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Fault Diagnosis System for an Industrial Gas Turbine by Means of Neural Networks

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ABSTRACT

This work deals with the use of Artificial Neural Networks (ANNs) for fault diagnosis of a medium-size industrial gas turbine. One healthy and ten faulty engine conditions have been simulated in order to produce a comprehensive and realistic data set, which is used for training and validation of the ANNs. After the learning process is over, the ANN is able to make a diagnosis about the gas turbine's condition when new data (not used during training) is presented to it. The data presented to the ANN system include only parameters that are actually measured in the real engines. The results obtained in this investigation show that an ANN-based fault diagnosis system is capable of fault isolation and identification with high reliability. Furthermore, the system is also able of identifying many fault types at an early stage, before they are fully developed and become obvious.

NOMENCLATURE

Alphabetical order

ANN	Artificial Neural Network.
C	Compressor.
CCh	Combustion chamber.
F	Transfer function.
F1, F2, etc.	Fault 1, fault 2, etc.
FL	Fault level.
FN	Turbine capacity (Flow Number).
GPA	Gas Path Analysis.
GT	Gas Turbine.
H	Number of hidden neurons *also* healthy operational condition.
H.I.	Human intervention.
IGV	Inlet Guide Vane.
IT	Information Technology.
LHV	Lower Heating Value.
MLP	Multi-Layer Perceptron.
M	Number of inputs to the ANN.
m	Mass flow.
mp	Missclassified points.
N	Number of outputs from the ANN.
o	ANN-output.
OEM	Original Engine Manufacturer.
p	Pressure.
P	Power.
s	Weighted input to the transfer function.
T	Temperature *also* Turbine.
TR	Target Ratio.
x	Input signal to the ANN.
y	Output signal from the ANN.
w	Weight connection

Greek symbol

Δ	Difference, drop.
η	Isentropic efficiency.

Subscripts

C	Compressor.
CCh	Combustion chamber.
f	Fuel.
h	Hidden layer.
i	Arbitrary node in the input layer.
j	Arbitrary neuron in the hidden layer.
k	Arbitrary neuron in the output layer.
lim	Limiter (firing temperature).
o	Output layer.
out	Output (Power).
T	Turbine.
0	Ambient condition *also* bias.
2	Compressor inlet.
3	Compressor outlet.
65	Turbine outlet.

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INTRODUCTION

Modern gas turbines have highly-loaded components in order to reach the economic goals imposed by the liberalized energy market of today. This situation leads to increased risk for malfunctions, as well as faster degradation of the engine's performance. Since the owners of the plant are interested in avoiding these faulty conditions, major revisions and maintenance work are carried out on a regular basis. Eventually, when a particular damage occurs or the performance degradation reaches a certain limit value, measures must be taken, e.g. compressor washing, reparation of a component, or replacement of the damage one by a spare part. These kinds of actions are very costly, but also down-time of the plant results in an economic punishment.

Advanced data acquisition and control systems are already available in most modern power plants. Furthermore, other modern IT-based solutions are being introduced to help broaden the economic margins; solutions which are considered as "high value, low cost" tools (Morton, 2002). Artificial neural networks (ANNs), a group of algorithms originated within the field of artificial intelligence, have been identified to be that kind of tool.

ANNs are not programmed; they learn from experience instead (Massie, 2001). The knowledge is extracted from data that is collected from the analyzed system, and then the ANN is able to find the patterns that rule the relationships between the inputs and the outputs of the system without previous physical knowledge about the system itself. ANNs have the advantage of handling multidimensional nonlinear systems, and therefore they have been widely used e.g. for function approximation and classification tasks. ANNs have become popular in many engineering applications, and now they are also being used in power plant technology for tasks that are difficult to solve with traditional techniques (Assadi et al., 2001), (Mesbahi et al., 2001), (Arriagada et al., 2002) and (Arriagada et al. 2003). Fault diagnosis of an industrial gas turbine is one of the fields where ANNs can be applied advantageously.

