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Fault detection in measuring systems of power plants

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ABSTRACT

This paper describes possibility of forming diagnostic relations based on application of the artifical neural networks (ANNs), intended for the identifying of degradation of measuring instruments used in developed power systems. As an example a steam turbine high-power plant was used. And, simulative calculations were applied to forming diagnostic neural relations. Both degradation of the measuring instruments and simultaneously occurring degradation of the measuring instruments and thermal cycle component devices, were taken into account. Good quality of diagnostic neural relations was stated. They make it possible to distinguish degradation of measuring instruments from degradation of thermal cycle components. The calculated errors of identification of dergraded devices and measuring instruments in the case of simultaneous occurence of three different degradations were on the level of 0.25 %. Performance of the relations was presented by using an example based on industrial practice.

Keywords: steam turbines, turbines exploitation, power units, efficiency, thermal diagnostics, diagnostic relations

INTRODUCTION

Development of diagnostic methods make it possible to undertake more and more difficult diagnostic tasks. To them belongs the need of diagnosing technical objects and devices in the case of incomplete measurement information and failures of sensors. Thermal-and-flow measurements of sophisticated power object belong to the most difficult. They are always non-stationary. Their results are influenced by many independent operational parameters of object, its size as well as arrangement of sensors and way of their attachment.

The diagnosing of energy conversion processes in ship power plants, both motor and steam turbine driven, is especially difficult because of their complex structure and interdependence of their operational parameters. This paper presents investigations on the problem of recognition of correctness of gathered measurement results. Examples based on characteristics of a land steam power plant are given. Complexity of the power plant makes it possible to draw conclusions which would be valid, at least to a certain extent, also for ship power plants.

For a long time the problem of quality of results of measurements carried out in power plants has been a subject of interest of researchers and practitioners in the field of operation of complex systems [1, 3, 4, 5, 6, 7, 9, 11, 12, 13, 14, 16, 17, 18, 19, 20, 21, 22, 23].

Among the methods intended for solving the problem, it is compensation calculus which plays important role [19].

Measurement information often concerns sum of influence of several devices at once. As showed in [7], in the case of a complex power object in which disturbances in work of one device propagate to other devices, to separate component measurement signals is possible. The observation can be used to identify sensors. Unserviceability of a sensor influences result of measurement of only one quantity and does not find any reflection in indications of other sensors.

The distinguishing of sensor failure from operational degradation of component devices of thermal cycle constitutes one of the most important tasks of thermal-and-flow diagnostics of steam power plants. The results of simulative calculations, given in further part of this paper, answer the following questions:

- ✰ how much detailed can be diagnostics of a considered subsystem of devices?
- ✰ is it possible to distinguish a sensor failure from degradation of a device?

The answer is of a great importance for designers of measuring systems and for users of diagnostic systems. The investigations on diagnostic relations based on the method of artificial neural networks (ANN), intended for the finding of incorrectness in measurements, are presented in further part of the paper.

Determination of degradation symptoms on the basis of measurements - on the one hand - and a model of correct performance - on the other hand - is one of more important operations in thermal-and-flow diagnostics. The correct performance is described by the so called reference state. It is a functional model since object-dependent variables determined with its help are functions of independent parameters, i.e.: structure, geometry and independent variables. The functional model makes it possible to determine the reference state for all operational points of the object in question.

It is not possible to perform measurements without errors, whereas erroneously indicated symptoms lead to an erroneous diagnosis. Hence it is important to determine an acceptable level of error, after exceedance of which a given measurement result should be rejected. Methods and procedures for detecting measurement errors and uncertainties are to take into account also varying load conditions of power plant, as it gives chance to distinguish changes in measurement results, caused by a measurement error, from normal changes of parameters resulting from changeable loads, external conditions and actions of operators.

SELECTED SPECIFIC CONDITIONS OF MEASUREMENTS

The author's attention is further focused on the high-power steam turbine cycle shown in Fig. 1. In it can be distinguished several points in which measurement data are ambiguous from the point of view of thermal-and-flow diagnostics [10, 15]. In them for instance the mixing of fluxes of different working media occurs, hence to distinguish influence of degradation of various component devices of the cycle on the basis of measurements of only one quantity, is difficult. Whereas measurement data taken form various measurement points make such differentiation possible. The mutual interaction brings prospects for searching for diagnostic relations in spite of lacking results of certain measurements [10, 15].

