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APPLICATION OF FUZZY NEURAL NETWORKS FOR INSTRUMENT FAULT DIAGNOSIS OF CONDENSATION TURBINE CONTROL

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Abstract: In the paper an application of fuzzy neural networks (FNN) for sensor fault diagnosis in condensation turbine control unit was given. The FNN are applied for fault detection and isolation processes. This approach gives the homogenous solution of fault detection and isolation process (FDI). The FNN models of turbine power, live steam pressure and steam mass flow rate were created and verified. Satisfactory models' performance indexes were obtained. The fault sensitivity of residuals was investigated and approved. *Copyright © 2002 IFAC.*

Keywords: fault diagnosis, power control, power generation, turbines, fuzzy modelling, neural networks, fault tolerant systems.

1. INTRODUCTION

High reliability of contemporary condensation turbines have been achieved due to applying of hardware redundancy. In the recent years the intensive research works were done in the field of application of analytical redundancy for diagnostics and system reconfiguration. The theory of fault tolerant systems have been strongly developed nowadays. The survey papers from this field were published by Patton (1997) and Blanke *et al*. (2000). A lot of contributions were devoted to the applications of fault tolerant systems (Yang and Lu, 1991; Kościelny and Wasiewicz, 1993, 1996; Won-Kee Son *et al.* 1997; Candau *et al*. 1997). On Fig.1 the general idea of application of fuzzy neural networks for instrumentation fault diagnosis was presented (Syfert and Kościelny 2001). There are to distinguish two main steps of fault diagnosis procedures: fault detection and fault isolation. For performing fault detection tasks, the fuzzy neural partial models (FNN-PM) are used. FNN-PM are models of subsections of decomposed system. Those models are representing the behaviour of the system in fault free states. Then the residuum vector ***r*** is

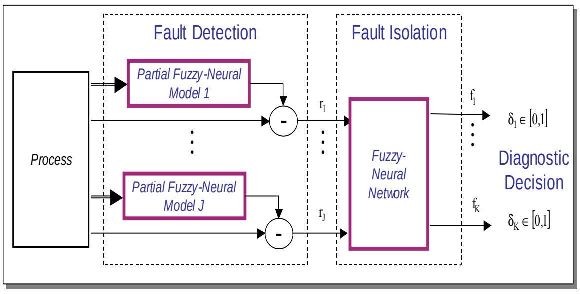

Fig. 1. Block diagram of fuzzy neural diagnostic system

obtained by comparing the process variables and model outputs. The residual values should be equal to 0 in fault free states. By further processing of the residuals applying FNN the diagnostics decision is to be obtained. This decision may be expressed as a set of k pairs of certainty degrees δ_k assigned to *k-th* fault f_k $\{<\delta_k, f_k>\}$.

2. CONDENSED TURBINE CONTROL UNIT

Condensation turbine is controlled by throttling the live steam mass flow using a set of turbine control valves. The set points for actuators acting on control valves are generated by turbine main controller. The controller input signals are used also for performing turbine protection tasks (Pawlak, 2002). The simplified block diagram of the turbine instrumentation is given in Fig. 2. The main turbine controller output signal Y_H is feed to electro-hydraulic transducer (pi/I) thus setting the