BRIEFLY ABOUT ANNs

ANNs are inspired by our present model of the human brain, however, they are by no means representations of the same. Similar to the biological nervous system, an ANN distributes the incoming data into several parallel-connected simple units (called artificial neurons) within which the data is processed. Owing to their high connectivity and parallelism, ANNs are able to perform non-linear mapping of a multidimensional input space onto another multidimensional output space. The computational speed becomes higher, making ANNs suitable for complicated tasks that require rapid response, e.g. real-time processing of several simultaneous signals. A deeper explanation of the theory of ANNs can be found in the textbook by Haykin (Haykin, 1999).

The type of ANNs used in this work is the feed-forward multilayer perceptron (MLP), in which the data flows strictly forward all through the network. MLPs are formed by one input layer, one or more hidden layers and one output layer, with a set of adaptable parameters, i.e. the synaptic weight connections, in between each pair of layers. The information from the system to be modeled is collected in the input layer, but no signal processing occurs here. All the processing occurs in the hidden and the output layers by means of superposition and transformation of the weighted signals. It has been shown that it is enough to have one hidden layer with a continuous sigmoidal transfer function to carry out multi-dimensional non-linear mapping of any continuous function; only the number of hidden neurons is increased (Cybenko, 1989). Consequently, only MLPs with one hidden layer with the log-sigmoid transfer function (F) are considered in this study. Eq. (1) presents the log-sigmoid function used here.

$$F(\mathrm{s}) = \frac{1}{1 + \mathrm{e}^{-\mathrm{s}}} \qquad (1)$$

Where, s: weighted input to the transfer function.

Before the ANN can make any meaningful mapping, it must be trained. The training of the MLP requires that a data set for which the targets are known is available (supervised learning). This data set is usually divided into three portions: one for training, a second for validation during training, and a third for testing the ANN after the learning is over. The data is normalized between 0.2 and 0.8 (in order to improve the extrapolation capacity of the network), and therefore the results obtained must be de-normalized. The most common method for training MLPs is the *backpropagation* algorithm, popularized in the 1980's (Rumelhart et al., 1986). The principle is to present inputs (x) to the ANN and then compare the generated outputs (y) with the desired target values. If they differ from each other, i.e. if there exists an error, then the weights (w) are adjusted implementing gradient descent in weight space. A step-by-step explanation of this method can be found in (Arriagada, 2001). During the training process, the MLP learns the internal representations for the training data and once the training is over, this information is stored in the weights; i.e. they are the long-term memory of the ANN. The ANN is now able to make predictions when new input patterns are presented to it.

The topology of the MLP is such that every input node corresponds to an input parameter and every output neuron corresponds to an output parameter. This allows the representation of the individual outputs from the network by the generic expression shown in Eq. (2).

$$\mathrm{y}_{\mathrm{k}} = F_{\mathrm{o}}\left(\sum_{\mathrm{j=1}}^{\mathrm{H}} \mathrm{w}_{\mathrm{kj}} \cdot F_{\mathrm{h}}\left(\sum_{\mathrm{i=1}}^{\mathrm{M}} \mathrm{w}_{\mathrm{ji}} \mathrm{x}_{\mathrm{i}} + \mathrm{w}_{\mathrm{j0}} \right) + \mathrm{w}_{\mathrm{k0}} \right) \qquad (2)$$

Where, F_h: transfer function in the hidden layer;
F_o: transfer function in the output layer;
H: number of hidden neurons;
M: number of input nodes;
N: number of output neurons;
k = 1 … N.

The parameters w_{j0} and w_{k0} are not weights, they are offsets or biases. For practical reasons they are treated as weights and determined through the same adjustment process.

H is usually tuned by trial-and-error in order to obtain the best performance from the ANN at a reasonable training time. After the network is trained, it is tested with a portion of the available data from the simulations not used during the training process in order to evaluate its generalization ability.

