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## **ALGORITHMS OF DETECTION AND ISOLATION FOR INSTRUMENTATION FAULTS IN CONTROL SYSTEM OF A CONDENSATION TURBINE**

### **Keywords**

Condensation turbine, instrumentation lines, control system, modelling, fault isolation, fault detection, diagnosis.

### **Abstract**

Control system of a condensation turbine with fault tolerant instrumentation lines is presented in this paper. The characteristics of instrumentation signals entering the controller and methods of fault detection are also presented. Application of modelling for diagnostic purposes is given. The creation of partial models used for fault detection as well as methods of fault isolation are described.

### **Introduction**

Increased complexity of steam turbine control systems as a result of an increase of demands connected with turbo-generator unit operation of an electric-power system is the basic reason to create methods and diagnostic means. Application of microprocessor controllers increases functionality and reliability of control systems operation, which leads to improvement of disposability and quality of the operation of the whole electric-power system.

For this reason, it is important to apply power controllers in turbo-generator units which would satisfy present requirements. Typical controllers tend to be substituted by modern electro-hydraulic systems. In these systems signal transformation, performance of very complex control algorithms and the introduction of reliable signalling, and protection and visualization systems are made in an electric manner.

New control algorithms of different types of turbines that result from current operation criteria force the application of microprocessor controllers equipped with proper diagnostic systems with detection and isolation of instrumentation faults.

Analytical redundancy of the instrumentation line takes place when the additional value of the process variable is calculated from a mathematical model which connects the calculated variable with other measured signals. Instead of using excessive instrumentation in the system structure, mathematical models are utilized to calculate the values of process variables. In faulty situations, a control algorithm must be reconfigured to the proper reserve structure and these are called fault tolerant systems [3]. To perform modelling of connections for diagnostic purposes fuzzy neural networks (FNN) may be used.

## **1. Characterization of instrumentation lines in the condensing turbine control system**

Power control of turbo-generator unit is performed by activating turbine control valves (turbine power control). The appropriate analog and binary signals are introduced to the turbine controller for control and protection of the system [3].

Measurement lines and control signals are divided into four basic groups:

1. Direct measurements of physical quantities (e.g. power, pressure),
2. Outside signals entering directly from the electric-power system or directly from the main controller,

Signals from the first group are of a determined type and from the second group of a random type.

3. Electric signals inside the controller (e.g. between main controller, switch panel and terminal),
4. Auxiliary measurements for actuator diagnostics.

The appropriate measurement lines and output signals for the control system of turbo-generator unit connected with the electric-power system are presented in Fig. 1 [1].