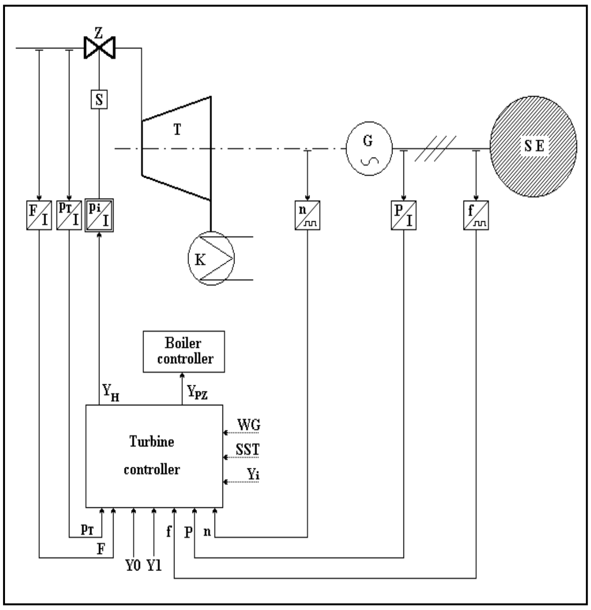

Fig.2. The simplified diagram of instrumentation of condensation turbine. Notations: Z – set of control valves; S – set of actuators; T – power turbine; K – condenser; G – generator; SE – electric power system; F- live steam mass flow rate; p_T – steam pressure; p_i – hydraulic oil pressure; f – electrical power system frequency; G – power generator; n –turbine rotational speed; Y0,Y1 – external control set point signals; ARCM – frequency and power control system; WG – generator on-off switch; SST – turbine efficiency binary signal from turbine diagnostic module; Yi – binary signal of power demand from ARCM; Y_H – controller output; Y_{PZ} – auxiliary controller output for boiler control unit.

positioners *A* driving the set of control valves *Z*. The outputs of the control system are: turbine power P and rotational turbine speed n. This signals are feed back for main controller. The turbine is operated in two modes. First mode is switched on when turbine is not synchronised with the electrical power system. Just before pulling turbine into step the controller is switched into turbine rotational speed controlling mode. In the second control mode (just after pulling turbine into step) the power signal replaces rotational speed in control system feedback. The set point for power control system is feed to controller (Y0, Y1) from the national power load-dispatching agency. Live steam pressure and live steam pressure signals are also feed into control unit. Most of the signals are analogue. The list of input signals of condensation turbine is presented in table 1.

3. FAULT DETECTION

Significant advantage of fuzzy neural models (FNN) is the ability of modelling the non-linear processes. Huge real process data files are nowadays available from the DCS control systems commonly applied in industrial automation. This gives the opportunity of modelling processes based on real process data and process knowledge. The process knowledge is used for defining the qualitative models rather than quantitative. FNN models may be tuned on the basis of real data using various learning techniques. Rapid development of computer technology has been broken the essential barrier concerning with reasonable computational power demands for this purposes. For modelling of MISO fuzzy systems (Bossley, 1997; Fuller, 1995; Horikawa *et al.*, 1991; Zhang, *et al.,* 1996) defined the set of *i* following rules:

$$R_i : If\ \ x_1\ \ is\ \ A_{1i}\ \ and\ \ x_2\ \ is\ \ A_{2i}\ and ...\ and\ x_N\ \ is\ \ A_{Ni} \quad Then\ \ y = y_i^* \tag{1}$$

where:
$i = (1, 2, \ldots, M)$ – consecutive rule's number,
M – number of rules,
x_j $(j = 1, 2, \ldots, N)$ –j-th input, N – number of inputs,
A_{ij} – fuzzy premise
y – model output,
y_i^* – successor

The number of rules is equal to $M = \prod_{j=1}^{N} K_j$, where

K_j is the number of fuzzy sets assigned for *j-th* input.

Tab.1. Set of input signals and fault detection methods applied for condensation power turbine

Item	Signal	Symbol	Unit	Fault detection method
1	Turbo set power	P	MW	Fuzzy neural networks
2	Live steam pressure	p_T	MPa	Fuzzy neural networks
3	Live steam mass flow rate	F	t/h	Fuzzy neural networks
4	Rotational speed of turbine	n	min^{-1}	Hardware redundancy (voting 2 from 3)
5	Electric system frequency	f	Hz	Test of correlation with turbine rotational speed Threshold technique
6	Power set-point signal	Y0	MW	Threshold technique
7	Power velocity set-point signal	Y1	MW	Threshold technique

The gaussian functions are used for fuzzyfication of crisp inputs. Thus the membership functions of the x_j input have a form :

$$\mu_{A_{ji}}(x) = \exp - (w_g^k (x_j + w_c^k))^2 \qquad (2)$$

The parameters (weights) w_c and w_g are used for defining the partitioning rules of the space of discourse. w_g is used for setting the function wideness when w_c parameter is an offset in the space of discourse x_j.