THE SELECTION AND SIMULATION OF THE FAULTS

The gas turbine engine

The gas turbine studied is a mid-size industrial engine conceived for continuous operation, either as a stand alone power unit or in a combined cycle. This single-shaft engine is also suitable for cogeneration applications and presents very low NOx emissions.

Selection of the faults

A list with frequent faults in industrial gas turbines was put together with the experts from the engine manufacturer company (ALSTOM Power Sweden AB). It was accorded that the faulty conditions to be simulated for this study have to fulfill the following criteria:

a. To represent realistic conditions habitual in industrial gas turbine engines.
b. To be distributed over the main components of the engine, i.e. compressor (C), combustion chamber (CCh) and turbine (T).
c. To include both usual deterioration of the engine performance and engine faults.

Of course, an ultimate condition must be satisfied, namely that the faults can actually be simulated with the available tools in a realistic way.

Simulation of the faults

The healthy and faulty conditions were simulated with two advanced software tools developed by the OEM for modeling and simulation of the engine's heat and mass balances (performance deck), as well as advanced 1- and 2-D turbine calculations (Genrup, 2003). All calculations are performed with the real firing temperature control algorithm in order to take into account the influence that the control system may have in some operational cases.

In the performance deck, main parameters of the gas turbine components were manipulated by applying deltas (i.e. relative changes) and factors in order to obtain the desired behavior. This process was carried out based on the experience and knowledge possessed by expert engineers at the company. Some of the manipulated parameters are:

- Compressor inlet mass flow (m_2);
- Compressor isentropic efficiency (η_C);
- Combustor section pressure drop (Δp_{CCh});
- Turbine isentropic efficiency (η_T);
- Turbine capacity (FN);
- Different air cooling flows in the turbine.

Several sets of data were generated for varying engine-load (100, 90, 80 and 70%) and ambient temperature (-30, -10, 10 and 30°C). It is known from a previous study that the effect of the ambient pressure (p_0) is linear and the effect of the relative humidity of the air is rather small (Assadi, 2001). Therefore, these two figures were not varied in the present study and they were assumed to be 1.013 bar and 60%, respectively. The fuel was assumed to be natural gas (LHV = 46800 kJ/kg).

Different fault levels

All the selected faults were simulated at five different fault levels (FLs), spanning from fully developed (100% FL) down to incipient fault (20-33% FL). The idea was to test the capability of the ANN to diagnose faults that are just partially developed. All these faults imply an economic loss for the plant owner when they occur, thus a tool that can generate a warning as early as possible is highly interesting. Lots of efforts have been put into the development of techniques to diagnose such faults successfully, including gas path analysis (GPA), which is the traditional one for this aim today (Doel, 1994).

Table 1 below presents the selected faults and the gas turbine components that mainly are related to or affected by the faults. The FLs considered are 25 (alternatively 20 or 33), 50, 66, 80 and 100% developed faults.

Table 1. The selected faults, their distribution over the engine sections and the simulated fault levels.

Fault	Description	GT-section affected			FL (%)
		C	CCh	T	
F1	Compressor fouling	X			20, 50, 66, 80, 100
F2	Compressor tip rubbing	X			33, 50, 66, 80, 100
F3	Air path into combustor section partly blocked		X		25, 50, 66, 80, 100
F4	Sealing diaphragm leakage (in front of 1st stage vane)		X	X	25, 50, 66, 80, 100
F5	Cooling air leakage from mid-pressure level into turbine	X		X	20, 50, 66, 80, 100
F6	Worn central casing sealing		X	X	25, 50, 66, 80, 100
F7	Vane 1 showerhead erosion			X	25, 50, 66, 80, 100
F8	Blocked cooling air channels stage 1			X	20, 50, 66, 80, 100
F9	Turbine blade trailing edge erosion			X	33, 50, 66, 80, 100
F10	Turbine blade aging			X	33, 50, 66, 80, 100

