Appl. Math. and Comp. Sci., 1993, vol.3, No.3, 613–630

KNOWLEDGE–BASED FAULT DETECTION AND ISOLATION SYSTEM FOR POWER PLANT SIMULATOR[†]

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A knowledge–based fault detection and isolation computer system for the power plant simulator in which the power boiler with $380t/h$ capacity collaborates with $125MW$ power turbine has been developed and implemented with the use of the expert system shell EXSYS. This system is designed to assist the operator during the power plant nominal work and is fully separated from the model of the process to be diagnosed. The set of rules (heuristic knowledge of the plant, operator's knowledge) as well as mathematical models and algorithms (analytical knowledge) create two–part coupled knowledge base of the computer system regarding the power plant processes. Such a combined knowledge of the power plant on one hand increases the complexity of the knowledge base, but on the other hand it gives possibilities for a more efficient process of inference and making a decision by the system. The efficiency of the proposed fault detection and isolation computer system is shown for a few typical faults occuring in the power plant.

1. Introduction

The growing complexity of many contemporary technological processes in the power, chemical and steel industries as well as their computer control systems increase considerably the reliability and safety demands. Traditionally, a solution of the reliability problems can be achieved through the use of hardware redundancy, i.e. the repeated hardware elements and systems should be then spatially distributed around the system to provide protection against possible damage. This approach to fault–tolerance is simple and reasonably straightforward to apply in many cases but for more complex processes the reliability problems should be solved by the computer fault detection and diagnosis systems (Patton *et al.*, 1989). Such systems base on analytical redundancy and artificial intelligence methods and their operation consists in the appropriate processing of measurement data without any additional equipment.

[†] This work was supported by the Polish State Committee for Scientific Research under grant No. 7–1086 91 01

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So far analytical redundancy problems for technical processes have been considered in the literature by many authors and among them there are the excellent book edited by Patton *et al.*, (1989) and several survey papers (Willsky, 1976; Isermann, 1984; Frank, 1990 and 1992; Korbicz *et al.*, 1991; Patton and Chen, 1991; Gertler, 1991). More comprehensive sources of the state–of–the–art in the fault detection and diagnosis area are the preprints of the IFAC/IMACS symposium SAFEPROCESS'91 (Isermann, 1991) and the IFAC symposium (Dhurjati, 1992). In general, various known approaches and techniques to the fault detection and isolation (FDI) problems for technical processes can be divided into three groups:

i) statistical methods based on modern signal processing methods (Young and Clarke, 1989; Cempel, 1991; Neumann, 1991; Bokor *et al.*, 1991),

ii) model–based methods including parity equations (Gertler and Singer, 1990; Gertler, 1991; Gertler and Anderson, 1992), diagnostic observers (Frank, 1991; Ding and Frank, 1992), Kalman filtering (Yoshimura *et al.*, 1979; Wallace and Clarke, 1983; Tylee, 1983; Patton *et al.*, 1989; Korbicz *et al.*, 1993; Fathi *et al.*, 1992; Frank, 1992) and parameter identification (Isermann, 1984; Gomm *et al.*, 1992),

iii) artificial intelligence approaches including expert systems (Kramer and Palowitch, 1987; Finch *et al.*, 1990; Tzafestas, 1989 and 1991; Milne, 1991; Bokor *et al.*, 1991; Fathi *et al.*, 1992), and artificial neural networks (Venkatasubramanian and Chan, 1989; Kramer and Leonard, 1990; Ungar *et al.*, 1990; Sorsa *et al.*, 1991; Koshijima and Niida, 1992).

Among the above mentioned groups of methods and algorithms the artificial intelligence approach becomes more and more important in applications. This approach provides the means and flexibility in gathering and organizing the types of knowledge related to the process operation as well as symbolic and numeric processing of information. The expert system approach to solving technical diagnostic problems is discussed in books edited by Tzafestas (1989) and Patton *et al.*, (1989). In turn the second generation diagnostic expert systems in comparison with first–generation expert systems are considered by Tzafestas (1991) and Milne (1991). So far many of the diagnostic expert systems have been implemented, for example in chemical industry (Terpstra *et al.*, 1992) and power engineering (Bokor *et al.*, 1991; Fathi *et al.*, 1992). In most of applications the knowledge base is created with the use of the heuristic knowledge (i.e. operator's knowledge) regarding technological process under consideration.

This paper deals with the computer diagnostic system for the power plant simulator which is designed to help the operator in fault detection and isolation during the work of the power plant. To increase the efficiency and flexibility of knowledge–based diagnostic system the two–part knowledge base was created. This base consists of heuristic knowledge (set of rules and principles of system behavior) and analytical knowledge (set of mathematical models, Kalman filter algorithms and tests of random sequences). In fact, an integrated approach based on combining the analitycally-redundant FDI schemes and the knowledge-based techniques is considered. The task of the diagnostic system is to determine the true fault and its source. Both a state and the parameter estimator and a statistical analyzer are included in the loop of diagnostic reasoning. The design methodology is a hierarchical knowledge structure with compiled knowledge at higher levels of abstraction and analytical redundancy at lower ones. Such an integrated approach reduces the computational complexity associated with functionally-redundant schemes and increases the effectiveness of the knowledge-based approach.

We will start the main body of the paper with a brief description of a physical boiler-turbine control subsystem of a power plant and some mathematical models. Next, the overall structure of our computer diagnostic system is presented. Then, based on this structure the main modules will be described in detail. First, the signal pre-processing module is discussed and then, the analytical redundancy and the design of local filters for state and parameter estimation are presented. Questions related to the knowledge base and system implementation are then considered. Finally, we examine a few diagnosis examples which complete the paper.

