APPLICATION OF ARTIFICIAL NEURAL NETWORKS (ANN) AS MULTIPLE DEGRADATION CLASSIFIERS IN THERMAL AND FLOW DIAGNOSTICS

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Abstract: Application of a neural network of the classifier type for diagnostic purposes is presented. The described ANN solves the task of recognizing causes of degradation of power units' thermal cycle components. Verification of the applied ANN responses is based on the presented research in the numerical simulation of selected power installations. The obtained results could be used in diagnostics of power cycle being properly measured. Considerably good obtained results prove that the ANN technique can be applied as an automatic detector of operational faults. Thus an ANN can serve as a support tool for operational decisions. The present work also offers a way of reducing training time.

Keywords: rotating cavity, direct method, laminar-turbulent transition

1. Introduction

Complex power installations require making decisions that will assure their safe, reliable and efficient operation. These decisions are based on measurements of various parameters of the installation's performance. Deviations of these measurements' results from their patterns, referred to as symptoms, are used in diagnostics consisting in estimating the installation's condition and in amendments to operational procedures or repair decisions resulting from this condition. There are many kinds of diagnostics depending on the processed symptoms.

The development of measurement techniques based on computer systems, among other things on DCS (Distributed Control Systems), enables obtaining and storage of measurement results. This is especially important for complex power installations, the performance of which is influenced by the condition of all their components. Steam power units of power plants are such installations. Their thermal and flow diagnostics is the subject of this paper.

The aim of thermal and flow diagnostics is to estimate the efficiency of the power units' operation. It consists in the determination of indicators of improper operation and the resulting symptoms. Apart from the measurement results, the efficiency, steam flow capacity or specific heat consumption of the whole installation and of its components belong to such indicators. They are determined by universally known rules. When inefficient operation is detected it is necessary to indicate the responsible devices and causes of the inefficiencies. Causes of inefficient operation include geometrical degradations due to wear and tear or incidents.

DCS systems used in the industry usually contain modules determining the above mentioned indicators, but their reliability (and that of their patterns) is questionable. Figure 1 illustrates the problem, with particular focus on the framed numbers (indicators). The reasons of such poor reliability have been widely discussed, *e.g.* in [1]. Additionally, such indicated differences between quantities obtained from measurements and their patterns are not suitable for the procedures of automatic concluding about causes of inefficient operation.

Causes of degradation can be qualified with diagnostic relations, which formulate dependences between symptoms of inefficient operation and its causes. Diagnostic relations are based on various methods. In this paper we have focused on the usage of artificial neural networks, ANN's. Their main advantage is their working speed. They are expected to quickly qualify the causes of degradation on the basis of symptoms and automate this process. In [3] efficient use of such an ANN is shown in finding