The final data set

The resulting data files from simulations, including all the thermodynamic data for each station in the engine for every single case, were very extensive. Not all of this data was utilized for training the ANNs, thus only the parameters which are actually measured in the real engine were considered for accomplishing as realistic conditions as possible (See Fig. 1). These parameters are:

- Ambient temperature (T_0);
- Inlet Guide Vane angle (IGV);
- Compressor inlet mass flow (m_2);
- Compressor inlet pressure (p_2);
- Compressor outlet pressure (p_3);
- Compressor outlet temperature (T_3);
- Fuel mass flow (m_f);
- Combustion section pressure drop (Δp_{CCh});
- Turbine outlet pressure (p_{65});
- Turbine outlet temperature (T_{65});
- Mid-pressure cooling air pressure drop in strainer ($\Delta p_{strainer}$);
- Power output (P_{out}).

Additional parameters included in the ANN study were those that can be controlled by the operators or by the control system, e.g.:

- Engine load;
- Firing temperature limiter (T_{lim}).

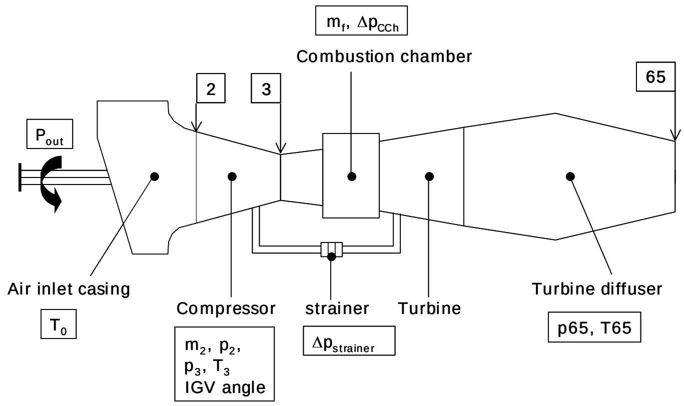

Fig. 1 Schematic drawing of the gas turbine showing the main components and the measured parameters.

ANN SYSTEM FOR FAULT DIAGNOSIS

The distribution of the operational data for training the ANNs

The approach adopted in this study was to extract data from the simulation results of the healthy operational condition as well as the ten different faulty conditions described in Table 1. It must be noted that only data for full grown faults (100% fault level, FL) was included in this group designated for the ANN's learning process. Each operational condition was represented by 16 operational points, i.e. 176 operational points in total.

Half of the data (i.e. 88 points) was randomly chosen and used for the training process, and another 26 points, also randomly chosen, were used for cross-validation. To determine the optimal length of the learning process, the method of *early stopping* was applied. In this method the network training goes on until the cross-validation error (which is continuously monitored) starts to increase. Then the weights were frozen and the resulting ANN was confronted with an independent test set (the remaining 62 operational points) in order to check the diagnostic performance on "unseen" data.

The performance of the resulting neural network is expressed as a target ratio (TR), defined as the percentage of right identified conditions of the total, see Eq. (3).

$$TR = \frac{\text{Number of correct predictions on the data set}}{\text{Total number of points in the data set}} \cdot 100 \quad [\%] \qquad (3)$$

Fault diagnosis with early warning of emerging faults

A system that can deliver early warnings for emerging faults would be important in avoiding major damages; therefore the diagnostic capability of the ANNs on partially developed faults was investigated. For this purpose, another four data sets with partially developed faults were extracted from the simulation results. The first data set contains 160 data points (16 points for each faulty condition) for incipient faults (20 to 33% FL). The second data set also contains 160 data points (once again 16 for each fault) for half developed faults (50% FL). In similar way, the third and the fourth data sets contain 160 points each corresponding to 66 and 80% FLs, respectively. It must be emphasized that these four data sets were not used during the learning process; however, the ANN was tested with them.