2. Process Description

The simplified schematic diagram of power boiler capacity of $380t/h$ and coupled with it $125MW$ power turbine is shown in Figure 1. The basic physical processes taking place in the boiler-turbine unit can be described in the following way. As you can see steam is generated from water pumped by the feedwater

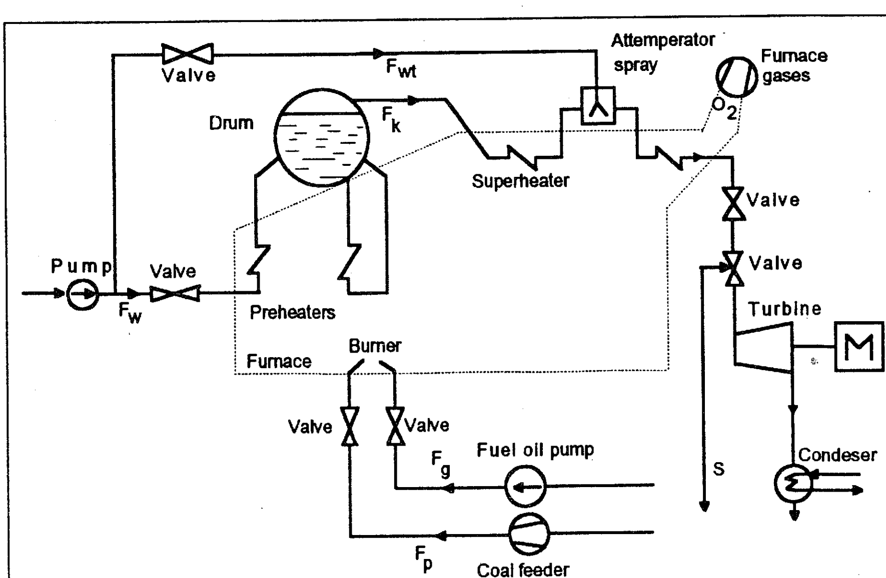

Fig. 1. Simplified schematic diagram of the boiler-turbine unit.

pump to the drum. Before reaching the pump, water is preliminary preheated in the regenerative heater and heater. Mass–flow rate of feedwater F_w is controlled by a dumper value. Saturated vapour from the drum with pressure p_w is then overheated in a superheater and transported to the turbine driving unit. After leaving the turbine, steam is led to a condenser. Vapour superheaters are usually multisection heat exchangers of *furnace gases–metal–vapour* type with individual sections located in a radiant and convectional zones of the superheater. The steam overheated to the temperature level of $520°C - 540°C$ results in growing steam enthalpy which has a positive impact on the thermodynamic efficiency of the turbine. Temperature control of the overheated steam is done by attemperator spray which is fed by water controller using the attemperator spray valve.

The steam is generated with desired the characterics (pressure p_k, temperature T_k, mass flow rate F_k) due to energy from the burning process of fuel–air mixture. In most cases the amount of transported fuel F_g is controlled by pressure stabilization system of steam in the boiler. In turn, the amount of transported air F_1 to the burning process is controlled using a fan for a mill ventilation and it depends on amount of transported fuel as well as on its calorific value. In the control system of flows ratio fuel–air important for economical burning, apart from measurement of air mass flow rate, F_1, an output from the controller steam pressure is used. This controller intermediately defines the amount of transported fuel, F_g. During the process operation of the cascade fuel–air ratio control system, the ratio value is changed using the output from an oxygen content controller O_2 in furnace gases. From balancing investigation it was concluded that the content of oxygen is an intermediate index of economical burnig.

During collaborating of generator with power system, frequency of electric signal output as a function of variable power consumption is a very important parameter. From technical point of view this frequency should be constant which is to be assured by a control system. In the computer simulator of the boiler–turbine unit it was assumed that the following variables were controlled:

- water level in the drum h
- steam pressure in the boiler p_k
- temperature of overheated steam T_k
- content of free oxygen in furnace gases O_2
- rotations of the turbine n

Mathematical models of particular units and modules used in the computer simulator implementation according to the diagram presented in Figure 1, have been discussed in detail by Pieczyński and Korbicz (1993). Below, only the mathematical model of the boiler as a control object of water level in the drum will be considered.

3. Expert System Structure

The global scheme of the diagnostic expert system for the computer simulator of the boiler–turbine unit is shown in Figure 2.

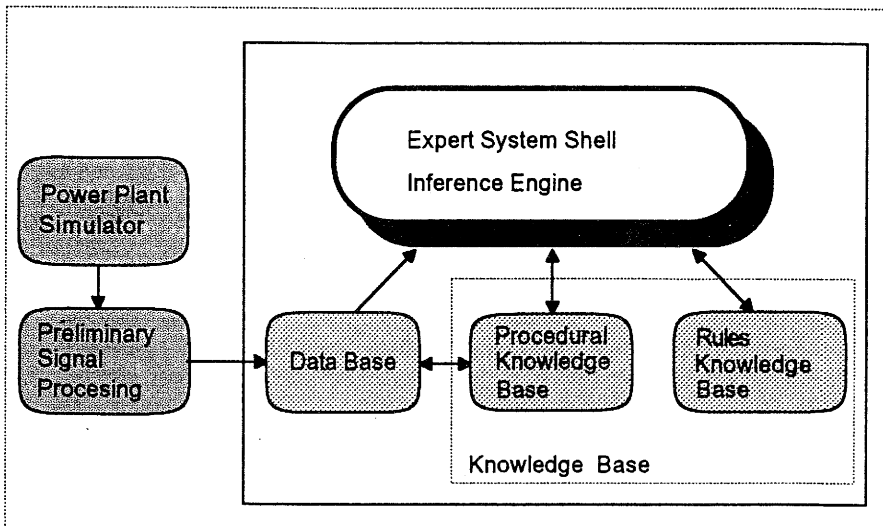

Fig. 2. The structure of the expert system.

Here, the knowledge base is divided into two parts: a rule knowledge base and a procedural one. As it was noticed by many authors (Fathi *et al.*, 1992; Milne, 1991) such an integrated knowledge regarding to real plant is more complete and makes it possible to design a more flexible and efficient diagnostic system. For knowledge representation the most popular (and at the same time the most natural) approach based on the rules of IF–THEN type was accepted. The rules describe principles of operation and relations between different processes in the boiler–turbine unit. It is a very clear, simple and concise way of knowledge representation regarding power plant processes. Our expert system can operate on-line while monitoring the power plant or only when operator needs assistance of the diagnostic system. All the modules of the diagnostic system showen in Figure 2 will be described in detail below.