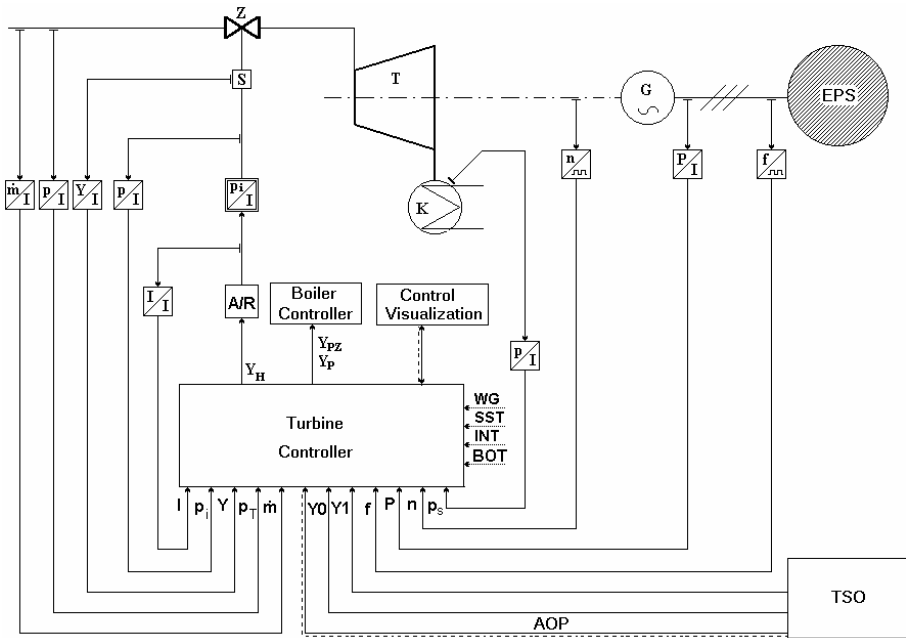


Fig. 1. Instrumentation lines of condensing turbine control system

Notations in Fig. 1:  $Z$  – set of control valves,  $S$  – set of actuators,  $T$  – turbine,  $K$  – condenser,  $G$  – generator, EPS – electric power system, A/R – manual control panel,  $m_{DT}$  – steam mass flow rate,  $p_T$  – live steam pressure,  $p_i$  – hydraulic oil pressure,  $p_s$  – pressure in condenser,  $f$  – electric power system frequency,  $P$  – generator power,  $n$  – turbine rotational speed,  $I$  – control current,  $Y$  – position of valves,  $Y_0, Y_1$  – external control set point signals, ARCM – frequency and power control system,  $WG$  – binary signal of generator on-off switch,  $SST$  – turbine efficiency binary signal from the turbine diagnostic module,  $BOT$  – binary blocking signal of thermal limitations,  $INT$  – intervening power binary signal of ARCM,  $Y_H$  – controller output,  $Y_p, Y_{pz}$  – auxiliary controller output for the boiler control unit, AOP – Actual Operating Point, TSO – Transporting System Operator

The basic controller output signal is set-up signal  $Y_H$  for turbine control valve operation. Through an electro-hydraulic transducer ( $I/p_i$ ), an electric signal is converted into oil pressure, which controls the position of turbine valves' servomotors. Additional signals  $Y_{pz}$ ,  $Y_p$  can also be sent from the turbine controller and are used to the interconnect boiler control system with turbine control system.

Controlled quantities in the system are active power and rotational speed. Active power is supplied to the system through a converter measuring generator active power in a three-phase system.

Ahead of the generator synchronization with an electric-power network, turbine rotational speed is a controlled parameter. Rotational speed measurement is performed by three sensors, which count impulses generated by a toothed disk placed on turbine shaft. Measuring the signal created in the frequency form is introduced into the proper controller counter input.

Condensing turbine controllers enable the electric-power unit operation of the electric-power system control, so they must be adapted to accept signals of secondary control (Y1). The exchange of information between turbine control system and TSO is performed by means of electronic links, according to the appropriate data exchange protocol.

The remaining signals entering the condensing turbine controller, which include live steam pressure, absolute pressure in the condenser, position of valves and live steam mass flow rate, are delivered to the system in order to assure proper cooperation of steam pressure control in the boiler with the condensing turbine power control system.

The list of analog signals entering the condensing turbine control system is presented in Table 1 [3].

Table 1. The set of analog input signals for electro-hydraulic control of condensing turbine.

Item	Analog signals	Symbol	Unit
1	Turbo-generator power	P	MW
2	Live steam pressure	$p_T$	MPa
3	Absolute pressure in condenser	$p_s$	kPa (%)
4	Live steam mass flow rate	$\dot{m}_{DT}$	t/h
5	Position of control valves	Y	%
6	Hydraulic oil pressure	$p_i$	MPa
7	Turbine rotational speed	n	1/min
8	Electric power system frequency	f	Hz
9	Slow-changing power signal	Y0	MW
10	Fast-changing power signal	Y1	MW
11	Actual Operating Point	AOP	MW
12	Control current	I	mA

AOP signal and secondary control signals (Y1, Y0) are sent to the system from the outside. These quantities are used to control electric-power unit by the Transporting System Operator (TSO). Peculiarity of changes and type of

presented quantities forces application of particular fault detection methods of instrumentation lines. Detection methods evaluating the correctness of the received signal exclusively on the basis of one variable analysis must be used. These methods are based on process variable parameter control.