The differentiation of degradation causes among those dealing with the thermal cycle devices and those dealing with set of measuring instruments is made additionally difficult due to the overlapping of measurement uncertainty onto measurement results obtained in the above described way.

The investigations, described in the further part, which lead to building a method for detecting degradation of measuring instruments, are based on simulative calculations of degradation of component devices of complex thermal cycles and measuring instruments as well.

RESULTS OF SIMULATION AND IDENTIFICATION OF DEGRADATION BY THE ANN

Computational simulations lead to determination of degradation signature composed of symptoms. Each of the symptoms determines deviation of value of thermal-and-flow parameter corresponding with it (e.g. mass flux, pressure, temperature) or characteristics (of e.g. efficiency, flow capacity of particular component elements) from its reference value characteristic for non-degraded object. In the considered case such degradation signature was selected.

The signature together with relevant cause of degradation was used for training the artificial neural network intended for identifying the causes of degradation. The signature forms input to the network, and combinations of degradations represented by relevant zero-one series (0 – no degradation; 1 – occurrence

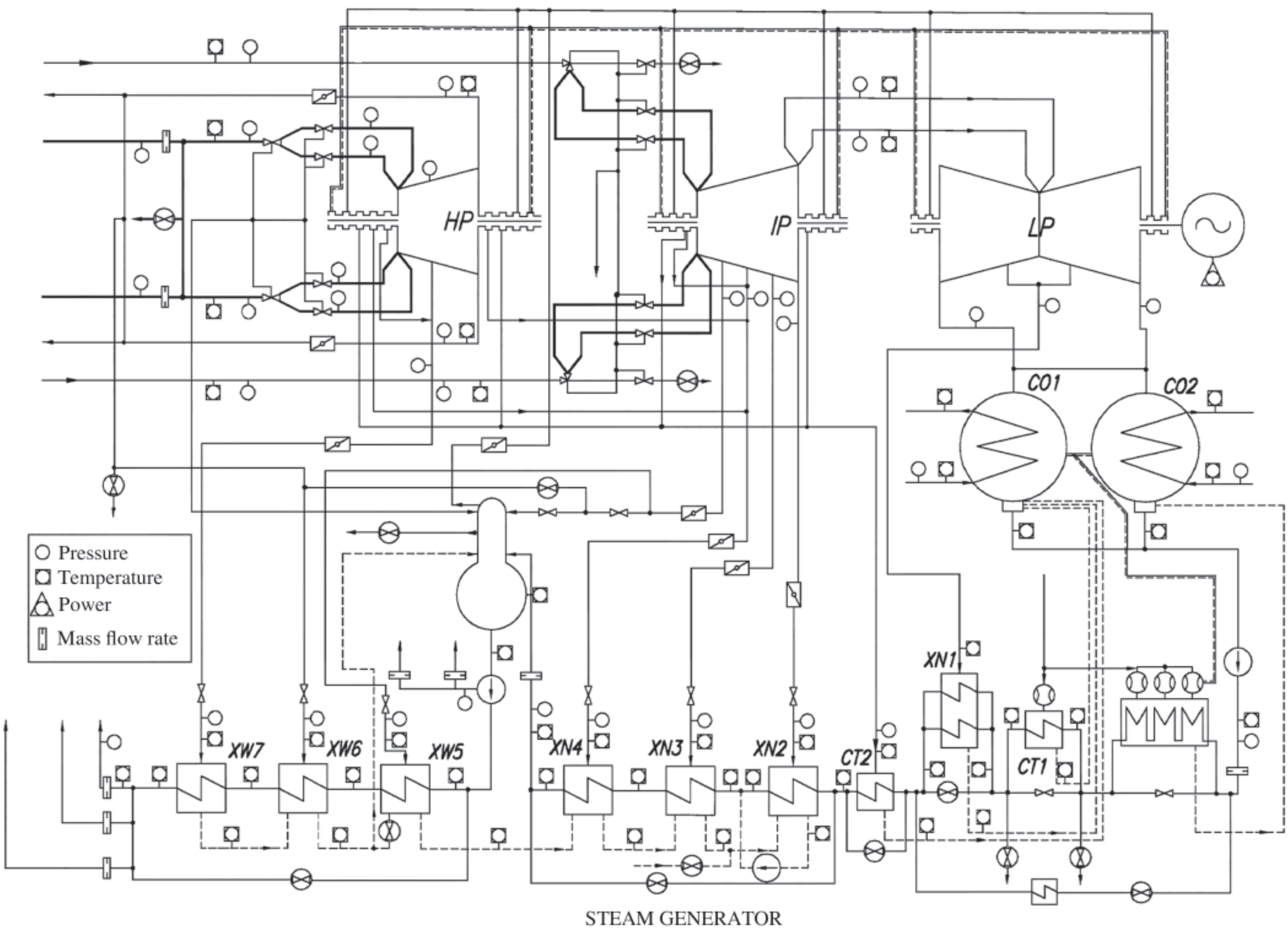

Fig. 1. *Schematic thermal cycle diagram of a high-power unit with indicated measurement points*

of degradation) form output from the network. Taking into account experience gained from the preceding investigations [8, 10, 15], one assumed that to obtain a better accuracy, several ANNs, each of them focused on identifying only one cause will be applied instead of one ANN intended for identifying all causes of degradation.

The ANN was assumed to have structure of multi-layer perceptron with application of step transition functions [2]. It ensures to get result in the form of „0" or „1", in compliance with the above described nomenclature of degradation causes. Hence, operation error of the ANN consists in incorrect determination of the quantity „0" or „1". For effective operation of such network application of a large number of neurons in intermediate layer of the network is required. Their maximum number results from a number of training samples. In the case in question it was possible to apply a few hundred of neurons.