3.1. Preliminary Signal Processing

During the simulator operation of the boiler–turbine unit data are gathered from the sensors installed in several unit plants. The following quantities are measured: mass flow rate of fuel, F_g; mass flow rate of air, F_1; content of oxygen in furnace gases, O_2; steam pressure in boiler, p_k; amount of used steam, F_k; mass flow rate of feedwater, (in front of the feedwater valve), F_w; mass flow rate of feedwater (behind of the feedwater valve), F_2; level of water in drum, h; mass flow rate of spraywater, F_{wt}; final temperature of overheated water, T_k; rotations of the turbine, n; opening degree of the release valve, s. It is assumed that most of them are noised and therefore the measured signals should be preliminary processed. The signal processing module contains algorithms of meaning, normalization, digital filtering, smoothing by aproximated polynomials and parameter identification of the linear regression equation. Parameter identification algorithm can be described as follows.

Only N past samples for each of processed signals (in realization $N = 50$) are stored in system memory. For each set of samples y_j, $j = 1, 2, \ldots, N$ the optimal line $y = at + b$ in the sense of the least square method is looked for. The parameter estimates $\widehat{a}$ and $\widehat{b}$ are as follows

$$\widehat{a} = \sum_{j=1}^{N} t_j y_j \Big/ \sum_{j=1}^{N} t_j^2 \qquad \widehat{b} = \frac{1}{N} \sum_{j=1}^{N} y_j \tag{1}$$

where t_j denotes the time instant for j–th measurement (it is assumed for simplicity that the origin of t–oxis is the centre of such a moving window). The parameters and quantities defined in this module are then transferred to the data base of the system. In this way data are accessible for the inference engine.

3.2. Data Base

The data base of the system consists of a set of processed measurement signals, statistical parameters and a set of parameters and constants characterizing properties of the boiler–turbine unit. This data is directly used by the inference engine, for example, the parameter estimate $\widehat{b}$ defines the mean value, while $\widehat{a}$ is a measure of the upward or downward slopes.

3.3. Procedural Knowledge Base

In general, the procedural knowledge base consists of analytical methods for fault detection and localization in dynamic systems based on the Kalman filter theory (Patton *et al.*, 1989; Korbicz and Bidyuk, 1993). According to this approach, the procedural knowledge base contains:

- mathematical models of components of the boiler–turbine unit,
- the suboptimal Kalman filter algorithm for state and para– meter estimation,
- the test for random sequences.

3.3.1. Mathematical Model of Boiler

For the power boiler of drum type, the water level in the drum is the balancing index between the amount of feedwater coming into the drum and amount of outcoming steam from the boiler. Changes of water level in the drum can be caused by the following changes of:

i) steam consumption by the turbine,

ii) steam pressure following from oscillatation of quality and amount of incoming fuel,

iii) consumption of spray water,

iv) capacity of the water pump,

v) opening or closing of the reduceral–descending units.

The increase of feedwater inflow is related with some delay in increasing water level (only in the case of unheated water the transient drop of water level can appear). Decreasing steam consumption from the boiler causes the process of steam condensation as a result of pressure increase in the drum. Therefore, a drop in water level in the drum is first observed (more precisely the steam–water mixture), although, in fact, during this period water mass increases. After some time condensation of steam bubbles is stopped and then the water level in the drum starts increasing. This phenomenon is called the water swelling and complicates the control process of level liquid during disturbances of steam consumption.

Assuming that the mass flow rate of steam, $F_k(t)$ (steam consumption) and the mass flow rate of feedwater, $F_w(t)$ are inputs, and the water level in the drum, $h(t)$, is an output, the set of differential equations describing physical processes in the drum is given by (Pieczyński and Korbicz, 1993):

$$\frac{\mathrm{d}^2}{\mathrm{d}t}h(t) + a\frac{\mathrm{d}}{\mathrm{d}t}h(t) = b_1\frac{\mathrm{d}}{\mathrm{d}t}F_k(t) + b_2F_k(t) + b_3\frac{\mathrm{d}}{\mathrm{d}t}F_2(t) + b_4F_2(t) \tag{2}$$

$$\frac{\mathrm{d}^3}{\mathrm{d}t^3}F_3(t) + c_1\frac{\mathrm{d}^2}{\mathrm{d}t^2}F_2(t) + c_2\frac{\mathrm{d}}{\mathrm{d}t}F_2(t) + c_3F_2(t) = dF_w(t) \tag{3}$$

where $F_2(t)$ denotes the mass flow rate of water leaving the feedwater valve, and the initial conditions take the form of:

$$\frac{\mathrm{d}h(0)}{\mathrm{d}t}h(0) = 0, \qquad \frac{\mathrm{d}^2F_2(0)}{\mathrm{d}t^2} = \frac{\mathrm{d}F_2(0)}{\mathrm{d}t} = F_2(0) = 0$$

Parameter values in equations (2) and (3) are equal to:

$a = 2.5 \cdot 10^{-2}$,

$b_1 = -5 \cdot 10^{-3}$, $c_1 = 0.15$,

$b_2 = 1.75 \cdot 10^{-4}$, $c_2 = 7.5 \cdot 10^{-3}$,

$b_3 = 6.75 \cdot 10^{-3}$, $c_3 = 1.25 \cdot 10^{-4}$,

$b_4 = 1.75 \cdot 10^{-4}$, $d = 1.25 \cdot 10^{-4}$

3.3.2. Suboptimal Filtering

Various techniques for solving the problem of state estimation are available and a short survey of the recursive state estimation techniques is given by Misawa and Hedrick (1988). Among these techniques, the Extended Kalman Filter (EKF) method is widely used by most investigators to solve practical problems (Sorenson, 1985). This algorithm has been applied in the design of state and parameters estimators as from the fault detection viewpoint. It is important to consider the joint parameter and state estimation.