From (1) the normalised fire level of the *i-th* rule is given by:

$$\hat{\tau}_i = \frac{\prod_j \mu_{Aij}(x_j)_i}{\sum_k \prod_j \mu_{Aij}(x_j)} \qquad (3)$$

where the network output:

$$y^* = \sum_{i=1}^{n} \hat{\tau}_i \, y_i \qquad (4)$$

For detection of instrument faults the following set of models may be considered:

$$\hat{P}_t = f_1(F_{t-1}, P_{t-1}) \qquad (5)$$

$$\hat{F}_t = f_2(Y_{H_{t-1}}, F_{t-1}) \qquad (6)$$

$$\hat{Y}_t = f_3(p_{T_{t-1}}, P_{t-1}, Y_{H_{t-1}}) \qquad (7)$$

Basing on the models (5), (6) and (7) the following residuals are generated:

$$r_1 = P - \hat{P} \qquad (8)$$

$$r_2 = F - \hat{F} \qquad (9)$$

$$r_3 = Y_H - \hat{Y}_H \qquad (10)$$

Data acquired from the real plant were used for model tuning. Separate data sets were used for model learning and validation. The quality of modelling was estimated using performance index J (Kościelny *et al.* 2000)

$$J = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i} \times 100[\%] \qquad (11)$$

where:

N – learning data set samples count

$\hat{y}_i$ – model output,

y_i – measurement.

The results of modelling turbine's power are given on Fig.3. The model quality performance index is sufficiently good (J=0.28). Similar values of performance indexes were obtained also for models described by equations (6) and (7). The investigation of the residuals sensitivity in faulty states was also done.

The instrumentation faults are generally classified into two main classes: abrupt and incipient (parametric) faults. Abrupt and incipient faults cause the residuum excursion. In the case of abrupt faults the extraordinary measures must be immediately undertaken to ensure process safety.

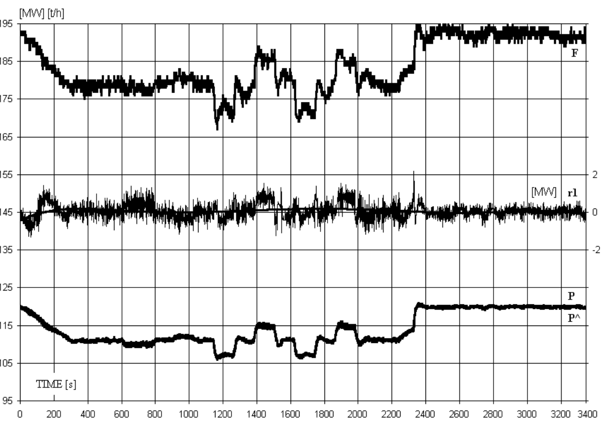

Fig.3. An example of the modelling the turbine power. Notations: F – live steam mass flow rate, P – measured power , $\hat{P}$ - power model output, *r1* – power residuum