The second group of process variables read by the controller consists of local signals received from an electric-power unit. Determination of model based residuals is the most resistant and confident detection method, on the condition that the model is sufficiently precise. Utilization of models for diagnostics of instrumentation lines enables the detection of parametric and catastrophic faults of these lines.

The controller's internal signals, such as the connection between operator switch panel or terminal as well as communication link with visualization system, must be constantly controlled in on-line mode. Detection of failure must properly reconfigure the structure of the controller hardware.

## 2. Structure of diagnostic system

The control system diagnostic process consists of two stages: fault detection and fault isolation. Fault detection is performed on the basis of measured values of object variables  $z_i$ . Signals read by the control system belong to a certain set of variables  $Z$ . During fault detection fault symptoms are found that may be signalled by appropriate alarms. These symptoms indicate improper functioning of the control system, but they do not determine the reason of the fault [2]. Many different faults may be the reason of the same symptom, but each fault creates several different symptoms. The activity undertaken in order to detect one symptom is called the diagnostic test.

Fault isolation is performed on the basis of set of diagnostic test results. The isolation algorithm is based on relations between faults and their symptoms. The final result of the fault isolation stage is the elaboration of diagnosis indicating a fault existing in the system.

On the basis of this location, a fault is detected and appropriate decisions may be undertaken in order to assure the correct operation of the control system [3]. The general diagram of the diagnostic and protective system is presented in Fig. 2.

Undertaken protecting actions may be in the form of control system reconfiguration or changes in the object's operating mode. Protections of this type may be performed automatically. The visualization system should possess signalisation and recording of disturbances which occurred in the object.

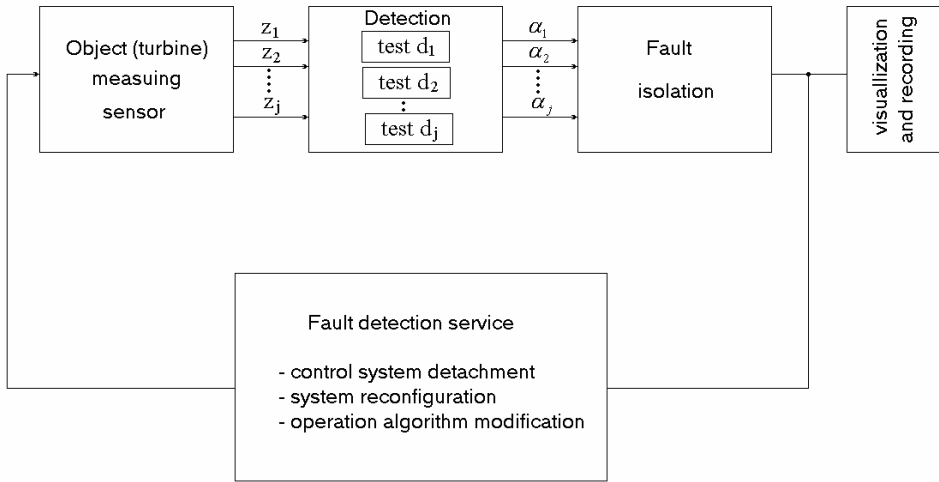


Fig. 2. Diagram of diagnostic and protective system

### 3. Detection of instrumentation faults in control system

In the elaborated instrumentation fault detection system of the first group (see Chapter 1), the method based on relations between object variables was used. Utilization of software redundancy requires finding relations in the control system between parameters entering the controller.

Looking for proper relations requires special attention paid to the object parameters that influence the controller in the power control process. It is a group of parameters measured by the controller, i.e. generator power and live steam pressure as well as controlled live steam mass flow rate and vacuum in the condenser. For simplification, it was assumed that the remaining boiler parameters such as live steam temperature and superheated steam temperature, water level, flue gas pressure in the combustion chamber are kept on the proper level by independent control systems.