In the discrete–time framework, the model of general stochastic system with unknown parameter vector θ can be described mathematically by the following equations

$$z(k+1) = A(k,\theta)z(k) + B(k,\theta)u(k) + w(k) \tag{4}$$

$$y(k) = H(k,\theta)z(k) + v(k) \tag{5}$$

where k is a discrete time; $z(k)$ is a n–dimensional state vector; $u(k)$ is a p–dimensional input (control) vector; $y(k)$ is a m–dimensional output measurement vector; $v(k)$ is a m–dimensional observation noise vector; $w(k)$ is a q–dimensional system noise vector; $A(k,\theta)$ is a $(n \times n)$–dimensional system matrix; $B(k,\theta)$ is a $(n \times p)$–dimensional input matrix, and $H(k,\theta)$ is a known $(m \times n)$–dimensional observation matrix. Note, that $\dim z > \dim y$. It is assumed that the system noise $w(k)$, measurement noise $v(k)$, and the initial condition $x(0)$ are Gaussian random variables with known covariance matrices: $Q(k)$, $R(k)$ and $P(0/0)$, respectively.

To cope with time–varing parameters we postulate that the true parameter vector θ varies according to:

$$\theta(k+1) = \theta(k) + w_\theta(k) \tag{6}$$

where $w_\theta(k)$ denotes a s–dimensional parameter noise vector.

To tackle the joint state and parameter estimation problem, the augmented state vector x is defined as:

$$x^T(k) = [z^T(k)\ \theta^T(k)] \tag{7}$$

By means of the nonlinear Kalman filter approach (Anderson and Moore, 1979) and its suboptimal modification (Korbicz *et al.*, 1991), the estimate of $x(k)$ based on the sequence of measurements $Y(k) = \{y(0),\ y(1),\ ...,\ y(k)\}$ for the augmented stochastic system described by equations (4)–(6), is given by the sequential use of the following recursive algorithm (Korbicz *et al.*, 1991):

$$\widehat{x}(k+1|k) = f(\widehat{x}(k|k), k) \tag{8}$$

$$\delta x(k+1|k) = A_f(k)\delta x(k|k) + w_z(k) \tag{9}$$

$$\widehat{P}(k+1|k) = \widehat{P}(k|k) + \gamma(k)[\delta x(k+1|k)\delta x^T(k+1|k) - \widehat{P}(k|k)] \tag{10}$$

$$V(k+1) = H(k+1)\widehat{P}(k+1|k)H^T(k+1) + R(k+1) \tag{11}$$

$$K(k+1) = \widehat{P}(k+1|k)H^T(k+1)V^{-1}(k+1) \tag{12}$$

$$\nu(k=1) = y(k+1) - H(k)\widehat{x}(k+1|k) \tag{13}$$

$$\widehat{x}(k+1|k+1) = \widehat{x}(k+1|k) + K(k+1)\nu(k+1) \tag{14}$$

$$\delta x(k+1|k+1) = \delta x(k+1|k) - K(k+1)\nu(k+1) \tag{15}$$

$$\widehat{P}(k+1|k) = \widehat{P}(k+1|k) - K(k+1)H(k+1)\widehat{P}(k+1|k) \tag{16}$$

with the initial conditions: $\widehat{x}(0|0) = \widehat{x}_0$, $\widehat{P}(0|0) = \widehat{P}_0$. In equations, (8)–(16) the following notation is used:

$$f(x(k),k) = \begin{bmatrix} A(k,\theta)z(k) + B(k,\theta) \\ \theta \end{bmatrix}, \quad A_f(k) = \left. \frac{\partial \infty f(x(k),k)}{\partial x} \right|_{x=\widehat{x}(k|k)}$$

$$w_z^T(k) = [w^T(k) w_\theta^T(k)], \qquad \delta x(k|k) = x(k) - \widehat{x}(k|k) \tag{17}$$

Furthermore, $\widehat{x}(i|j)$ denotes the estimate of $x(i)$ given the available data $Y(j) = \{y(0)\ y(1) \dots y(j)\}$, $\widehat{P}(i|j)$ is the estimate of the covariance matrix $P(i|j)$ of $\widehat{x}(i|j)$, $\delta x(i|j)$ denotes the estimation error, and $\nu(k)$ is the innovation sequence.

In general, the structure of the modified EKF algorithm given by the set of equations (8)–(16) is the same as the standard EKF for nonlinear dynamic models (Anderson and Moore, 1979; Sorenson, 1985). The main difference is based on the computation of the estimate of covariance matrix $\widehat{P}$ (Korbicz *et al.*, 1991).

3.4. Statistical Test

A variety of statistical tests can be performed on the innovations or residuals to determine the validity of the mathematical model used in the filter design (Chien and Adams, 1976; Yoshimura *et al.*, 1979). If the filter reflects the actual system properly, the innovation sequence is an independent Gaussian random sequence with zero mean, and covariance $V(k)$ (see eq. (11)). However, if a system abnormality occurs due to parameter changes, the statistics of innovation changes. To detect these changes, the modified Sequential Probability Ratio Test (SPRT) (Chien and Adams, 1976) can be applied. The SPRT method is one of the simplest tests for the presence of unmodelled phenomena in the system (4), (5). In our diagnostic system this test was implemented, too. As a result of the test operating, the truth of one of the hypotheses:

H_0: normal mode,

H_1: failure mode

is determined.

3.5. Rule Base

Rules describing the experience in the diagnostics of the power plant control problem are obtained from the operators at the plant center and from special literature.

The collected rules are converted to the rule base format according to principles of the popular expert system shell, EXSYS. These rules can be written in the deterministic way (absolute certainty of hypotheses) or regarding to uncertainty (hypotheses with different certainty factors).

In our diagnostic system for the boiler–turbine unit the rules are divided into three main groups.

i) Rules defining the ranges of measured values, e.g. a rule defining water level in the drum is:

IF $h < 48$ THEN *the water level in the drum is low*
IF $48 \le h$ AND $h \le 52$ THEN *the water level in the drum is normal*
IF $h > 52$ THEN *the water level in the drum is high*

ii) Rules defining slopes of the level change (upward or downward factors), e.g. the rule defining the steam pressure in the boiler is:

IF $dp_k < -0.05$ THEN *the steam pressure in the boiler is decreasing.*
IF $-0.05 \le dp_k$ AND $dp_k \le 0.05$ THEN *the steam pressure in the boiler is constant*
IF $dp_k > 0.05$ THEN *the steam pressure in the boiler is increasing.*

According to the change slopes of levels, the condition is divided to four cases as in Table 1. We use the value 0.05 as the boundary between the serious and the safe increasing or decreasing slope values.