Description of the ANN-based fault diagnosis system

The ANN-architecture is determined by the selection of the inputs, the outputs and the number of hidden neurons. The inputs are determined to correspond to the measured parameters in the real engines, as well as the ones controlled by the operators and the control system, i.e.: T_0, IGV, m_2, p_2, p_3, T_3, m_f, Δp_{CCh}, p_{65}, T_{65}, $\Delta p_{strainer}$, P_{out}, load, T_{lim}. As can be seen, 14 input parameters are considered.

The number of hidden neurons is varied within a wide range, repeating the training of ANN for each value adopted by H. Finally, the weights for the network with the best performance are saved.

The desired outputs from the ANN are unique combinations of 28 binary numbers that are arranged in graphical display as shown in Figure 2.

The ANN can then be named according to its structure, i.e. 14-H-28.

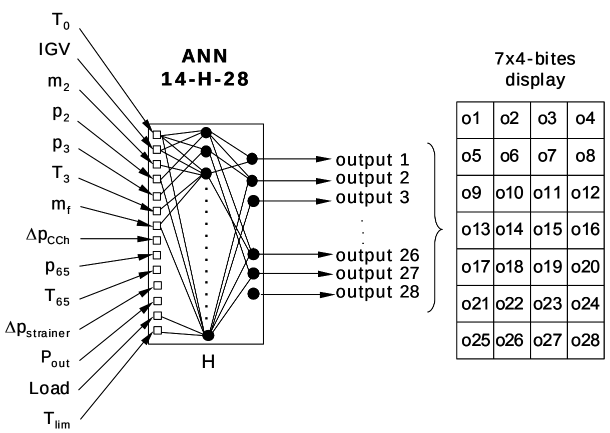

Fig. 2 Schematic drawing of the ANN and the interpretation of the outputs in a graphical display.

The output value "1" gives a black bite and the output value "zero" gives a white bite in the display, thus building signs that show the different operational conditions of the engine according to the key presented in Table 2 below.

However, the real outputs from the ANN are not binary numbers as the desired ones, they are real numbers between 0 and 1. Therefore the following filter is applied in order to translate them into a sign in the display:

If output > 0.6 then output = "black", else
If output < 0.4 then output = "white", else
output = "grey"

This graphical method permits human interaction with ANN in the fault detection process. It also introduces more flexibility to the system because it lets the operator discern in the cases that are not clearly classified by the ANN from the beginning. The three-color map is especially favourable for this purpose. This added flexibility, together with the inherent pattern recognition capacities of neural networks, is expected to allow the detection of emerging faults and those not full developed.

Table 2. Desired binary outputs and their interpretation.

Operational Condition	Desired output (binary combination)	Sign displayed
Healthy	1001-1001-1001-1001-1111-1001-1001	H
Fault 1	0100-1100-0100-0100-0100-0100-1110	1
Fault 2	0110-1001-0001-0010-0100-1000-1111	2
Fault 3	1110-0001-0011-0001-0001-0001-1110	3
Fault 4	1010-1010-1111-0010-0010-0010-0010	4
Fault 5	1111-1000-1110-0001-0001-0001-1110	5
Fault 6	0010-0100-1000-1110-1001-1001-0110	6
Fault 7	1111-1001-0001-0010-0010-0100-0100	7
Fault 8	0110-1001-1001-0110-1001-1001-0110	8
Fault 9	0110-1001-1001-0111-0001-0010-0100	9
Fault 10	0100-1010-1010-1010-1010-1010-0100	0

RESULTS AND COMMENTS

The main results from the fault diagnosis with this ANN-based method are presented in Tables 3, 4 and 5 both as a TR in % and as the number of missclassified points (mp). The best results were achieved by an ANN with a structure of 14-27-28 (i.e. H = 27).

In Table 3 is shown the performance of this ANN on the training, cross-validation and test data sets. The results are shown both without and with human intervention (H.I.). From the table it can be seen that the ANN has excellent prediction capacity for the operational conditions included in this data group, i.e. healthy and fully grown faults (100% FL). The performance of the ANN on the total data set (at the different FLs) is presented in the subsequent tables.