Operational degradation was simulated by means of calculations with application of appropriate 1-D computational methods adjusted to reliable measurements. In the calculations both degradations of devices and measurement instruments were simulated. And, were taken into account degradations of geometry of blade system and sealing system of groups of HP and IP stages of turbine cylinders as well as degradations of sensors usually placed at extraction pipelines. The set of geometrical quantities taken into account in the simulation is presented in Tab. 1. To them was attached a set of measuring instruments fastened to extractions and subjected to degradation. Finally, the set of 37 units in number, of devices and measuring instruments subjected to degradation, was obtained.

In the simulative calculations the following was assumed:

❖ unchanged geometry of all devices of the thermal cycle, beyond currently investigated subsystem
❖ geometry changes represent possible operational failures, either of partial or maximum values, of the devices in question (0 ÷ 100% degree of degradation)
❖ load conditions of the power unit are represented by 8 independent parameters: mass flow rate of live steam supplying the unit, live steam inlet pressure, live steam inlet temperature, secondary steam inlet temperature, condensation pressure, degasing pressure, primary injection flux, secondary injection flux.
❖ searching for degradation symptoms is carried out among the following parameters which can be either measured or determined on the basis of measurement:
    - output of the power unit
    - specific heat consumption
    - pressure and temperature values in the extractions marked 1 through 7
    - steam flow capacity coefficients and efficiency indices.

Computational simulations lead to the forming of a degradation signature composed of symptoms. Eeach of the symptoms determines deviation of value of respective thermal-and-flow parameter (mass flow rate, pressure, temperature, or characteristics) from its reference value (i.e. characteristic for non-degraded object). The signatures consisted of 66 symptoms. Description of the quantities comprised in the signature is given in Tab. 2.

For the simulating of degradations of measurement instruments, was used the observation described in [8], which concerns lack of propagation of sensor errors into indications of measurement instruments located in other parts of thermal cycle. This way, sensor's unserviceability is able to change only one symptom in degradation signature. For the simulation it was assumed that sensor's indication error can vary within the range of ± 2%. Fig. 2 shows a fragment of the signature which describes degradation of the sealings in 4-th group of