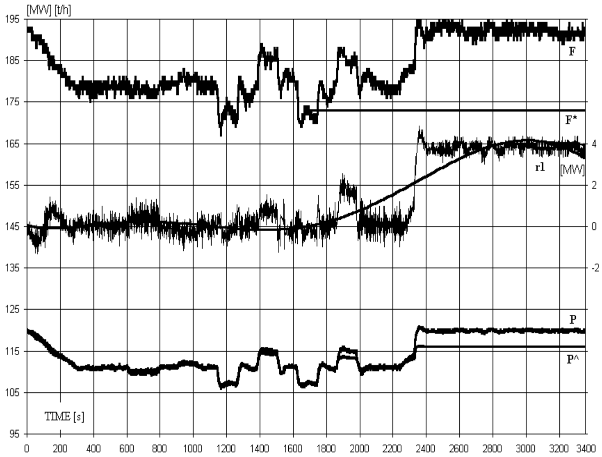

Fig. 4. Flow sensor fault simulation
Notations: P – measured power , $\hat{P}$ - power model output, F – measured flow rate, $\hat{F}$ - flow rate model output, *r1* – flow rate residuum

The incipient faults are slowly developing faults resulting from system degradation. Monitoring of this faults may help when prediction of the system lifetime is important.

On Fig. 4. the model output and residuum are shown in the case of power transducer fault. On Fig.5. the system behaviour is to be observed in the case of live steam mass flow transducer fault. The faults were injected artificially into the real data stream by applying tracking and holding technique.

On Fig. 6 the model (7) and residuals in the case of steam pressure sensor fault are shown. The residual sensitivity to the faults is clearly visible on the graphs shown in Fig. 4, 5, 6. Some additional residual processing (filtering) is to be applied to reject high frequency components of the residual signal spectrum. The time-window moving averaging filters may be applied for instance.

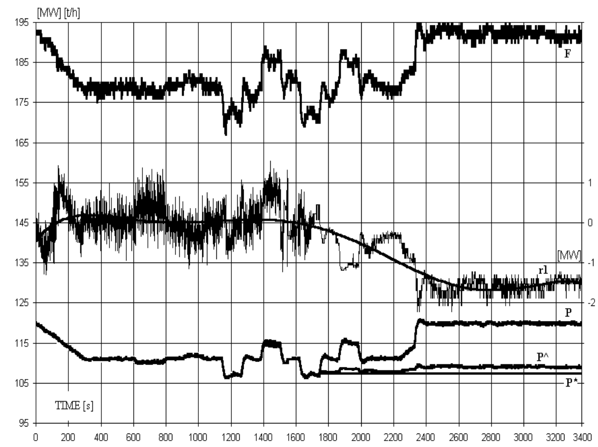

Fig. 5. Power sensor fault simulation. Notations are the same as on Fig. 4.

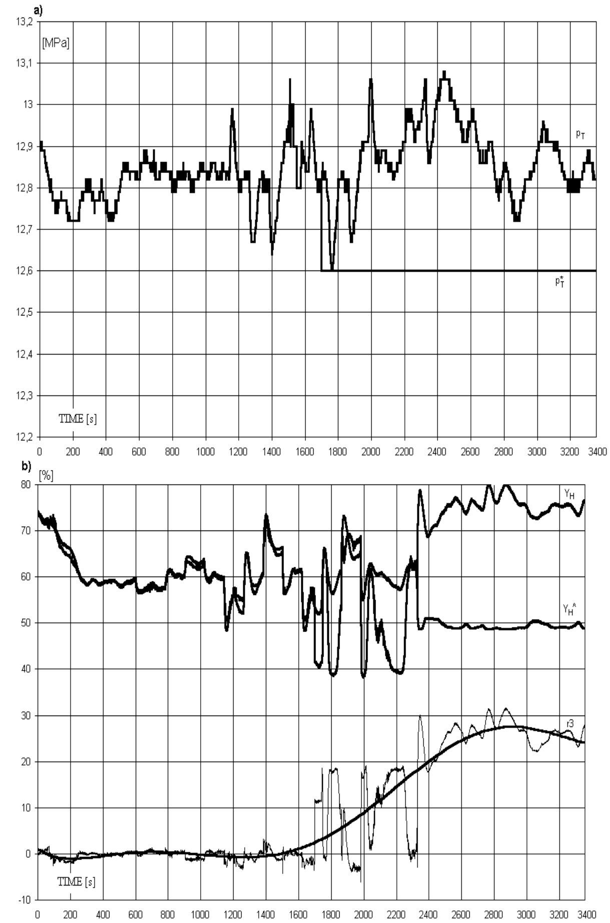

Fig. 6. a) Steam pressure sensor fault simulation (pressure drop from 12.8 to 12.6 MPa). p_T – measured pressure , $\hat{p}_T$ - pressure model output,
b) Turbine controller output fault simulation Y_H – measured controller output, $\hat{Y}_H$ - model output, *r3* – controller output residuum

