Доклади на Българската академия на науките
Comptes rendus de l'Académie bulgare des Sciences

Tome 66, No 1, 2013

SCIENCES ET INGENIERIE

Théorie des systèmes

CBR APPROACH FOR TECHNICAL DIAGNOSTICS OF MILL FAN SYSTEM

Mincho B. Hadjiski, Lyubka A. Doukovska

(*Submitted on June 25, 2012*)

Abstract

Fault diagnostics shares with other process operations the realization that with powerful knowledge representation schemes one can capture the expertise of operators and control engineers all that was gained over the years of experience with process plants. Process specific knowledge can be used to improve general purpose methodologies. There is a close coupling between diagnostics and process operations design of plants. The proper design of a plant can reduce the burden upon the task of diagnostics. Also, the information from diagnostics can be used to continuously improve the performance of process operations. The information from fault diagnostics can be incorporated into the traditional solution paradigms of other process operations. The aim of this paper is to provide a Case Based Reasoning (CBR) approach for technical diagnostics of mill fan system that would particularly share information with the fault diagnostics module and also outline the nature of interaction that one can expect.

Key words: intelligent diagnostic, Case Based Reasoning, mill fan system

1. Introduction. Automated fault detection and technical diagnostics depend heavily on input from sensors or derived measures of performance. In many applications, such as those in the process industries, sensor failures are among the most common equipment failures. So a major focus in those industries has to be on recognizing sensor problems as well as process problems. Distinguishing between sensor problems and process problems is a major issue. Our usage of the term "sensors" includes process monitoring instrumentation for flow, level, pressure, temperature, power, vibration and so on. In other fields such as network and systems management, it can include other measures such as error rates, queue lengths, dropped calls, etc. Also, the technical diagnostics as a decision support activity rather than a fully automated operation is common in the management

This work has been supported by the National Science Fund of Bulgaria under Project No TK-01-485/09.

of large, complex operations such as those found in the process industries and network and systems management.

The current operational mode could be a degree of functionality performance. In the contemporary predictive diagnostics it is not classified only in two or three classes ("normal-non-normal" or "normal-included-non-normal"), but is assumed as a continuous degradation process. The quantitative estimation of the degradation degree is a result of diagnostics method applications to the current sensor data, gathered from SCADA, DCS and special measurements. In this way, the prognostics must be considered as predictive process and future behaviour assessment [1]. A highly critical stage is the installation degradation prognosis. The accuracy of the predictions is a subject of many discussions. Two approaches for rating are outlined [2]. The first one deals with the prognosis risk assessment. The second one is based on the quality of the activities, adopted as a preventive or rectification maintenance activities.

A main problem caused by prognostication in the damage of supplies is development of smart technologies, e.g. prognostication models. Two main scientific fields of the development of prognostication models such as diagnostic tasks are formed. These approaches have been processed in a huge number of monographs and publications [3–6]. In the last years the most interesting and famous approach in diagnostics of based model is Case Based Reasoning – CBR [7–9]. This Case Based Reasoning approach is also applied successfully by diagnostics of real processes [7, 9]. This approach is very useful by lack of sufficient measurements and by analysis and derivation of precedents with their attributes. The adaptation process of the procedure is realized using rule base derived by the experts.

2. Case Based Reasoning approach. Due to the substantial ambiguity and variety of possible situations there is an additional procedure to specify diagnostic features and symptoms using Case Based Reasoning, an approach enjoying an increasing popularity in the intelligent diagnostics [10–12]. In accordance with the settled tradition [12], precedents are represented in the form "problem-solution"

$$C_i = (p_i, s_i). \tag{1}$$

The problem p_i is accepted with the structure "attribute-value"

$$p_i = (a_i, v_i). \tag{2}$$

The vector of the attributes

$$a_i = (a_{i1}, a_{i2}, \dots, a_{ir}) \tag{3}$$

includes the diagnostic features a_{ij}.

