Intelligent Technical Fault Condition Diagnostics of Mill Fan

Mincho Hadjiski and Lyubka Doukovska

Abstract The mill fans (MF) are centrifugal fans of the simplest type with flat radial blades adapted for simultaneous operation both like fans and also like mills. The key variable that could be used for diagnostic purposes is vibration amplitude of MF corpse. However its mode values include a great deal of randomness. Therefore the application of deterministic dependencies with correcting coefficients is non-effective for MF predictive modeling. Standard statistical and probabilistic (Bayesian) approaches are also inapplicable to estimate MF vibration state due to non-stationarity, non-ergodicity and the significant noise level of the monitored vibrations. Adequate for the case methods of computational intelligence [fuzzy logic, neural networks and more general AI techniques—the precedents' method or machine learning (ML)] must be used. The present paper describes promising initial results on applying the Case-Based Reasoning (CBR) approach for intelligent diagnostic of the mill fan working capacity using its vibration state.

1 Introduction

The mill fans (MF) are a basic element of dust-preparing systems (DPS) of steam generators (SG) with direct breathing of coal dust in the furnace chamber. Such SG in Bulgaria is the ones in the Maritsa East 2 thermal power plant (TPP), in the Maritsa East 3 TPP and also in the Bobov Dol TPP.

The principal graph of a MF is shown in Fig. 1. After the row fuel bunker, the coal is dozed by a row fuel feeder 2, which is controlled by a cascade control system 3 as a task by the main power controller of the boiler-turbine unit. MF intake drying gases with a temperature 900–1000 °C from the upper side of the furnace

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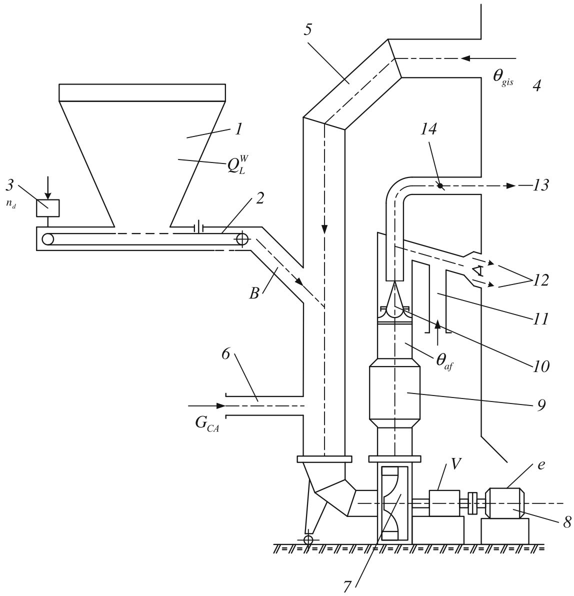

Fig. 1 Structure scheme, where *1*—Row fuel bunker, *2*—Row fuel feeder, *3*—Controller of row fuel feeder, *4*—Upper side of the furnace chamber, *5*—Gas intake shaft, *6*—Added cold air, *7*—Mill fan, *8*—Electric motor, *9*—Separator, *10*—Dust concentrator, *11*—Hot secondary air, *12*—Main burners, *13*—Discharge burner, *14*—Synchronized valves of discharge burners, θ_{af}—Temperature of air-fuel mixture, θ_{gis}—Temperature of intake drying gases, *V*—Vibration, *e*—Relative electric energy consumption, *B*—Throughput capacity of fuel, G_{CA}—Flow rate of added cold air, n_d—Position of discharge duct valve, Q_L^W—Low fuel caloricity of working mass

chamber 4 which in the drying shaft 5 are mixed with the raw coal and also with the additionally fed cold air 6. The MF 7 breaks and dries the raw coal actuated by the electric motor 8. The vibrations V of the MF are the basic topic of interest of the present research. The gravity-fed separator 9 guarantees the desired granularity of grinding of the output dust-air mixture which is directed towards the basic burners 12 via the dust concentrator 10 together with the added hot secondary air 11. The finest components (the discharges) are directed towards the discharge burners 13 which are controlled by synchronized valves 14.

The mill fans are a part of the equipment of power units that are most often repaired due to intensive erosion of the operating wheel blades in the process of grinding of low-calorific lignite coal from the Trayanovo 1 and Trayanovo 2 mines with high percentage of dust (28–45 % of the dry mass).