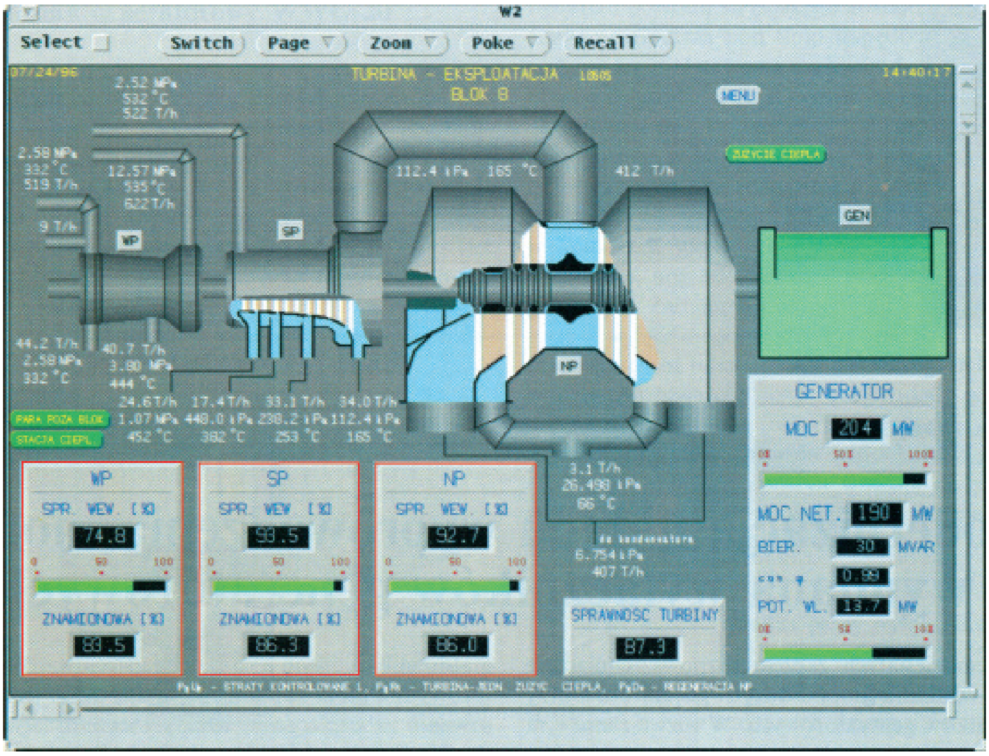

Figure 1. An example of efficiency information given by DCS systems [2]

inefficient devices of steam turbines' thermal cycles. It is demonstrated in [4] that it is possible to use this method to qualify geometrical reasons of degradation.

The aim of this paper is to present the improvement in the accuracy of these methods available through changes of the ANN architecture. Single as well as multiple degradations are considered.

The presented research results refer to the application of correct measurement results. Inefficient operation of the installation is simulated computationally by means of the DIAGAR numerical program [5], based on a 1D computational model of the components of the thermal cycle [6, 7]. It is tuned with good accuracy to verified measurement results of a Polish power plant [8]. Only obtaining exact results for this assumption permits to continue further research over the use of ANN in thermal and flow diagnostics of cycles operating under real industrial conditions.

2. Description of the installation

The object of our research is the cycle of a power system equipped with a steam turbine of about 200MW of power. Its schema is presented in Figure 2, where the locations of thermal and flow measurements are presented, *i.e.* points of measurement of pressure, temperature, the mass flow rate and power. On the basis of such measurement results efficiency and other characteristics of the cycle can be calculated. Deviations of parameters values and characteristics from their reference values constitute symptoms of inefficient operation. These, when applied in diagnostic relations, enable one to qualify causes of degradation.