The basic peculiarity of the application of the precedents' method in the case of diagnostics with mill fans with continuous degradation of their vibrational and technical state is the offer to use dynamic precedents depending on the time of observation k

$$C_i = C_i(k). \tag{4}$$

Here (k) is the discrete time from the beginning of the mill fan campaign after the basic repair. So the source to form dynamic precedents are the archival records for all mill fans (eight of them) from the steam generator, operating with exploitation cyclic periodicity of 2000–2500 h. In this way each problem p_i (2) and the value v_i from the substantiation of the attribute a_i (3) are related to a fixed time moment k

$$\begin{aligned} p_i &= p_i(k) \\ v_i &= v_i(k). \end{aligned} \tag{5}$$

It was postulated that the formation of the cases will be performed via a time interval of $T_{\mathrm{CBR}} = 2$ h according to the available data from DCS, softsensing, mathematical modelling or an operator's decision.

The mill fan attributes in (3) have the following meaning: a_1 – current time from the beginning of the campaign k; a_2 – quantity of fuel (from softsensing) B; a_3 – low fuel caloricity of working mass (from softsensing) Q_L^W; a_4 – temperature at the entry of the intake drying gases (from DCS) θ_{gis}; a_5 – temperature of the air-fuel mixture at the exit from the mill fan (from DCS) θ_{af}; a_6 – state of the dust concentrator blades (manually from the operators) z_{CB}; a_7 – quantity of the drying agent (from softsensing and modelling) G_{DA}; a_8 – quantity of secondary air (from DCS, data fusion, mathematical modelling and softsensing) G_{SA}.

The values

$$v_i(k) = (v_{i1}(k), v_{i2}(k), \dots,\ v_{ir}(k)) \tag{6}$$

are related to the attributes a_i at the moment k and they are defined as creeping average analogical to formula (4). The averaging interval L, is as it is known [13], an optimization problem and it is established experimentally.

The solution s_i, in cases of diagnostics, is presented in the form diagnostic state S – technical actions for technical support M

$$s(k) = (S, M(k)). \tag{7}$$

According to the already made assumptions three diagnostic states are accepted: S_1 – operative; S_2 – conditionally allowed; S_3 – unallowable.

Each of the diagnostic states S_j is related to a given discrete moment of time k and it also has a structure of the "attribute-value" type.

$$S_j(k) = (G, H(k)) \quad (i = 1, 2, 3). \tag{8}$$

The set of attributes G consists of elements g_i

$$G = (g_1, g_2, \dots, g_m), \tag{9}$$

where g_1 – amplitude of vibrations ($g_1 \equiv A_V$); g_2 – root deviation of the amplitude of vibrations ($g_2 \equiv \sigma_A$); g_3 – mill fan efficiency ($g_3 \equiv B$); g_4 – fan productivity ($g_4 \equiv w$); g_5 – radial flame deviation ($g_5 \equiv \rho$).

Each attribute g_i has a value $h_i(k)$ at the discrete moment of time k and it belongs to the vector $H(k)$

$$H(k) = (h_1(k), h_2(k), \ldots, h_m(k)). \tag{10}$$

All values $h_i(k)$ are calculated as average with a procedure for creeping average for a given discrete time k using a formula analogous to (4).

The current state $S_{\mathrm{MB}}(k)$ of a mill fan is related to some diagnostic state $S_j(k)$ using a classifier of the "comparison-with defined-thresholds" type based on the values $h_i(k)$ using a system of N rules R_i, for $(i = 1, N)$.

$$R_i : \text{IF } h_1 < h_1^t \text{ AND } h_2 < h_2^t \text{ AND } \ldots\ h_5 < h_5^t \text{ THEN } S \subset S_i. \tag{11}$$

In the present paper a multistage procedure is accepted to estimate the mill fan vibrostate – S_{MB}^V where the defined limits h_i^t are changed adaptively depending on the estimate of the root-mean-square value for the reduced noise in the registered vibrations.

The actions for technical support M are presented as a multiset

$$M = (M_1, M_2, M_3, M_4). \tag{12}$$

The components M_i $(i = 1, 4)$ are subsets with the following components:

M_1 – change in the mode parameters in cases of conditionally allowed diagnostic state, e.g.: M_{11} – load decrease; M_{12} – turnover decrease.

M_2 – current repair, e.g.: M_{21} – cleaning sensors and pulse lines; M_{22} – test and calibration of sensors; M_{23} –jalousie and valves set up; M_{24} – lubrication improvement; M_{25} – tightening bolt compounds.