4. FAULT ISOLATION

Fuzzy neural network was applied also for sensor fault isolation of power, steam pressure and steam mass flow rate. Application of fuzzy logic for residuum evaluation and fault isolation make an advantage by delivering the fault uncertainty degrees (Kościelny, 1999). This gives more precise description of diagnostic state.

A FNN, unlike artificial neural networks, is not a “black box”. The expert knowledge may be “injected” directly in the form of network weights values.

Fault isolation procedures of: power, steam pressure and steam mass flow rate sensor faults are based on a set of five following rules:

$$IF\ r_1=0\ and\ r_2=0\ and\ r_3=0\ THEN\ fault\ free \quad (12a)$$

$$IF\ r_1=1\ and\ r_2=1\ and\ r_3=0\ THEN\ fault\ P \quad (12b)$$

$$IF\ r_1=0\ and\ r_2=1\ and\ r_3=0\ THEN\ fault\ n \quad (12c)$$

$$IF\ r_1=1\ and\ r_2=0\ and\ r_3=1\ THEN\ fault\ p_T \quad (12d)$$

$$otherwise\ unknown\ state \quad (12e)$$

where:

0 – *"near zero"* absolute residual value (fuzzy term)

1 – *"non zero"* absolute residual value (fuzzy term)

The residuum evaluation technique is shown on Fig.7.

Fuzzy neural network used for fault isolation is given on Fig. 8. Three first layers are responsible for fuzzy evaluation of residuals. In the fourth layer the firing level for every rule is obtained and appropriate faults certainty degrees are calculated. The neural networks may be trained in two ways. First approach is based on the network training using the process data from fault free system operation. Afterwards the networks are trained also for faulty states. Fault free data are easy available in opposite

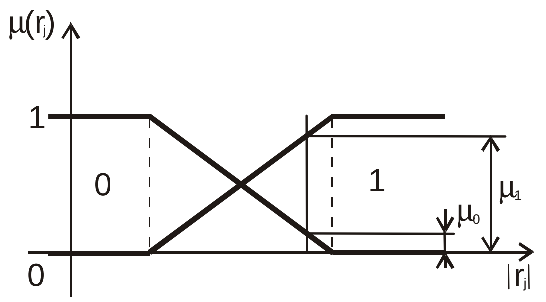

Fig. 7. Fuzzy evaluation of j-th normalised absolute value of fault residual r_{nj}. Notations: $\mu_1(r_j)$ – fuzzy set *"non zero"*; $\mu_0(r_j)$ – fuzzy set *"near zero"*;

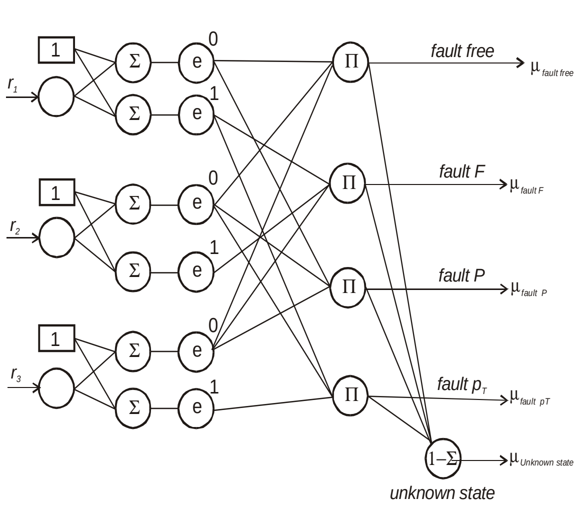

Fig. 8. The structure of FNN applied for fault isolation

to the data from faulty states what makes troubles in industrial applications. In the case of sensor faults the data might be relatively simple simulated in similar way as for residual sensitivity investigation. The unknown fault state data may be also generated artificially using similar procedures.