The purpose of the analysis was to find the simplest structural models that satisfy the assumed requirements [2]. The aim of the simple structure is to minimize the time of model output calculations. Presented relations should also include the dynamics of the changes of modelled parameters. Considering the above statements, six exemplifying model relations were isolated:

$$\overset{\wedge}{p}_i = f(I) \quad (1)$$

$$\overset{\wedge}{I} = f(P, p_T) \quad (2)$$

$$\dot{m}_{DT_i}^{\wedge} = f(Y, p_T) \quad (3)$$

$$P^{\wedge} = f(I, P_{t-1}) \quad (4)$$

$$P^{\wedge} = f(Y, p_s, p_T) \quad (5)$$

$$Y^{\wedge} = f(p_i) \quad (6)$$

where:  $\dot{m}_{DT}$  – live steam mass flow rate,  $P$  – generator active power,  $p_T$  – live steam pressure,  $p_s$  – pressure in condenser,  $p_i$  – hydraulic oil pressure,  $I$  – control current,  $Y$  – position of control valves.

One selected method of creating models for diagnostics is the application of structure based on fuzzy neural networks (FNN).

FNN is a combination of fuzzy modelling with a structure of artificial neural networks. When creating FNN, an expert knowledge is used to determine a number of rules and the preliminary distribution of the membership function. On the basis of data collected from the real object, the network learning process can be performed. Creation of the FNN model is started with choosing the input and output variables. These are respectively the input and output of FNN network. Next, the number of every input membership function must be determined. Further process of network identification takes place automatically, according to learning algorithm [2, 4].

The set of faults of the control system is:

$$E = \{e_k : k = 1, 2, \dots, K\}$$

This set contains faults which should be detected and isolated by the diagnostic system. In Table 2 the set of considered faults was given.

Any faults  $e_k \in E$  are detected by diagnostic tests performed in on-line mode of the diagnostic system. The diagnostic system is placed in the control system algorithm.

Table 2. Set of faults E

$E_k$	Set of faults E
$e_1$	Instrumentation fault of active power P
$e_2$	Instrumentation fault of steam pressure $p_T$
$e_3$	Instrumentation fault of steam mass flow rate $m_{DT}$
$e_4$	Instrumentation fault of pressure in condenser $p_s$
$e_5$	Instrumentation fault of hydraulic oil pressure $p_i$
$e_6$	Instrumentation fault of valves position Y
$e_7$	Instrumentation fault of control current I
$e_8$	Instrumentation fault of set power signal Y0
$e_9$	Instrumentation fault of set power signal Y1
$e_{10}$	Instrumentation fault of set power signal AOP
$e_{11}$	Instrumentation fault of frequency f
$e_{12}$	Instrumentation fault of rotational speed (measurement No 1)
$e_{13}$	Instrumentation fault of rotational speed (measurement No 2)
$e_{14}$	Instrumentation fault of rotational speed (measurement No 3)

For the purpose of fault detection, it is necessary to possess process variable values which create the set  $\mathbf{Z}$ :

As a diagnostic test  $d_j$ , we understand the sequence of operations performed by diagnostic algorithm on variable process values read by the control system in order to check the correctness of the reading of determined measuring line. The set of the diagnostic tests is used for isolation of faults.

The diagnostic test algorithm consists of the detection part assigning value of residuals and the decision part which, on the basis of calculation results and accepted conclusion rules, determines test result  $\alpha$  in the following way:

$$\alpha_j = \begin{cases} 0 - \text{positive test} \\ 1 - \text{negative test} \end{cases}$$

Test algorithms are based on different fault detection methods. In the condensing turbine control system, different instrumentation fault detection methods must be used. In Table 3 diagnostic tests used to detect faults of individual measuring lines are presented.