M_3 – replacing elements without big breaks of the mill fan operation, e.g.: M_{31} – replacing vibrosensors; M_{32} – change in the pulse lines; M_{33} – replacing elements in the pressure system.

M_4 – break for repair, e.g.: M_{41} – operative wheel repair; M_{42} – repair of bearings; M_{43} – repair of the separator; M_{44} – mill fan housing repair (armored plates); M_{45} – raw fuel feeder repair.

Part of the activities on technical support (12) may have also a value form for their representation in the precedent, like:

m_{11} – mill fan load value; m_{12} – mill fan turnovers; m_{13} – jalousie and valves state (in details).

It is accepted in the paper that the basic part of the attributes in the problem section P and the solution S are presented by the simplest type of data: "number" and "symbol". Still for some attributes such representation by pairs "attribute-value" is incomplete and they (especially in the portion of the supporting activities M (12)) may include free text or they may contain links to other related external information. Part of this information may not be directly used in the CBR algorithm but it gives the operators additional knowledge for secondary using of archived results from the mill fan exploitation. Certain difficulties arise to apply the approved procedure in order to follow the principle for local-global proximity [7] in cases of current diagnostics with a time attribute k from the beginning of the mill fan exploitation. The n-closest neighbours at the moment k are realized using the weighed proximity measure between two states I and J.

$$Sim(I, J) = \sum_{i=1}^{n} w_i sim_i(I_i, J_i) \qquad \sum w_i = 1. \tag{13}$$

Here I_i and J_i denote the values and $w_i > 0$ is the weight of attribute a_i from (3). The symbol sim_i denotes a local proximity between the pair of diagnostic states $I(k)$ and $J(k)$ at the moment k. It is accepted in the paper the proximity measure sim_i to be normalized for the range [0, 1]; the Euclidean distance is used for the calculation in [7]. At the arrival of new data, obtained through an interval of $T_{\mathrm{CBR}} = 2h$, in cases of successive usage, formula (13) is transformed in the following form:

$$Sim(p(k), p_i(k)) = \sum_{i=1}^{n} w_i sim_i(a(k), a_i(k)). \tag{14}$$

Where $p(k)$ is the current "new" problem for the mill fan state, $p_i(k)$ is the existing i-th precedent for the mill fan state at moment k; $a(k)$ and $a_i(k)$ are the respective attributes the values of which are presented by the vectors $v(k)$ and $v_i(k)$. The fraction $sim_i(a(k), a_i(k))$ representing the local proximity between the attributes a and a_i contains first of all knowledge for a specific domain (mill fan diagnostics) and the weight coefficients w_i reflect the relative meaning of these attributes over the determination of the common proximity between p and p_i. In the case greater weights are assigned to the fuel amount (recursively), the temperature of the aeromixture and the temperature of the gases in the gas intake shaft because they are measured following DCS data.

Generally the application of the method with precedents to determine the vibrational $S_{\mathrm{MB}}^{V,\mathrm{CBR}}(k)$ and the common $S_{\mathrm{MB}}^{\mathrm{CBR}}$ diagnostic state is shown in [14]. Block CBR(n, k) is the generally accepted four-stage CBR procedure introduced in [7] and widely used in the last 15 years [10, 13, 14]. Estimates of the mill fan diagnostic state may be obtained with a discretization of $T_{\mathrm{CBR}} = 2h$, i.e. this is a slower approach than the one of intelligent filtration where the interval of discretization may be 20 min.

3. Numerical results. This paper considers diagnostics of the coal mill fan system of unit 3 boiler 6 at Maritsa East 2 complex. The mill fan structure is presented in [14]. The boiler which milling system is studied is a Benson type once-though sub-critical boiler. There are four mills per boiler. Each mill fan system has four radial bearings – two in the mill and two in the motor. The

Distributed Control System (DCS) installed on the site is Honeywell Experion Process Knowledge System (PKS R301). This is a cost-effective open control and safety system that expands the role of distributed control. All the data used in the present research are obtained from the DCS historian system. The duration of the observations is 8 months in 2010.