Second approach is based on the set of rules (12a-e). The network is not trained in the early begin at all. Fuzzy partitioning may be done arbitrary. The network weights w_f however are related to (12a-e). If the combination of residual input values is present in the rule premise the value of w_f =1, otherwise w_f =0. In the case of w_f =0, the network is switched in the inference mode basing exclusively on the rules given by an expert.

Example of fault isolation

Let $\mu_0(r_j)$ denotes residuum membership function values of the *"near to zero"* set and $\mu_1(r_j)$ denotes membership function values of the *"non zero"* set. Thus:

$$\mu_1(r_j)=1-\mu_0(r_j) \quad (13)$$

Following residuum fuzzy evaluation results were achieved in time t_i

$$\begin{aligned} &\mu_0(r_1)=0.1;\ \ \mu_1(r_1)=0.9 \\ &\mu_0(r_2)=1.0;\ \ \mu_1(r_2)=0.0 \\ &\mu_0(r_3)=0.2;\ \ \mu_1(r_3)=0.8 \end{aligned} \quad (14)$$

Applying *PROD* operator for fuzzy reasoning the following firing levels are calculated

$$\begin{aligned} &\mu(fault\ \ free)=0.1\cdot 1.0\cdot 0.2=0.02 \\ &\mu(fault\ \ P)\ \ =0.9\cdot 1.0\cdot 0.8=0.72 \\ &\mu(fault\ \ p_T)=0.1\cdot 1.0\cdot 0.8=0.08 \\ &\mu(fault\ \ F)=0.9\cdot 0.0\cdot 0.2=0.00 \\ &\mu(unkn.\ state)=1-(0.02+0.72+0.08)=0.18 \end{aligned} \quad (15)$$

The set of firing levels given in (15) is generated by on the net at time t_i. The firing levels are interpreted as a fault certainty degrees. Diagnosis that will be feed forward have to be appropriately tuned applying e.g firing level threshold technique. In the example the diagnosis point out relative certain fault of turbine power measurement chain.

$$DGN=\left\{\ 0.72,\ \ fault\ \ P\ \right\} \quad (16)$$

5. SUMMARY

The diagnosis of instrumentation with application of FNN for condensation turbine were presented. Fuzzy neural models are useful for fault detection. For the fault detection the bank of fuzzy neural partial models (FNN-PM) was used. A significant advantage of fuzzy and neural methods is ability of modelling of non-linear processes and generalisation features. Models of processes being fully efficient are obtained on the basis of experimental data, with the application of various learning methods. It must be taken into consideration, that generalisation features of FNN models are strictly limited to the space determined by the signal spans used for the model learning.

Fuzzy neural networks approach applied for fault isolation allows fault isolation combined with delivering some additional information interpreted as fault certainty degrees. This take advantage over FI methods basing on classical crisp logic.

Fuzzy neural networks approach. is more robust to false symptom values comparing to FDI methods basing on threshold methods of residual evaluation. This significantly reduces number of false diagnosis.

When taking into consideration industrial applicability, the three extremely important features of presented above FDI methods based on FNN must be underlined:

- FDI methods does not need any process data from faulty states. For sensor faults the data may be easily simulated.
- fault inference rules for FNN structures may be based on expert knowledge
- fuzzy reasoning allows to obtain fault uncertainty degrees.

The approved FDI system based on FNN may be applied as software redundancy support in fault tolerant systems.

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