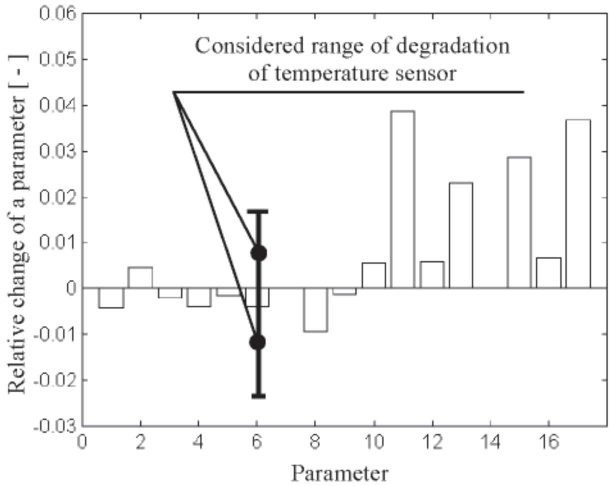

Fig. 2. *An example fragment of signature for twofold degradation concerning the sealings of 4-th group of stages and the temperature measuring instrument at 2-nd extraction. (**Note**: meaning of the successive parameter numbers is in accordance with the signature description given in Tab. 2).*

Tab. 1. *Geometrical parameters of devices and measuring instruments subjected to degradation, selected for simulation*

No	Geometrical parameters and measuring devices subjected to degradation
1	Clearance in nozzle box gland of HP control valves
2	Clearance in external glands of HP cylinder
3	Clearance in glands of 1-st HP stages group
4	Surface roughness of 1-st HP stages group
5	Leading edges destruction of 1-st HP stages group
6	Clearance in glands of 2-nd HP stages group
7	Surface roughness of 2-nd HP stages group
8	Leading edges destruction of 2-nd HP stages group
9	Clearance in nozzle box gland of IP control valves
10	Clearance in external glands of IP cylinder
11	Clearance in glands of 3-rd IP stages group
12	Surface roughness of 3-rd IP stages group
13	Leading edges destruction of 3-rd HP stages group
14	Clearance in glands of 4-th IP stages group
15	Surface roughness of 4-th IP stages group
16	Leading edges destruction of 4-th HP stages group
17	Clearance in glands of 5-th IP stages group
18	Surface roughness of 5-th IP stages group
19	Leading edges destruction of 5-th HP stages group
20	Clearance in glands of 6-th IP stages group
21	Surface roughness of 6-th IP stages group
22	Leading edges destruction of 6-th HP stages group
23 ÷ 37	Temperature and pressure sensors at extractions 1 ÷ 7

turbine stages and is modified by simultaneous occurrence of unserviceability of the temperature sensor located at the extraction 2.

Hence, 37 ANNs, each intended for identifying only one cause of degradation, were trained and tested. It was peliminarily stated that the identification of degradation of particular sensors and geometrical parameters was faultless [7]. The investigations on indentification of this kind have been extended to multiple degradation cases.

Finally, the following degradations were considered in various combinations:

- ⇨ single–time one – one kind of geometry or one degraded sensor
- ⇨ twofold one – all combinations of two simultaneously degraded quantities out of the set of sensors and kinds of geometry of devices
- ⇨ threefold one – all combinations of three simultaneously degraded quantities out of the set of the quantities in question.

Tab. 2. *Description of the quantities used to form symptoms of which full signature of degradation of the flow system of HP and IP turbines in question, is consisted*