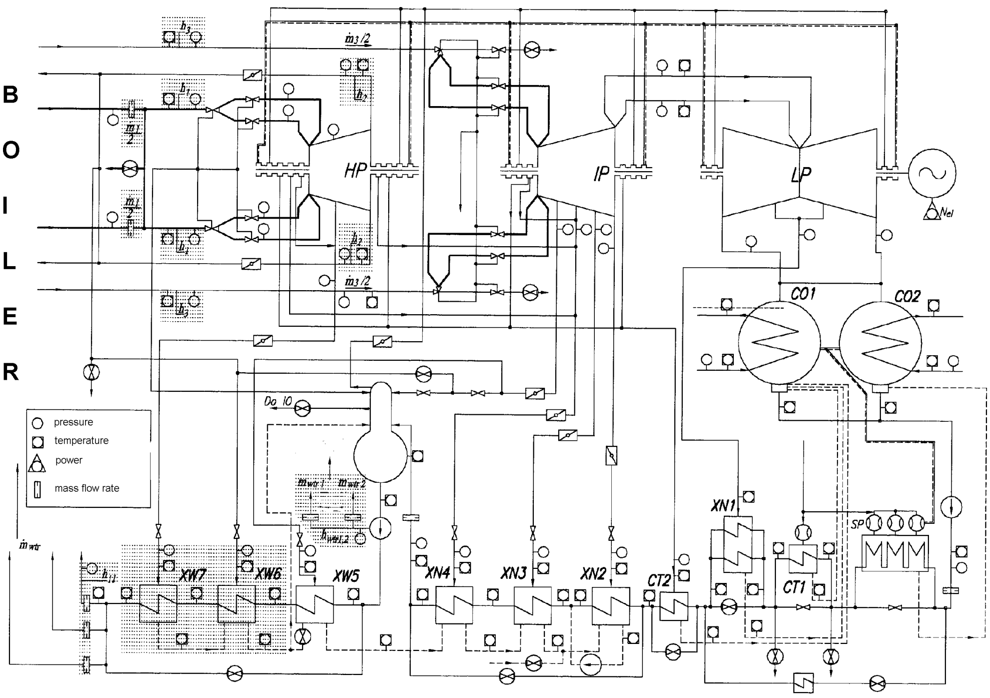

Figure 2. Schema of a 200MW steam power cycle

The operation of the installation depends on values of several quantities put in independently by the operator. In the considered case there are eight such quantities as follows: the unit's power, the pressure and temperature of live steam, the reheat temperature, the condensation pressure, the mass flow rate of primary and secondary injection, and the deareation pressure. These quantities may be referred to as independent variables. At the same time, the installation's operation depends on the condition of the cycle components' geometry. Operation with the correct geometry constitutes the reference state and determines patterns of correct operation. The current state refers to the installation's operation under everyday conditions, usually with degraded geometry.

The thermal cycle presented above can be modeled for calculation purposes by the DIAGAR program [5]. Every device and every connection have their own image in the computational model. The program requires that the following are introduced:

- the installation's structure,
- the independent variables, and
- geometry of the component devices.

Thanks to tuning the computational model to reliable measurement results, the cycle's operation can be simulated, as well at the correct and degraded geometry of components.

Usually, results for the current state can be obtained from measurements. However, not all the possible causes of geometrical degradations occur during operation. The application of simulation calculations to the assumed geometrical degradations enables a greater number or even all kinds of degradation to be considered. When measurement noise is not excluded from the calculations, only the geometrical degradations of the installation itself can be simulated computationally, in compliance with the conditions of correct measurement results. Such a procedure has been used in the analyses presented in this paper.

Some geometrical degradations of components of the considered installation have been taken into account. Analytical results for degraded geometry quoted in this paper concern 6 groups of stages of HP and IP turbines. According to experience the following degradation of individual stages have been assumed:

- surface roughness,
- trailing edges,
- gland clearances of blading.

Within each group of stages the same degree of degradation of each geometrical quantity has been assumed. A list of these quantities is included in Table 1. Each of the quantities is identified by its individual number. A total of 22 such quantities have been qualified.

The degree of degradation has been assumed on the basis of the turbine's design features. Both maximal and partial geometrical degradations have been introduced in the calculations. Combinations of some maximally degraded geometrical quantities are dangerous for running machinery, but they can safely appear in computational simulations. Their usage in ANN training enables better accuracy of a trained ANN.

It is very rare geometrical degradation is due to only one cause, a situation referred to as a single degradation. Usually, a number of causes of geometrical

Table 1. Identification of turbine blading geometrical parameters subject to operating degradation in HP and IP casings

Degradation identifier	Name of geometrical parameter subject to degradation
1	HP control valve nozzle box sealing clearance
2	HP external gland clearance
3	IP control valve nozzle box sealing clearance
4	IP external gland clearance
5	HP stage group No. 1 sealing clearance
6	HP stage group No. 1 blade system roughness
7	HP stage group No. 1 profile trailing edges
8	HP stage group No. 2 sealing clearance
9	HP stage group No. 2 blade system roughness
10	HP stage group No. 2 profile trailing edges
11	IP stage group No. 3 sealing clearance
12	IP stage group No. 3 blade system roughness
13	IP stage group No. 3 profile trailing edges
14	IP stage group No. 4 sealing clearance
15	IP stage group No. 4 blade system roughness
16	IP stage group No. 4 profile trailing edges
17	IP stage group No. 5 sealing clearance
18	IP stage group No. 5 blade system roughness
19	IP stage group No. 5 profile trailing edges
20	IP stage group No. 6 sealing clearance
21	IP stage group No. 6 blade system roughness
22	IP stage group No. 6 profile trailing edges

degradation appear simultaneously in various combinations (multiple degradations). Numerous combinations of the 22 geometrical degradations shown in Table 1 have been considered for the purposes of this paper. Both single and multiple (up to quintuple) degradations have been considered.

Following numbers have been adopted: "0" for the lack of degradation of a particular geometrical quantity and "1" for an occurrence of degradation of the considered geometrical quantity.