In this paper we focus mainly on online monitoring systems, based on sensor or other automated inputs. The main sensor information we have access to is based on the vibration of the nearest to the mill fan rotor bearing block. The determination and the usage of mill fan vibration state indicators are realistic and profitable for the operative staff because vibrosensors are obligatory for contemporary DCS systems.

The next four Figures contain some of the processed vibrations data aimed at excluding outliers. Only data that are around maximal density value of each 12 h sub-period are left. This is done due to the mentioned high non-stationary nature of these data. Another purpose of this processing was to exclude stopping periods from our investigation.

The results show that the power plant processes are inherently nonlinear in nature. While the theory of linear quantitative model-based approaches is quite mature, the design and implementation for nonlinear models is still an open issue. The standard statistical and probabilistic (Bayesian) approaches for diagnostics are inapplicable to estimate mill fan vibration state due to non-stationarity, non-ergodicity and the significant noise level of the monitored vibrations. Promising results are obtained only using computational intelligence methods (fuzzy logic, neural and neuro-fuzzy networks), [15–19].

4. Conclusions. In this paper the problem of using the CBR design to operate in the field of technical diagnostics is considered. Since the possibility to predict eventual damages or wear out without switching off the device is significant for providing faultless and reliable work avoiding the losses caused by planned maintenance. It is also important to be able to predict failures on time. Thus predicting the time of failure will allow determining of the moment to stop it for replacement. This will allow prolongation of its working period ensuring at the same time failures prevention. The future directions in the present work will be the creation of predictive model able to reveal dangerous situations on time.

The achieved results show that the vibrosignals may be successfully used as a substantial additional symptom for isolation and diagnostics of mill fan system which is not done at present. The assessment of the mill fan vibration state is a complex problem due to the exceptionally big uncertainty in the measurements which follows from the temporally recovered changes of multimode factors. The mill fan vibration state $S_{\mathrm{MB}}^{V,\mathrm{CBR}}$ is a valuable integral indicator for its working capacity. In this paper are presented promising results using only computational intelligence methods. Adequate for the case methods of computational intelli-