Tabl. 1. Degrees of a slope.

Series Increasing	1	Slope= 0.05
Safe Increasing	2	Slope= 0.0
Safe Decreasing	3	
Serious Decreasing	4	Slope= −0.05

iii) Rules defining a kind of a failure, e.g. the rule defining the failure of the release valve is:

IF *water level in the drum is low*
and *the amount of used steam is increasing*
and *rotations of the turbine are normal*
and *steam pressure in the boiler is decreasing*
THEN *release valve is damaged – Probability=8/10*

The rule defining correctness of the unit operation is assumed as the separate one. This rule is described as follows:

IF *water level in the drum is normal*
and *steam pressure in the boiler is normal*
and *temperature of overheated steam is normal*

and *contents of oxygen in furnace gas is normal*
and *rotations of the turbine are normal*
THEN *failures are missing – Probability=10/10*
and {*table of all failures with zero probability coefficients*}
ELSE *failures are missing – Probability=0/10*

During diagnosis process this rule is always tested first which essentially reduces the time of diagnosis in the case of conclusion that failures are missing.

4. Implementation

Numerical processing tasks such as process simulation, preliminary data processing, estimation and testing random sequences, have been implemented on a Turbo Pascal v.5.5 based software. The EXSYS v.3.0 tool with its knowledge representation paradigm based on rules constitute an efficient medium for our knowledge–based system development. For the boiler–turbine unit, the knowledge base that defines the entities of the system and their characteristics and contains the problem–solving knowledge in terms of rules has been created. This knowledge base has been developed through preliminary knowledge aquisition based on background knowledge, use of different documents, and detailed knowledge aquisition based on meetings with the power plant operators.

5. Examples

In the current version of the prototype diagnostic system inputs are taken from the power plant computer simulator. These inputs are preliminary processed in the separate module of the system. The knowledge processing is activated in case when operator suspects abnormal behavior of the plant. To illustrate the system trail and its efficiency in performing a diagnostic task, an example is presented below. In this example, fouling in the feedwater control valve and a failure of a water level sensor in the drum are simulated. In these two cases the procedural knowledge base is included during inference process. The filter is run using a window of past and current data including last data transfer.

Two filters have been designed for the drum. The augmented state vector and the output vector for these filters are defined as follows:

$$\text{Filter I} \quad \boldsymbol{x}^T = [h \ \mathrm{d}h/\mathrm{d}t \ \ \mathrm{d}^2h/\mathrm{d}t^2 \ k_v], \quad \boldsymbol{y} = [h]$$

$$\text{Filter II} \quad \boldsymbol{x}^T = [h \ \mathrm{d}h/\mathrm{d}t \ \ \mathrm{d}^2h/\mathrm{d}t^2 \ \theta_y], \quad \boldsymbol{y} = [h]$$

where $h(t)$ denotes the water level in the drum, k_v is the gain of the feedwater control valve and θ_y is the parameter of the water level sensor. In Filter I and Filter II $h(t)$ (the state variable) k_v (the equivalent valve conductance) and θ_y (a sensor parameter) are the unknown parameters. Filter I simulates a fault model corresponding to a change in conductance (e.g., fouling, parameter fault) and Filter II models a fault that manifests itself as a change in water level in the drum (e.g., water level sensor failure). The state equations in both filters are obtained from the dynamic model given by the equations (2), and (3).

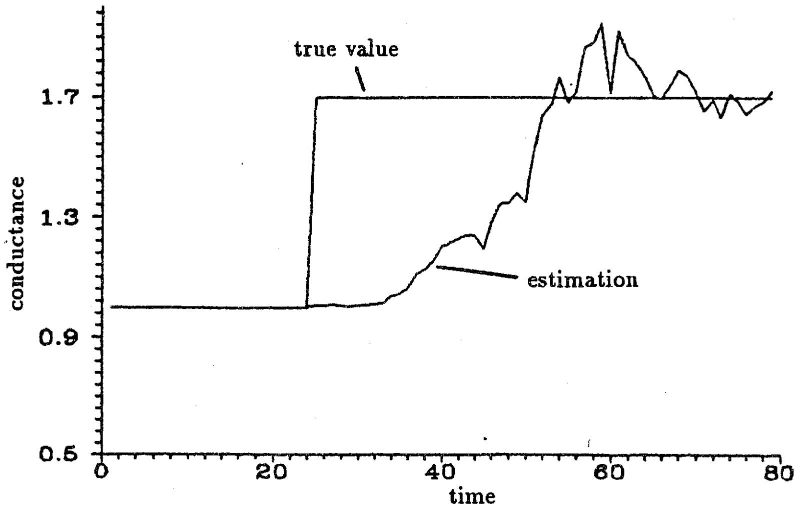

Fig. 3. True and estimated conductance (increase).

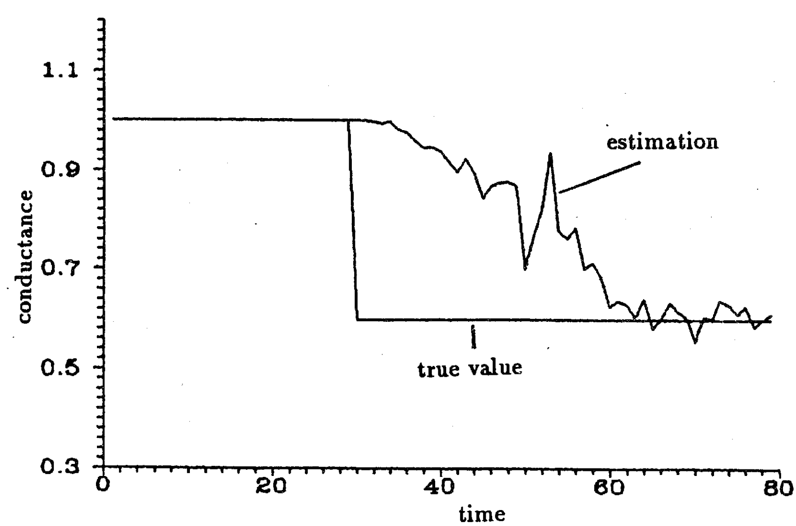

Fig. 4. True and estimated conductance (decrease).