3. Causes of operational degradation

Each of geometrical degradations influences the schedules of thermal and flow parameters of the cycle in a characteristic manner. The list of such parameters for the turbine neighborhood is given in Table 2. Their differences can be qualified as deviations in distribution of their actual values from their values for the non-degraded geometry. An individual deviation is called "a symptom", while the set of all symptoms of these deviations is called "a signature". Examples of fragments of such signatures for single geometrical degradations of maximum size are presented in Figure 3.

Table 2. The set of measurable parameters around HP & IP blading for reference and actual condition of a power unit

1	Power output
2	Specific heat consumption
3	Pressure in the control stage chamber
4	Steam pressure at extraction No. 1
5	Steam temperature at extraction No. 1
6	Steam pressure at extraction No. 2
7	Steam temperature at extraction No. 2
8	Steam pressure at extraction No. 3
9	Steam temperature at extraction No. 3
10	Steam pressure at extraction No. 4
11	Steam temperature at extraction No. 4
12	Steam pressure at extraction No. 5
13	Steam temperature at extraction No. 5
14	Steam pressure at extraction No. 6
15	Steam temperature at extraction No. 6
16	Steam pressure at extraction No. 7
17	Steam temperature at extraction No. 7
18	The live steam mass flow rate – m00
19	The secondary injection mass flow rate – msinj

Differences among signatures exist for each combination of degradation causes and they enable recognition of these combinations. This is a task for a diagnostic tool. Signatures create input values, while output values consist of codes describing combinations of geometrical degradations.

Searching for the causes of degradation is an inverse problem to the problem of the description of the cycle's operation for given independent variables and of the geometry. However, in this instance the diagnostic relation does not answer the question about the size of geometrical parameters (there is no univocal solution here), but it seeks the combination of geometrical degradations.

When using artificial neural networks (ANN's) as a diagnostic relation it is necessary to train them. The results of simulation calculations obtained from the DIAGAR program for the established values of degradation of the 22 quantities listed in Table 1 have been applied as the training data. All degradation combinations have been calculated up to quintuple taking into account different values of the independent variables.

4. ANN of the classifier type as a diagnostic tool

The accuracy of the applied ANN depends, among other things, on its architecture. The accuracy of the ANN of the feed forward type with step transfer functions is presented in the present paper. Such an ANN could also be called a multilayer classifier or a multilayer perceptron [9]. Earlier research with continuous transfer functions