No of symptom	Symptom based on:	No of symptom	Symptom based on:
1	Power	**34**	Mass flow rate at the 5-th extraction
2	Specific heat consumption	**35**	Mass flow rate at the 6-th extraction
3	Pressure behind the control stage	**36**	Mass flow rate at the 7-th extraction
4	Steam pressure at the 1-st extraction	**37**	Efficiency of control stage
5	Steam temperature at the 1-st extraction	**38**	Capacity coefficient of control stage
6	Steam pressure at the 2-nd extraction	**39**	Efficiency of the 1-st stages group
7	Steam temperature at the 2-nd extraction	**40**	Capacity coefficient of 1-st stages group
8	Steam pressure at the 3-rd extraction	**41**	Efficiency of the 2-nd stages group
9	Steam temperature at the 3-rd extraction	**42**	Capacity coefficient of 2-nd stages group
10	Steam pressure at the 4-th extraction	**43**	Efficiency of the 3-rd stages group
11	Steam temperature at the 4-th extraction	**44**	Capacity coefficient of 3-rd stages group
12	Steam pressure at the 5-th extraction	**45**	Efficiency of the 4-th stages group
13	Steam temperature at the 5-th extraction	**46**	Capacity coefficient of 4-th stages group
14	Steam pressure at the 6-th extraction	**47**	Efficiency of the 5-th stages group
15	Steam temperature at the 6-th extraction	**48**	Capacity coefficient of 5-th stages group
16	Steam pressure at the 7-th extraction	**49**	Efficiency of the 6-th stages group
17	Steam temperature at the 7-th extraction	**50**	Capacity coefficient of 6-th stages group
18	Live steam mass flow rate	**51**	Capacity coefficient of 1-st stages group for extractions
19	Live steam pressure	**52**	Efficiency of the 2-nd stages group for extractions
20	Live steam temperature	**53**	Capacity coefficient of 2-nd stages group for extractions
21	Secondary steam mass flow rate	**54**	Efficiency of the 3-rd stages group for extractions
22	Secondary steam pressure	**55**	Capacity coefficient of 3-rd stages group for extractions
23	Secondary steam temperature	**56**	Efficiency of the 4-th stages group for extractions
24	Mass flow rate at the 1-st stages group	**57**	Capacity coefficient of 4-th stages group for extractions
25	Mass flow rate at the 2-nd stages group	**58**	Efficiency of the 5-th stages group for extractions
26	Mass flow rate at the 3-rd stages group	**59**	Capacity coefficient of 5-th stages group for extractions
27	Mass flow rate at the 4-th stages group	**60**	Efficiency of the 6-th stages group for extractions
28	Mass flow rate at the 5-th stages group	**61**	Capacity coefficient of 6-th stages group for extractions
29	Mass flow rate at the 6-th stages group	**62**	Capacity coefficient of 1-st stages group for extractions
30	Mass flow rate at the 1-st extraction	**63**	Efficiency of HP cylinder
31	Mass flow rate at the 2-nd extraction	**64**	Capacity coefficient of HP cylinder
32	Mass flow rate at the 3-rd extraction	**65**	Efficiency of IP cylinder
33	Mass flow rate at the 4-th extraction	**66**	Capacity coefficient of IP cylinder

In the case of single-time degradations three intermediate values within the range between zero degradation and maximum one (i.e. 25%, 50% i 75% of its maximum value) were taken into account. In the case of multi-time degradations only maximum values of degradations of particular quantities were considered.

The ordered sets of simulation results were used for training the ANNs in order to made them tought in detecting geometrical degradations.

Size of databases for models

The prepared combinations of single-time, twofold and threefold degradations, associated with 37 geometrical quantities sufferring operational degradation and measuring instruments subjected to degradation, are presented in Tab. 3. Each of them is represented by the vector of 37 components. Number of combinations of possible particular degradations in which only one scale of degradation and one set of independent variables have been taken into account, results from the following combinatorial relations:

- single-time $\binom{37}{1} = 37$
- twofold $\binom{37}{2} = 666$
- threefold $\binom{37}{3} = 7770$.

During planning operations for simulative calculations the sets of data and results were split into the part used for training and that used for testing. Size of the so obtained sets is presented in Tab. 3. It is equal to the number of performed simulative calculations of degradations.

In the database not intended for using in training all the degradation sets contain both full scale of degradation and partial one (of 50 % of its maximum value) of the geometrical quantities.

Tab. 3. *Size of simulation sets – models of degradation of component devices of the thermal cycle within the HP and IP cylinders, obtained for the determined set of independent variables*

Characteristics of partial databases	Database used for training	Database used for testing
Total size of the database	8584	17612
Size of the database for single-time degradations	4 * 37 = 148	2 * 37 = 74
Size of the database for twofold degradations	1 * 666 = 666	3 * 666 = 1998
Size of the database for threefold degradations	1 * 7770 = 7770	2 * 7770 = 15540

IDENTIFICATION OF DEGRADATIONS BY THE ANN TRAINED ON THE BASIS OF SIMULATION RESULTS

To identification of degradations the ANNs of a multi-layer perceptron kind were applied, like e.g. in [8, 10, 13].

In building a diagnostic relation based on the ANN methods one can apply:

- one global network which determines degradation code in the form of vector
- a set of networks each of which identifies only one cause of degradation.