A typical fault of the feedwater valve is its partial plugging which can be detected by the on-line identification of the conductance respectively. The Filter I is designed to model this case. Figures 3 and 4 depict the true and estimated conductance, for the increased (Fig. 3) and the decreased (Fig. 4) values of conductance respectively. The quality of this modified EKF filter in tracking the system behavior is manifested by comparing the estimated and measured water levels in the drum (see Figs. 5 and 6).

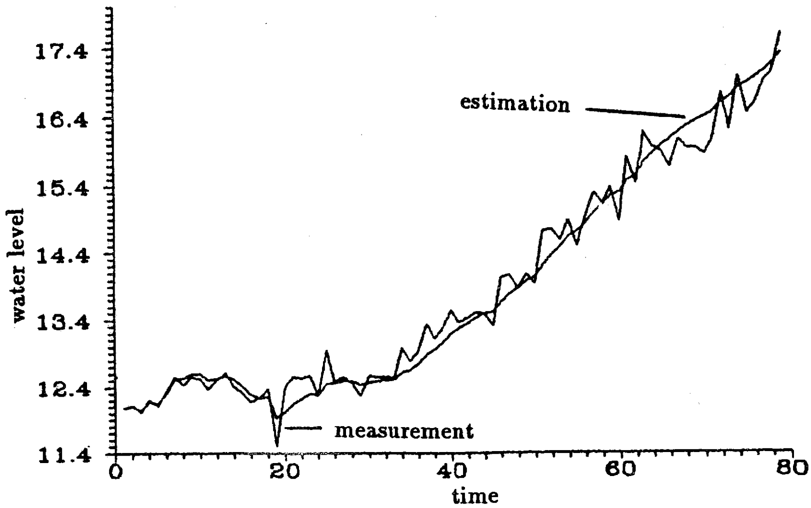

Fig. 5. Measured and estimated water level (increase).

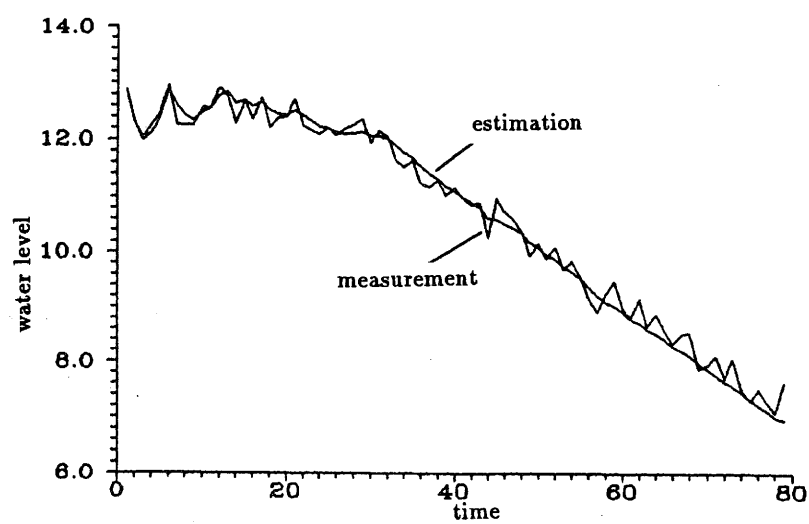

Fig. 6. Measured and estimated water level (decrease).

The drum module (Filter II) is used to estimate the water level in the drum and parameter θ_y describing the sensor. The estimation results for this case (Filter II) are depicted in Figures 7, 8 and 9. The filter is started from a value that differs from the actual water level (Fig. 7). As it can be seen, the estimation module quickly determines the correct value of the water level. Figures 8 and 9 show the Filter II behavior during the abrupt change of sensor parameter θ_y. This change is treated as the sensor failure. The estimation accuracy of this abrupt change of 1 to 2 is reasonably good. As it comes out of Figures 8 and 9 estimates of the sensor parameter and water level rather quickly approach their correct values (true values).

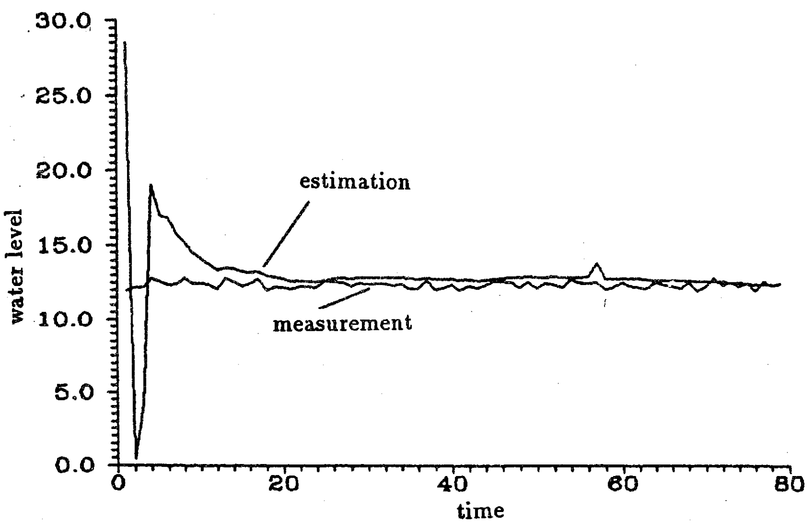

Fig. 7. Measured and estimated water level in the drum (wrong initial conditions).