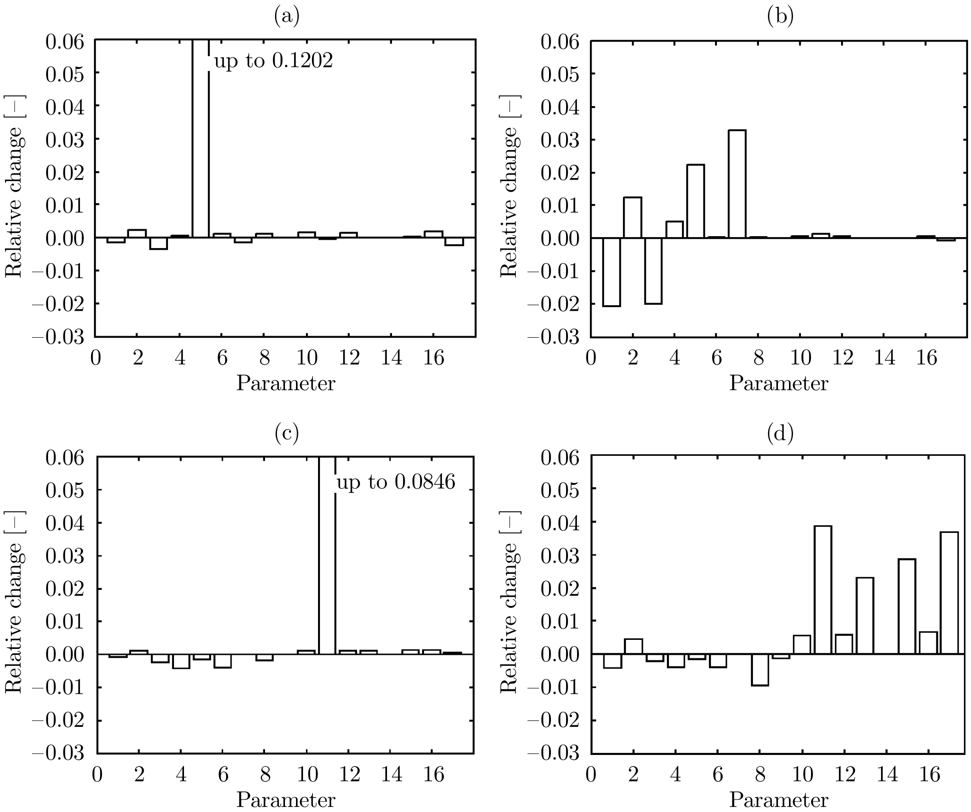

Figure 3. Fragment of the signature caused by degradation of:
(a) HP nozzle-box sealing; (b) 1st Group of Stages sealing; (c) IP nozzle-box sealing;
(d) 4th Group of Stages sealing; parameters description – see Table 2; m00 = const., msinj = const.

[10] did not yield satisfactory results, especially in the case of multiple degradations. Similar results can be found in the literature, *e.g.* [11], where acceptable results have been reached only for single and some instances of double degradation.

The schema of the adopted ANN with step transfer functions is presented in Figure 4. A three-layer ANN has been examined. The input layer delivered input signals (signatures) to the next layer. A training method similar to back propagation [9] was adopted, in which the weights and biases of the hidden layer were assumed at random and remained unchanged during the training, while the weights and biases of the output layer were obtained from the training. The training's accuracy depends on the assumed for the first iteration values of weights and biases of the hidden layer. Unsatisfactory results are corrected by the trial-and-error method. The quantity of necessary training data is related to the applied combination of geometry degradation.

ANN's with continuous transfer functions which well fit to direct calculations, do not usually demand large numbers of neurons in their hidden layers. As opposed to these, ANN's of the multilayer classifier type, as applied here, require a large number of neurons in the hidden layer for good discrimination between classes. Classes are related to combinations of geometrical degradations and should be recognized on the basis of signatures. The maximal number of neurons in the hidden layer depends on

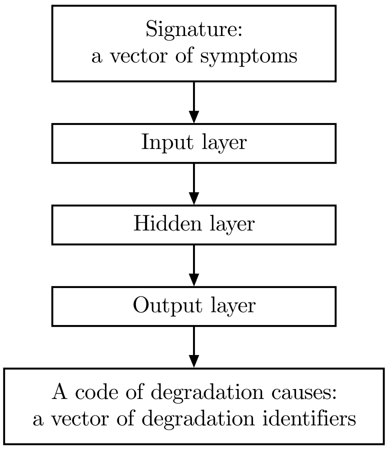

Figure 4. A scheme of the applied ANN

the applied training data, which are necessary for univocal determination of unknown weights and biases [4]. However, the maximum number has been never used, because it has a limited generalizing ability [9]. Usually less than a half of the maximum number of neurons has been applied.

The number of neurons in the input layer is equal to the number of symptoms in the signature, while the number of neurons in the output layer is equal to the number of single geometrical degradations. For the examined power plant, the latter is 22 (see Table 1).

The size of the signature vector, or the number of individual symptoms, has considerable influence on the results of recognition of degradation combinations (degradation classes). In the examined case of the power plant, 19 of the quantities shown in the Table 2 can be obtained directly from measurements. Fan *et al.* [12] have noticed that enlargement of the size of a given vector improves the quality of classification. It can be achieved for instance by creating additional quantities by arithmetical recalculations among known symptoms. They have also stated that if such recalculated values result from physical conditions, it is a better way to improve classification. In the considered case of the steam cycle, 47 additional quantities could be determined on the basis of dimensions given in Table 2. These additional quantities relate to efficiencies and steam flow capacities of groups of stages or turbine casings. They result from the physics of flow and energy conversion in the turbine. In total, signatures aggregate 66 components determined on the basis of directly measurable values.

The code of degradation causes, which has been the result of the subject classification, can be a vector of 22 dimensions described in Table 1. The same type of code was used in earlier research of the author's team [4]. The vector is composed of degradation identifiers, which are the "0" or "1" numbers. Number "0" stands for the lack of degradation, while number "1" stands for an occurrence of same. For instance vector [0010000000001000000010] describes a triple degradation of quantities numbered 3, 13 and 21 in Table 1.