The second solution is more favourable because of a lower demand for computer memory as well as a shorter training period as compared with the first case, at maintained similar accuracy [9]. Hence, 37 ANNs were subjected to investigations on identification of degradations; each of them was intended for the identifying of only one geometrical or measuring cause. The teaching inputs and outputs of the ANNs are presented in Fig. 3.

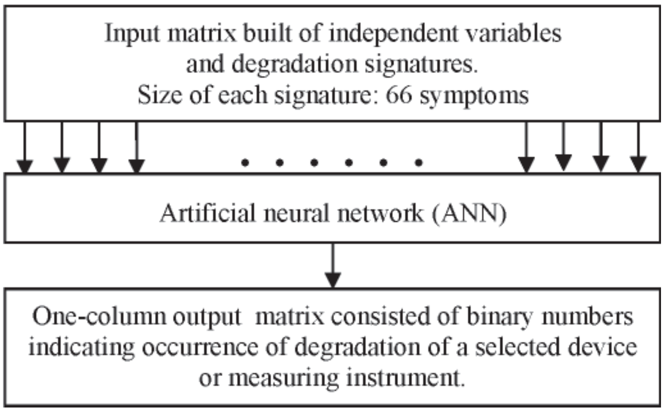

Fig. 3. *Inputs and outputs of one ANN (out of 37 dedicated ANNs) dedicated to fulfil role of a diagnostic relation which identifies degradation of one, out of 22 (see Tab.1), geometrical dimension of component devices of steam power unit or one, out of 15, (see Tab. 1, items No. 23 through 37), measuring instrument located at the cycle's extractions.*

Knowing from simulations, an expected response of the ANN one can assess correctness of neural calculations.

Single-time degradations were identified faultlessly both for the cases used for training and those not used for training, Tab. 4, as obtained also in [7, 10, 15]. Hence in this case it is possible to distinguish, without any trouble, degradations/faults of a measuring instrument from operational degradations of geometry of elements. Identification of multifold degradation cases is more difficult. The results of identification of such degradations, obtained from testing, are presented in Tab. 4. The number of considered cases, given in the denominator of each fraction, shown in Tab. 4, determines number of combinations between degradations beginning from single-time ones to threefold ones.

Identification errors, in consequence, distinctions between faults of measuring instruments and geometry degradations, are small. Hence it is possible to use the ANN methods for the combine diagnosing of devices and measurements of complex power systems. The described ANN can be taken as neural diagnostic relations capable of identifying locations of degradations.

IDENTIFICATION OF DEGRADED MEASURING INSTRUMENTS PRESENTED ON THE EXAMPLE TAKEN FROM OPERATIONAL PRACTICE

The trained, above described, neural networks which identify degradation of devices and measuring instruments, were tested by using a few examples of measurement data obtained from current power unit operation. The set was solely tested of the ANNs each of which identified only one

Tab. 4. Functioning quality of the network intended for the identifying of kind of degradations within HP and IP cylinders of high-power turbine

% contribution of erroneously identified degradation models	Erroneous responses to the test for which the database applied to training, was used	Erroneous responses to the test for which the database not applied to training, was used
Single-time ones	$\Delta_{3.1} = \frac{0}{4 \cdot 37} \cdot 100\% = 0\%$	$\overline{\Delta_{3.1}} = \frac{0}{2 \cdot 37} \cdot 100\% = 0\%$
Twofold ones	$\Delta_{3.2} = \frac{0}{666} \cdot 100\% = 0\%$	$\overline{\Delta_{3.2}} = \frac{4}{3 \cdot 666} \cdot 100\% = 0.202\%$
Threefold ones	$\Delta_{3.3} = \frac{5}{7770} \cdot 100\% = 0.064\%$	$\overline{\Delta_{3.3}} = \frac{39}{2 \cdot 7770} \cdot 100\% = 0.2509\%$

degradation on the basis of the processing of the complete degradation signature.