Table 3. Diagnostic tests

$d_j$	Algorithm of detection	Decisive algorithm
$d_1$	$r_1 = p_i - \overset{\Delta}{p}_i$	$ r_{1sr}  < K_1$
$d_2$	$r_2 = I - \overset{\Delta}{I}$	$ r_{2sr}  < K_2$
$d_3$	$r_3 = \overset{\bullet}{m}_{DT} - \overset{\Delta}{m}_{DT}$	$ r_{3sr}  < K_3$
$d_4$	$R_4 = P - \overset{\Delta}{P}$	$ r_{4sr}  < K_4$
$d_5$	$r_5 = P - \overset{\Delta}{P}$	$ r_{5sr}  < K_5$
$d_6$	$r_3 = Y - \overset{\Delta}{Y}$	$ r_{6sr}  < K_6$
$d_7$	$\alpha_7 = 1$ when $Y0_{\min} < Y0 < Y0_{\max}$	
$d_8$	$\alpha_8 = 1$ when $\frac{dY1}{dt} > K_s$	
$d_9$	$\alpha_9 = 1$ when $BPP_{\min} < BPP < BPP_{\max}$	
$d_{10}$	$r_{10} = f(n)$	$ r_{10}  < K_{10}$
$d_{11}$	$r_{11} =  n_1 - n_2 $	$ r_{11}  < K_{11}$
$d_{12}$	$r_{12} =  n_3 - n_2 $	$ r_{12}  < K_{12}$
$d_{13}$	$r_{13} =  n_1 - n_3 $	$ r_{13}  < K_{13}$

The calculated residuum value must be analysed in order to confirm fault occurrence in the control system. In the simplest case, the threshold test is used. After exceeding the permissible limit of residuum changes ( $K_n$ ) it is assumed that an instrumentation fault took place. The mean residuum value in the specified and travelling period of time may be checked. This mean value is a filter and decreases the sensitivity of the system on disturbances connected with measuring noise generated in the whole measuring line.

#### 4. Isolation of instrumentation faults

Fault diagnostics requires the determination of relations between detected symptoms, i.e. test results and faults. A binary relation in the form of a binary diagnostic matrix may be used for this purpose.

Table 4. Binary diagnostic matrix

	e <sub>1</sub>	e <sub>2</sub>	e <sub>3</sub>	e <sub>4</sub>	e <sub>5</sub>	e <sub>6</sub>	e <sub>7</sub>	e <sub>8</sub>	e <sub>9</sub>	e <sub>10</sub>	e <sub>11</sub>	e <sub>12</sub>	e <sub>13</sub>	e <sub>14</sub>
d <sub>1</sub>	0	0	0	0	1	0	1	0	0	0	0	0	0	0
d <sub>2</sub>	1	1	0	0	0	0	1	0	0	0	0	0	0	0
d <sub>3</sub>	0	1	1	0	0	1	0	0	0	0	0	0	0	0
d <sub>4</sub>	1	0	0	0	0	0	1	0	0	0	0	0	0	0
d <sub>5</sub>	1	1	0	1	0	1	0	0	0	0	0	0	0	0
d <sub>6</sub>	0	0	0	0	1	1	0	0	0	0	0	0	0	0
d <sub>7</sub>	0	0	0	0	0	0	0	1	0	0	0	0	0	0
d <sub>8</sub>	0	0	0	0	0	0	0	0	1	0	0	0	0	0
d <sub>9</sub>	0	0	0	0	0	0	0	0	0	1	0	0	0	0
d <sub>10</sub>	0	0	0	0	0	0	0	0	0	0	1	0	0	0
d <sub>11</sub>	0	0	0	0	0	0	0	0	0	0	0	1	1	0
d <sub>12</sub>	0	0	0	0	0	0	0	0	0	0	0	0	1	1
d <sub>13</sub>	0	0	0	0	0	0	0	0	0	0	0	1	0	1

This matrix is determined by an expert on the basis of knowledge about the control system and the control object. The binary diagnostic relation determines standard test results for individual tests of single faults. In case of fault detection (e<sub>k</sub>), every element of relation equal 1 corresponds with negative diagnostic rest result (d<sub>j</sub>). Every column of diagnostic matrix describes the signature of a fault. Elements of set E are instrumentation faults. The diagnostic matrix is built in such a way to enable detection and isolation of faults explicitly by diagnostic algorithm.