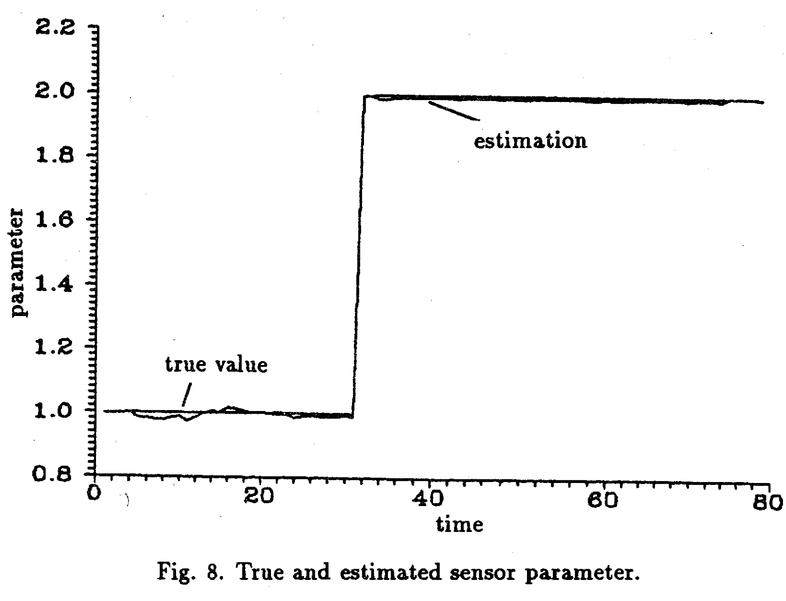

Fig. 8. True and estimated sensor parameter.

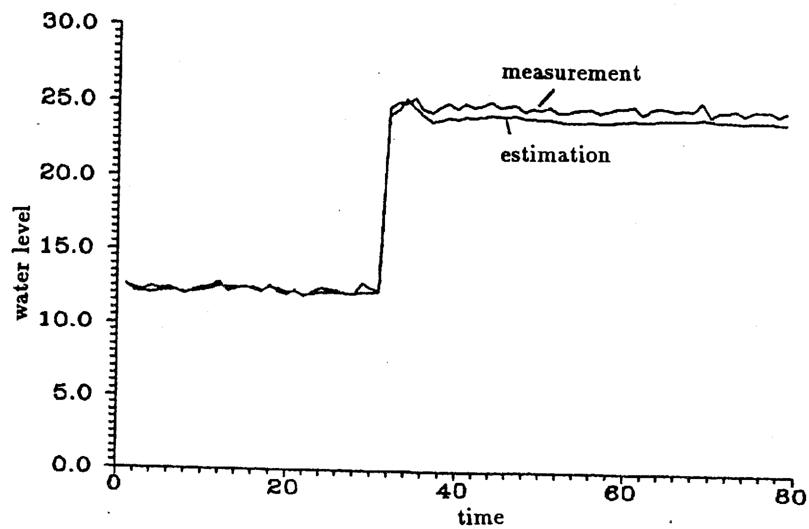

Fig. 9. Measured and estimated water level in the drum.

6. Conclusions

This paper presented a diagnostic methodology in which the symbolic reasoning of knowledge-based systems is integrated with quantitative analysis of analytical redundancy methods. Such an integrated approach (analytical and knowledge-based redundancy) on the one hand complicates the knowledge base but on the other hand increases the effectiveness of the diagnostic knowledge-based system. The numerical experiments carried out with the use of a power plant simulator illustrate the efficiency of this approach. The Kalman filter as the analytical redundancy algorithm has been very successful in estimating both states and system parameters using available measurements.

References

Anderson B.D.O. and **Moore J.B.** (1979): *Optimal Filtering.* — Englewood Cliffs: Prentice Hall.

Będkowski L. (1991): *Technical Diagnostics.* — Warsaw: WAT Press (in Polish).

Bokor J.A., Edelmayer A., Soumelidis A., Tanyi M., Gaspar P. and **Nagy I.** (1991): *Knowledge-based noise analysis promising tool for early failure detection in nuclear power plants.* — Prep. IFAC/IMACS Symp. *Fault Detection Supervision and Safety for Technical Processes SAFEPROCESS 91*, Baden-Baden, Germany, v.2, pp.73–80.

Cempel C. (1991): *Vibroacoustical Condition Monitoring.* — Chichister: Ellis Horward Ltd.

Chien T.T. and Adams M.B (1976): *A sequential failure detection technique and its application.* — IEEE Trans. Automat. Control, v.AC–21, pp.750–757.

Ding X. and Frank P.M. (1992): *Fault diagnosis using non–linear adaptive observers.* — Prep. 8th Int. IMEKO Symp. *Technical Diagnostics*, Dresden, Germany, pp.710–719.

Dhurjati P.S. (Ed.) (1992): — Prep. IFAC Symp. *On–line Fault Detection and Supervision in the Chemical Process Industries*, Newark, Delaware, USA, pp.138–143.

Fathi Z., Korbicz J. and Ramirez W.F. (1992): *Fault detection in coal fired power plants using nonlinear filtering.* — Appl. Math. and Comp. Sci., v.2, No.1, pp.87–118.

Fathi Z., Ramirez W.F., Tavares A.P., Gilliland G. and Korbicz J. (1992): *A knowledge–based system with embedded estimation components for fault detection and isolation in process plants.* — Prep. IFAC Symp. *On–line Fault Detection and Supervision in the Chemical Process Industries*, Newark: Delaware, USA, pp.32–37.

Fathi Z., Ramirez W.F. and Korbicz J. (1993): *Analytical and knowledge–based redundancy for fault diagnosis in process plants.* — AIChE Journal, v.39, No.1, pp.42–56.

Frank P.M. (1990): *Fault diagnosis in dynamic systems using analytical and knowledge–based redundancy. A Survey and some new results.* — Automatica, v.26, No.3, pp.459–474.

Frank P.M. (1991): *Enhancement of robustness in observer–based fault detection.* — Prep. IFAC/IMACS Symp. *Fault Detection Supervision and Safety for Technical Processes SAFEPROCESS 91*, Baden–Baden, Germany, v.1, pp.275–287.

Frank P.M. (1992): *Robust model–based fault detection in dynamic systems.* — Prep. IFAC Symp. *On–line Fault Detection and Supervision in the Chemical Process Industries*, Newark, Delaware, USA, pp.1–13.

Finch F.E., Oyeleye O.O. and Kramer M.A. (1990): *A robust event–oriented methodology for diagnosis of dynamic process systems.* — Computers chem. Engng., v.14, No.12, pp.1379–1396.