It concerns results of the measurements whose illustration in the form of the expansion line based on pressure and temperature values recorded at extractions of high-power turbine, has been presented in Fig. 4. Such run of the current state expansion line (the red line in Fig. 4) and its comparison with the run of the reference state line (the blue line in Fig. 4) can be met during the monitoring performed short time after steadying the reference state. This is the case when component devices of thermal cycles are usually not yet degraded but degradations may occur in measuring system. Such graphical presentation makes the assessing of performance of the diagnostic relation elaborated to identify location of degradation, easier. The relation is based on transformation of the complete signature of degradation, that is the measurements possible to be found on the entropic diagram of expansion (Fig. 4) and the remaining quantities which build the degradation signature and are calculated from measured quantities. The result of operation of the neural relation indicates that degradation of the temperature measuring instrument at 3-rd extraction, occurs (see item 9 of Tab.1). It was identified by the ANN no. 31 of the set of neural networks. The calculation results of the remaining ANNs were equal to „0", this means that the degradations attributed to them have not been occurred at all.

SUMMARY

- The performed tests based on the simulations and selected operational measurements showed that the application of artificial neural networks as diagnostic relations which are capable of identifying locations of degradations of component devices of thermal cycles of steam power units and locations of degraded measuring instruments, is rational. The tests based on simulations are characterized by a small value of identification error. The tests making use of current measurement results show that to identify defected measuring instruments is possible. However possible identification of a kind of degradation of component devices of turbine thermal cycles has not been so far confirmed by observations after disassembly of the turbine under repair as until now such operation has not been performed.
- To simulate degradations of a larger size seems to be necessary. However to do it a better computer hardware, especially as regards its greater operation memory, is required. Development of computers provides such prospects.

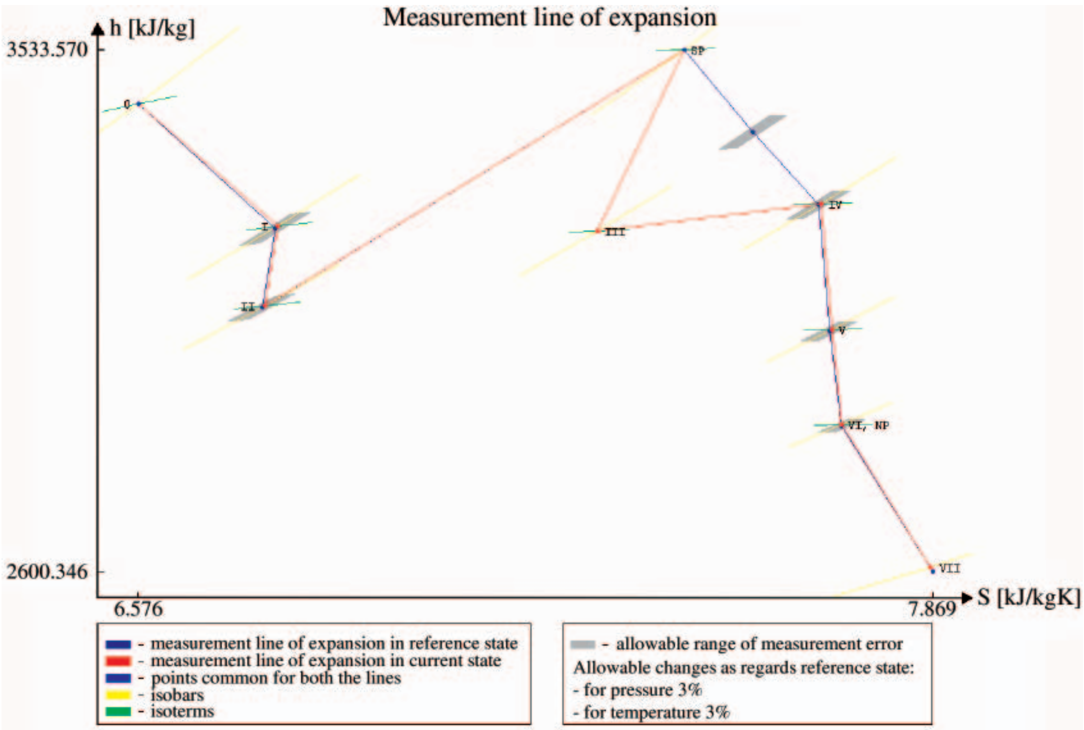

Fig. 4. Illustration of the expansion line determined for the parameters measured at extractions and achieved after a short period of operation of the power unit

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