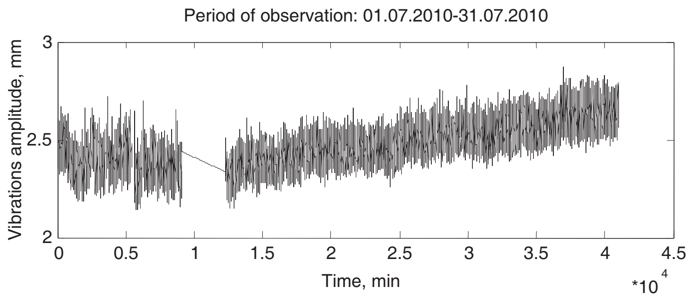

Fig. 1. Processed data for the period of observation 01.07.–31.07.2010

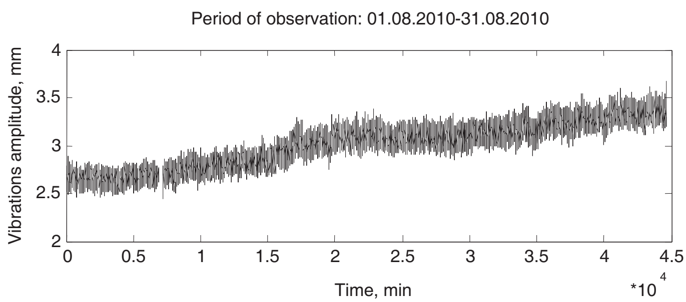

Fig. 2. Processed data for the period of observation 01.08.–31.08.2010

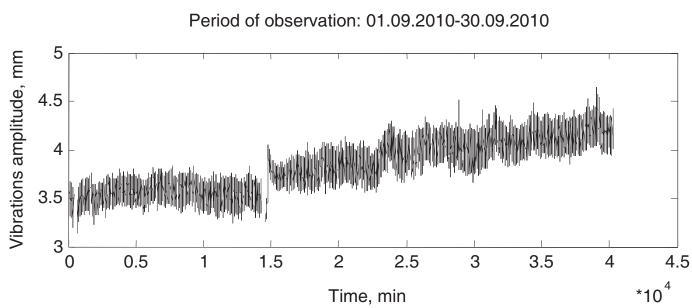

Fig. 3. Processed data for the period of observation 01.09.–30.09.2010

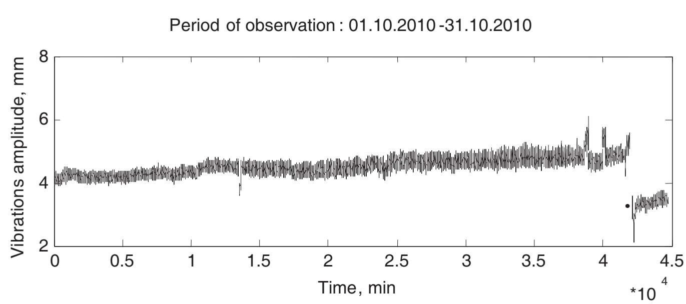

Fig. 4. Processed data for the period of observation 01.10.–31.10.2010

gence (fuzzy logic, neural networks and more general AI techniques – the case based reasoning method (CBR), machine learning (ML)) must be used.

REFERENCES

[1] DRAGOMIR O., R. GOURIVEAU, N. ZERHOUNI. JCCC, **3**, 2008, 271–276.

[2] VACHTSEVANOS G., F. LEWIS, M. ROEMER, A. HESS, B. WU. Intelligent Fault Diagnosis and Prognosis for Engineering Systems, Hoboken, New Jersey, Wiley & Sons, 2006.

[3] ISERMAN R. Fault-Diagnosis Systems, Springer, 2006.

[4] BANKE M., M. KINNAERT, J. LUNZE, M. STAROSWIECKI. Diagnosis and Fault-Tolerant Control, Springer, 2006.

[5] DING S. Model-Based Fault Diagnosis Techniques, Springer, 2008.

[6] CHANG L. H., E. L. RUSSELL, R. D. BRAATZ. Fault Detection and Diagnosis in Industrial Systems, Springer, 2001.

[7] KOLONDER J. L. Case-based Reasoning, Morgan Kaufmann, 1993.

[8] WIESE J., H. STEINMENTZ, A. STAHL. Application of Case-based Reasoning of Predict Sludge Settling and Endogenous Denitrification, London, IWA Publication, 2006.

[9] LUGER G. Artificial Intelligence, Addison Wesley, 2009.

[10] RECÈO-GARCIA J. A., B. DIAZ-AGUDO, A. A. SANCHES-RUIZ, P. A. GONZALES-CALERO. Expert Update, **10**, 2010, No 1.

[11] EREMEEV A., P. VARSHAVSKIY. Journal on Information Theories and Applications, **15**, 2008.

[12] PAL S., S. SHIN. Foundation of Soft Case-Based Reasoning, John Wiley, 2004.

[13] NORBICZ J., J. KOSCIELNY, Z. KOWALCZUK, W. CHOLEWA (eds). Fault Diagnosis Models, Artificial Intelligence, Applications, Springer, 2004.

[14] HADJISKI M., L. DOUKOVSKA. Compt. rend. Acad. bulg. Sci., **65**, 2012, No 12, 1731–1740.

[15] KOPRINKOVA-HRISTOVA P., L. DOUKOVSKA, S. BELORESHKI. XIX Int. Symposium PCPPS Proc., 2011, 25–28.

[16] BALABANOV T., P. KOPRINKOVA-HRISTOVA, L. DOUKOVSKA, M. HADJISKI, S. BELORESHKI. INISTA Proc., 2011, 410–414.

[17] KOPRINKOVA-HRISTOVA P., M. HADJISKI, L. DOUKOVSKA, S. BELORESHKI. JET, **57**, 2011, No 3, 401–406.

[18] HADJISKI M., L. DOUKOVSKA, P. KOPRINKOVA-HRISTOVA. IEEE-IS'12 Proc., 2012, 341–346.

[19] NIKOV V., P. KOPRINKOVA-HRISTOVA, L. DOUKOVSKA. FedCSIS Proc., 2012, 139–143.

Institute of Information and Communication Technologies
Bulgarian Academy of Sciences
Acad. G. Bonchev Str., Bl. 2
1113 Sofia, Bulgaria
e-mail: `hadjiski@uctm.edu, doukovska@iit.bas.bg`