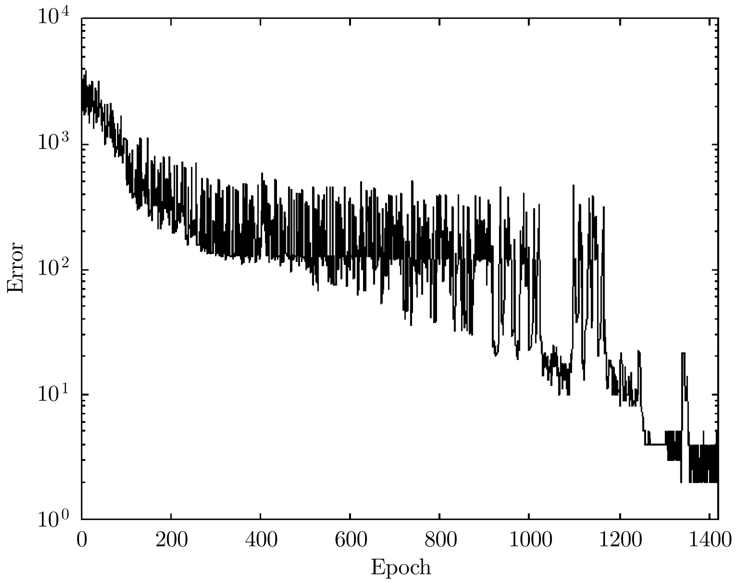

Figure 5. Training error for a global ANN recognising full degradation code for the triple degradations; training time – about 18 hours

Good quality of the recognition of degradation causes has been achieved by the above-mentioned ANN [4]. The following results have been obtained for data not used for training:

- faultless recognition of single degradations,
- error of about 1% of double degradation recognition,
- error of about 0.6% of triple degradation recognition,
- error of about 0.15% of quadruple degradation recognition,
- error of about 0.262% of quintuple degradation recognition.

It is worth mentioning that training was performed only up to quadruple degradations, while quintuple degradations were detected by extrapolation of the ANN function. Extrapolation is always more difficult to give an exact realization than interpolation and its reliability is more problematic.

The employed ANN contained about 10 000 neurons in the hidden layer. They required about 1 GB of RAM in the case of quadruple degradations applied for training. It was necessary to perform about 3 000 000 iterations to obtain the number of incorrect recognitions below 10. The training took about 72 hours with a 2 GHz processor. Calculating one case for the trained ANN lasts for a few milliseconds. This enables an easy application of diagnostic relations using such ANN's in the practical diagnostics of power plants.

An example of an ANN training for triple degradation is presented in Figure 5.

The weakest point of diagnostic relations based on ANN's consists in their extremely long training times. Moreover, a necessary enlargement of training sets would demand better equipment and even more time for training. A modified ANN architecture is proposed below to solve the problem, where modifications concern mainly the output layer.

5. Results of the new ANN application

The proposed modification of the classifier ANN architecture consists in replacing one network recognizing the total degradation code with a set of many ANN classifiers. Each of these single ANN's is provided for the recognition of only one type of geometrical degradation, transfer functions, the architecture of the input and the hidden layers remaining the same. In the output layer of each of these networks there is only one neuron. It is provided to identify one type of geometrical degradation only. For the considered power plant, it is necessary to build and train 22 ANN's. Each of them performs the diagnostics for particular geometrical degradations according to the description in Table 1.

The accuracy of one global ANN treated as a diagnostic relation and of the set of 22 ANN's is comparable.

This solution significantly reduces the volume of training data for each single ANN and the number of weights and biases of the qualification. It reduces the workload of RAM and the training time.

For the considered power plant, when the results of simulation calculations for quadruple degradation were used, training times not exceeding a dozen or so minutes were obtained most of the time. Faultless training was also predominant. For the most difficult cases, the number of iterations for the minimum error did not exceed 10 000 while the training time was less than an hour. A single iteration was sufficient in the most advantageous case.

Selected processes of the modified ANN training are presented in Figure 6.

Further advantages could be achieved, apart from reducing the training time of a single ANN. The process of a single ANN training could be performed simultaneously on many computers; the reduction of training time would then be significant. Greater multiplicity of degradation could be applied for training. This would let to extend of the area of ANN application. Better reliability of classification results would be achieved. It seems possible to use the modified ANN for training sevenfold degradation data on the present computer equipment.