Table 3. Performance of ANN 14-27-28 on the data used during the learning process.

TR	Without H.I.		With H.I.	
	mp	%	mp	%
Training	0	100	0	100
Cross-validation	0	100	0	100
Test	1	98.4	0	100
Tot.	1	99.4	0	100

When no H.I. is allowed, the performance of the ANN is very good on fully developed faults (100% FL) and acceptable on most of the faults at FL 80%, except F3 which turned out to be difficult to predict in all the calculations run. At FL 66%, the performance of the ANN further deteriorates reaching a poor average TR of just 62%, but there are still a couple of faults that can be recognized without problems, namely F8 and F10. At 50% FL the faults are not detected in major extends and at the lowest FL they are not detected at all. See Table 4 for details. The reason for the disparity in the recognition of some faults from one FL to the other is that the control system is very effective in counteracting the symptoms of some partly developed faults (e.g. F9), at least until a certain level.

When this level is exceeded, then the ANN can discover the fault.

The same neural network, 14-27-28, shows a dramically improved performance when H.I. is allowed. With H.I., the diagnosis of fully blown faults and at FL 80% is excellent. At FL 66% there is still an acceptable TR, with the exceptions of F1 and F3 that are still difficult to predict at lower FLs. At 50% FL, the TR has dropped to 42.5% and at the lowest FL, human intervention makes no major difference. See Table 5 for details.

Table 4. Performance of ANN 14-27-28 on all the operational conditions *without* human intervention.

FL	0%		20,25,30%		50%		66%		80%		100%	
TR	mp	%	mp	%	mp	%	mp	%	mp	%	mp	%
H	0	100										
F1			16	0	16	0	10	37.5	5	68.8	0	100
F2			16	0	12	25	4	75	1	93.8	0	100
F3			16	0	16	0	16	0	15	6.3	0	100
F4			16	0	16	0	8	50	1	93.8	0	100
F5			16	0	16	0	6	62.5	2	87.5	0	100
F6			16	0	9	43.8	5	68.8	1	93.8	0	100
F7			16	0	16	0	7	56.3	2	87.5	0	100
F8			16	0	16	0	0	100	0	100	0	100
F9			16	0	11	31.3	5	68.8	1	93.8	1	93.8
F10			16	0	14	12.5	0	100	0	100	0	100
Tot.	0	100	160	0	142	11.3	61	61.9	28	82.5	1	99.4

Table 5. Performance of ANN 14-27-28 on all the operational conditions *with* human intervention.

FL	0%		20,25,30%		50%		66%		80%		100%	
TR	mp	%	mp	%	mp	%	mp	%	mp	%	mp	%
H	0	100										
F1			16	0	14	12.5	7	56.3	2	87.5	0	100
F2			15	6.3	6	62.5	1	93.8	0	100	0	100
F3			16	0	16	0	16	0	2	87.5	0	100
F4			16	0	16	0	3	81.3	0	100	0	100
F5			16	0	8	50	0	100	0	100	0	100
F6			16	0	6	62.5	1	93.8	0	100	0	100
F7			16	0	7	56.3	0	100	0	100	0	100
F8			16	0	3	81.3	0	100	0	100	0	100
F9			15	6.3	8	50	0	100	0	100	0	100
F10			15	6.3	8	50	0	100	0	100	0	100
Tot.	0	100	157	1.9	92	42.5	28	82.5	4	97.5	0	100

