power, 123 (1) (2001) 70-77.
[16] A. Zwebeck and P. Pilidis, Degradation effects on combined cycle power plant performance – Part 1: gas turbine cycle power component degradation effects, Trans. ASME, Journal of Engineering for Gas Turbines and Power, 125 (1) (2003) 651-657.
[17] Alyuda Research Inc, Alyuda Neuro Intelligence ver 2.2 (2006).

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