A disadvantage of this solution is longer waiting time for results of calculations of a set of trained ANN's. However, the times of these calculations should not be longer than several seconds, what should be a satisfactory result for a diagnostician at a power plant.

Another disadvantage is the necessity to create the full code of degradation causes outside the set of ANN's. However, this should not be too problematic for the present computer equipment.

The advantages of shortening the training time are ultimately a convincing argument for the application of the modified diagnostic relations based on ANN.

6. Conclusions

The use of artificial neural networks (ANN's) for diagnostic relations for proper measurement has been presented in the paper. Such diagnostics can be illustrated for example with the use of numerical simulation results of geometry degradation of turbine cycle components.

Although this case does not reflect all conditions met in everyday operation, it shows that the used ANN can recognize types of geometrical degradation of a complex power installation with good accuracy. It may become a starting point for further development of diagnostic relations applying ANN's to real operational conditions, taking noises and error measurement into account.

Both one global ANN recognizing the full code of geometrical degradation combination and a set of ANN's each recognising only one type of degradation, assure good accuracy of recognition.

The use of a set of many ANN's enables considerable reduction of the training time, especially for training performed on many computers.

Greater multiplicity of degradation causes could be applied for training.

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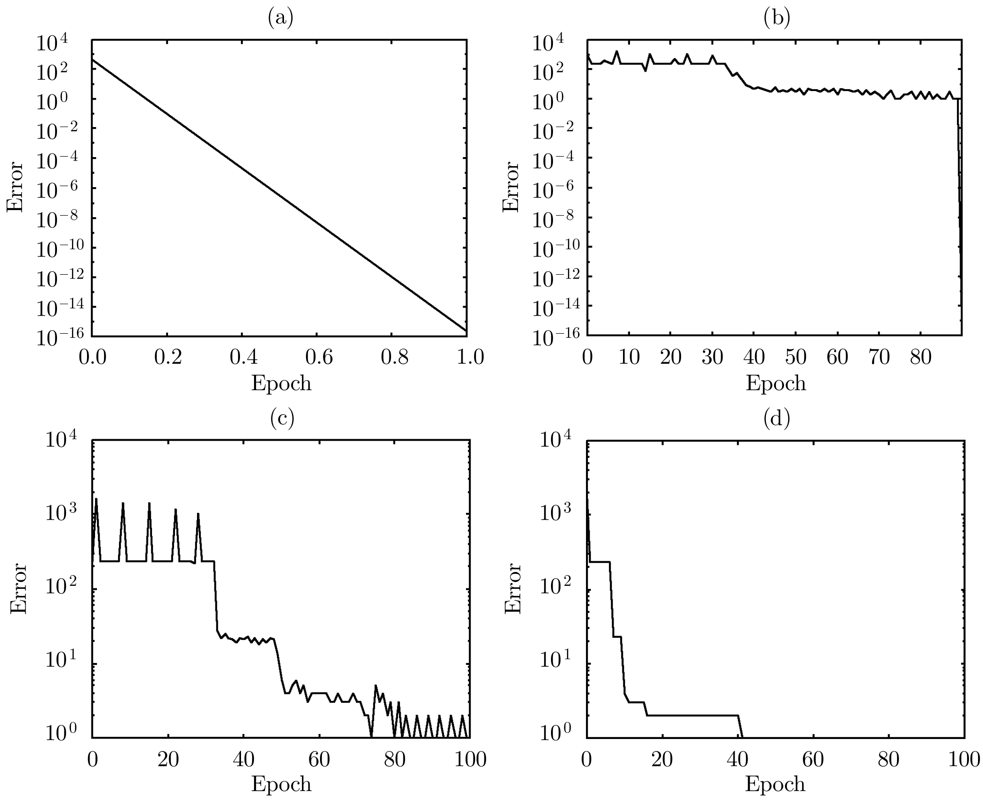

Figure 6. Training error for an ANN recognising degradation of:
(a) HP control valve nozzle box sealing clearance; (b) HP stage group No. 1 sealing clearances; (c) HP stage group No. 4 blade surface roughness; (d) HP stage group No. 4 trailing edges

The advantages of shortening the training time are ultimately a convincing argument for the application of the modified diagnostic relations based on ANN.

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