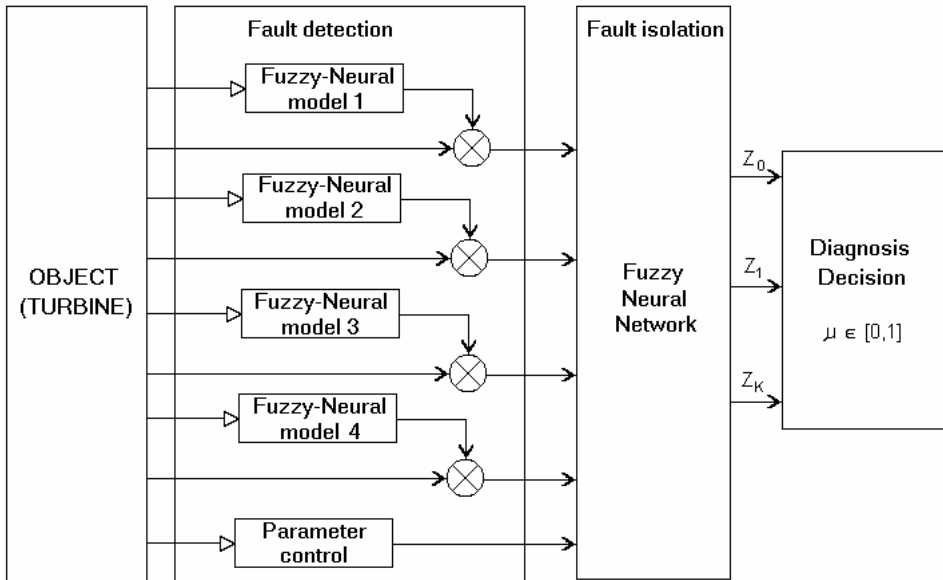


Fig. 2. Isolation of faults by FNN

Fuzzy neural networks may also be used for fault isolation and fuzzy evaluation of residuals. The idea of diagnostics by FNN for evaluation of residuals and fault isolation is presented in Fig. 3. Analytical, neural and fuzzy models (including FNN) may be used for fault detection as well as simple relations between variables. Fuzzy neural network is used for the “fuzzyfication” of residuals and simple diagnostic signals as well as fault isolation. The diagnosis indicates faulty states and ability states together with the calculated reliability factor [2, 4].

## Conclusions

Application of software redundancy methods increases the reliability of control system operation.

At present, in most of microprocessor turbine controllers, expensive hardware redundancy is used. Application of software redundancy methods decreases costs of the system and improves its operation.

Fuzzy neural network may be used for the “fuzzyfication“ of residuals and simple diagnostic signals. Application of fuzzy logic enables the inclusion uncertainty of diagnostic signals.

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## References

1. Pawlak M.: Detection and isolation of instrumentation faults in condensing turbine control system VII Conference – Research Problems in Power Engineering, Warsaw, December 6-9, 2005.
2. Kościelny J.M.: Diagnostics of automated industrial processes, AOW EXIT, Warsaw 2001.
3. Pawlak M., Karczewski J.: Reconfigurable control system of condensing turbine, Operation Problems 1/2006.
4. Korbicz J., Kościelny J.M., Kowalczyk Z., Cholewa W.: Diagnostics of processes, WNT 2002.

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## **Algorytmy detekcji i lokalizacji uszkodzeń torów pomiarowych w programie sterowania turbiny kondensacyjnej**

### **Słowa kluczowe**

Turbina kondensacyjna, tory pomiarowe, układ regulacji, modelowanie, lokalizacja uszkodzeń, detekcja uszkodzeń, diagnostyka.

### **Streszczenie**

Przedstawiono układ regulacji turbiny kondensacyjnej odporny na uszkodzenia torów pomiarowych. Zaprezentowano charakterystykę sygnałów pomiarowych wchodzących do regulatora i metody wykrywania uszkodzeń przykładowych torów pomiarowych. Przedstawiono wykorzystanie modelowania dla celów diagnostycznych. Opisano sposób budowy modeli cząstkowych wykorzystywanych do detekcji uszkodzeń. Zaprezentowano sposoby lokalizacji uszkodzeń.