Gertler J. (1991): *Analytical redundancy methods in fault detection and isolation.* — Prep. IFAC/IMACS Symp. *Fault Detection Supervision and Safety for Technical Processes SAFEPROCESS'91*, Baden–Baden, Germany, v.1, pp.9–21.

Gertler J.J. and Anderson K.C. (1992): *An evidential reasoning extension to quantitative model–based failure diagnosis.* — IEEE Trans. Systems, Man and Cybernetics, v.22, No.2, pp.275–289.

Gertler J. and Singer D. (1990): *A new structural framework for parity equation–based failure detection and isolation.* — Automatica, v.26, No.2, pp.381–388.

Gomm J.B., Williams D. and Harris P. (1992): *Detection of incipient process faults using approximate parametric models.* — Prep. IFAC Symp. *On–line Fault Detection and Supervision in the Chemical Process Industries*, Newark, Delaware, USA, pp.138–143.

Isermann R. (1984): *Process fault detection based on modeling and estimation methods. A survey.* — Automatica, v.20, No.4, pp.387–404.

Isermann R. (Ed.) (1991): — Prep. IFAC/IMACS Symp. *Fault Detection Supervision and Safety for Technical Processes SAFEPROCESS 91*, Baden–Baden, Germany, v.1 and v.2.

Korbicz J. and Zgurowski A.Z. (1991): *Estimation and Control of Stochastic Distributed Parameter Systems.* — Warsaw: Polish Scientific Publishers, (in Polish).

Korbicz J. and Bidyuk P.I. (1993): *State and Parameter Estimation. Optimal and Digital Filtering, Applications.* — Zielona Góra: Technical University Press, Poland.

Korbicz J., Fathi Z. and Ramirez W.F. (1993): *State estimation schemes for fault detection and diagnosis in dynamic systems.* — Int. J. Systems Sci., v.24, No.5, pp.985–1000.

Koshijima I. and Niida K. (1992): *Neural network approach to fault detection under unsteady state operation.* — Prep. IFAC Symp. *On–line Fault Detection and Supervision in the Chemical Process Industries*, Newark, Delaware, USA, pp.174–179.

Kramer M.A. and Leonard J.A. (1990): *Diagnosis using backpropagation neural networks. Analysis and criticism.* — Computers Chem. Engng. v.14, No.12, pp.1323–1338.

Kramer M.A. and Palowitch B.L. (1987): *A rule–based approach to fault diagnosis using the signed directed graph.* — AIChE Journal, v.33, No.7, pp.1067–1078.

Milne R. (1991): *Integration: the key to second generation applications.* — Prep. IFAC/IMACS Symp. *Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS'91*, Baden–Baden, Germany, v.2, pp.7–9.

Misawa E.A. and Hedrick J.K. (1988): *Nonlinear observers: A state–of–the–art survey.* — In: Benstsman J. and Joshi S.M. (Eds) Recent Advances in Control of Nonlinear and Distributed Parameter Systems, Robust Control and Aerospace Control Applications. - New York: ASME Press.

Neumann D. (1991): *Fault diagnostic of machine–tools by estimation of signal spectra.* — Prep. IFAC/IMACS Symp. *Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS'91*, Baden–Baden, Germany, v.1, pp.73–78.

Patton R., Frank P. and Clark R. (1989): *Fault Diagnosis in Dynamic Systems. Theory and Applications.* — New York: Prentice Hall.

Patton R. and Chien J. (1991): *A review of parity space approaches to fault diagnosis.* — Prep. IFAC/IMACS Symp. *Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS'91*, Baden–Baden, Germany, v.1, pp.239–255.

Pieczyński A. and Korbicz J. (1993): *Dynamic model of boiler– turbine unit.* — Rep. of Dept. of Robotics and Software Engng., Technical University of Zielona Góra, Poland (in Polisch).

Sorenson H.W. (1985): *Kalman Filtering: Theory and Application.* — New York: IEEE Press.

Sorsa T., Koivo H.N. and Koivisto H. (1991): *Neural networks in process fault diagnosis.* — IEEE Trans. Systems, Man and Cybernetics, v.21, No.4, pp.815–825.

Terpstra V.J., Verbruggen H.B., Hoogland M.W. and Ficke R.A.E. (1992): *A real-time, fuzzy, deep-knowledge based fault diagnosis systems for CSTR.* — Prep. IFAC Symp. *On-line Fault Detection and Supervision in the Chemical Process Industries*, Newark, Delaware, USA, pp.26–31.

Tylee J.L. (1983): *On-line failure detection in nuclear power plant instrumentation.* — IEEE Trans. Automat. Control, v.AC-28, No.3, pp.406–415.

Tzafestas S.G. (Ed.) (1989): *Knowledge-Based System Diagnosis, Supervision and Control.* — New York: Plenum.

Tzafestas S.G. (1991): *Second generation diagnostic expert systems: requirements, architectures and prospects.* — Prep. IFAC/IMACS Symp. *Fault Detection, Supervision and Safety for Technical Processes, SAFEPROCESS'91*, Baden-Baden, Germany, v.2., pp.1–6.

Ungar L.H., Powell B.A. and Kamens S.N. (1990): *Adaptive networks for fault diagnosis and process control.* — Computers Chem. Engng., v.14, No.4/5, pp.561–572.

Venkatasubramanian V. and Chan K. (1989): *A neural network methodology for process fault diagnosis.* — AIChE Journal, v.35, No.12, pp.1993–2002.

Wallace J.N. and Clarke R. (1983): *The application of Kalman filtering estimation techniques in power station control systems.* — IEEE Trans. Automat. Control, v.AC-28, No.3, pp.416–427.

Willsky A.S. (1976): *A survey of design methods for failure detection in dynamic systems.* — Automatica, v.12, pp.601–611.

Yoshimura T., Watanabe K., Konisch K. and Soeda T. (1979): *A sequential failure detection approach and the identification of failure parameters.* — Int. J. Syst. Sci., v.10, No.7, pp.827–836.

Young S.K. and Clarke O.W. (1989): *Local sensor validation.* — Measurement and Control, v.22, pp.132–141.

Received March 10, 1993