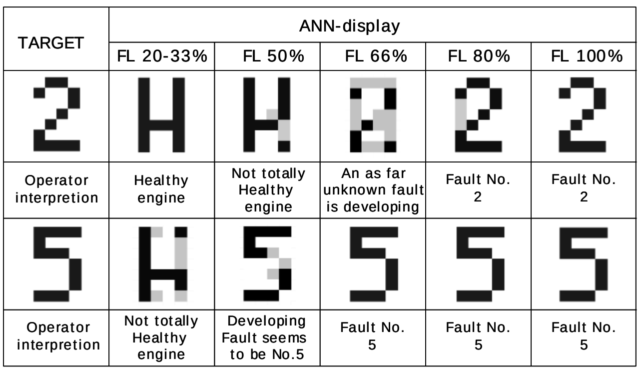

Fig. 3 The displayed ANN-outputs and the interpretation by the operator for fault No.2 (at 90% engine load and T_0=30°C) and fault No.5 (at 100% engine load and T_0=10°C).

In order to clarify how human intervention is accomplished, Figure 3 above shows a couple of practical examples of the displayed ANN-outputs for two specific operational conditions (namely fault No.2, at engine load 90% and T_0 = 30°C and fault No.5 at engine load 100% and T_0 = 10°C). In the figure it can be appreciated how the ANN output changes during the fault development sequence and the observations made by an hypothetical operator are included. For instance, fault No.2 becomes evident to the operator at FL 80%, while fault No.5 can be clearly distinguished already at FL 50%.

Another interesting aspect of the diagnostics results is revealed at a closer look at the ANN-outputs: the fault diagnosis capability of the ANN is deteriorated at part-load engine operation. This situation is shown in Table 6, where it can be appreciated that at FL 100%, 80% and 66%, the TR is lower at part-load than at full-load. This effect is partly remediated when the fault diagnosis with H.I. is applied. The performance of the ANN is improved at all FLs and at all gas turbine loads, as shown in Table 7.

Table 6. Performance of ANN 14-27-28 at part-load and full-load operation *without* human intervention.

FL	0%		20,25,30%		50%		66%		80%		100%	
TR	mp	%	mp	%	mp	%	mp	%	mp	%	mp	%
load 70%	0	100	40	0	34	15	21	48	11	73	1	98
load 80%	0	100	40	0	35	13	13	68	6	85	0	100
load 90%	0	100	40	0	37	7.5	16	60	7	83	0	100
load 100%	0	100	40	0	36	10	11	73	4	90	0	100

Table 7. Performance of ANN 14-27-28 at part-load and full-load operation *with* human intervention.

FL	0%		20,25,30%		50%		66%		80%		100%	
TR	mp	%	mp	%	mp	%	mp	%	mp	%	mp	%
load 70%	0	100	38	5	24	40	10	75	2	95	0	100
load 80%	0	100	39	2.5	21	48	6	85	1	98	0	100
load 90%	0	100	40	0	24	40	7	83	0	100	0	100
load 100%	0	100	40	0	23	43	5	88	1	98	0	100

CONCLUSIONS

The selected neural network (14-27-28) performs very well when diagnosing fully developed faults as well as healthy conditions. Therefore, this network is selected to be the keystone of the ANN-based diagnosis system that allows the operator to interact with the ANN, thus improving the overall performance. On fully developed faults as well as healthy conditions the TR is 100%. On partially developed faults the performance is good (97.5% at 80% FL and 82.5% at 66% FL). On more incipient faults, this diagnosis capacity becomes poorer (42.5% at 50% FL and 2% at the lowest FL).

One of the main reasons for the lower target ratios here is that the control system of the engine compensates for the symptoms of partly developed faults very effectively. At part-load, the ANN fault-diagnosis capability is also affected by the non-linear behavior of some componenents (e.g. compressor and turbine). Summarizing, the following points can be made:

- Neural networks are useful tools that can be utilized for diagnostics purposes in an industrial gas turbine.
- At part-load, the fault diagnosis is difficulted by non-linear behavior of some gas turbine components.
- Human intervention makes the diagnosis process more flexible and expands its recognition capability, both at

part-load conditions and at full-load operation.

- Early detection of partially developed faults by the ANN can be used to generate early warnings and implement corrective actions in good time.

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