In spite of the constructive measures to use steels with high resistance index in critical parts of MF, their interval between two successive repairs equals to 2–2.5 months. The MF are of critical importance for the automation of the power-unit (PU) supply, so their technical state is an object of strict monitoring, repair and on-line duty according to the operative dispatcher time-table. The control range of mill fan is small, therefore the primary power control and especially the secondary power control is realized by stopping and starting some of the mill fan. Out of totally 8 grinding systems (two on a wall) in the 210 MW monoblocks in the Maritsa East 2 thermal power plant, 5–7 ones usually operate, 1 is ready and one/two of them are under repair. In this presentation the object of interest comprise fan MF with a horizontal axis of the operating wheel.

2 Mill Fan Technical Diagnostics

The mill fan has specificities that hamper significantly their diagnostics. The basic specifics are the following:

- The model-based MF diagnostics is insecure compared to e.g. rolling mills of coal with a vertical axis of rotation [1, 2] and ball mills [3–5]. The design of precise enough mathematical models are a sophisticated task due to the following items:
  - Basic thermo-mechanical and mode parameters are hampered or are impossible to be measured [6–8] (fuel consummation, granulometric composition, coefficient of grindability, coal quality).
  - Complex dependency of MF operation on a set of lots of parameters (coal composition, process hydrodynamics, exchange of heat and also of masses under changeable boundary conditions) [8–12].
  - Asymmetric wear of operative wheel blades, variable fan and grinding capacity between two successive repairs, Fig. 2 [6, 7, 13, 14].

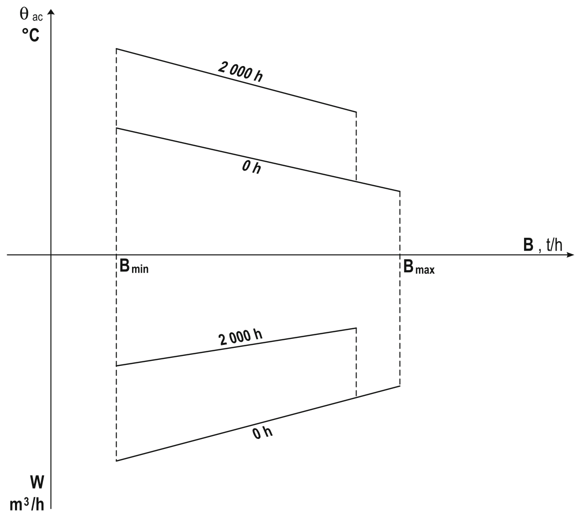

Fig. 2 Exploitation nomograms

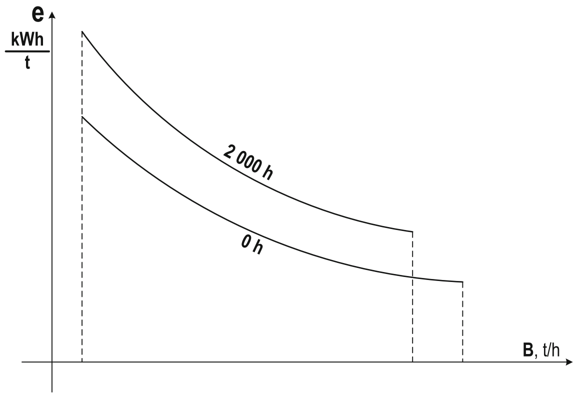

Fig. 3 Relative power consummation for coal grinding

- The measurements of the necessary mode quantities for mill fan in the DCS or SCADA system are rather inaccurate due to the significant changeability of the conditions for measurements (wear, slagging, sensor pollution) and also due to the great amount of external disturbances (dust and humidity of fuel, imprecise dosing of coal, stochasticity of temperature of the intake oven gases due to non-stationarity of the torch position) [6, 7, 10–12].
- The period of starting work for MF after repairs must be set as a separate diagnostic problem because MF indicators for this period differ from the operational ones for the following 2000 h.
- The symptoms in a diagnostic problem are always indirect and they are of stochastic nature [changes of temperature of the dust-air mixture (DAM) at the separator output related to the average one for the DPS, the torch position (horizontal, vertical), the relative power consummation for grinding (Fig. 3), corrected rotating frequency for the raw fuel feeders (RFF)] [7, 10–12, 15].
- Vibrodiagnostics did not prove to be a serious diagnostic method for MF because regular measurements of their vibration state of the new DCS and SCADA turn out to be quite insufficient for a detailed diagnostics.

The MF vibration state may become a rather useful component of their diagnostics to determine their affiliation to some zone of efficiency: S_1—the normal one; S_2—partial damages; still possible exploitation with lowered mode parameters (e.g. loading) and measures for current maintenance (lubrication, jamming bolt joints of MF to the bearers, technological adjustments (angles of rotation of valves, jalousie); S_3—zone of serious damages, requiring immediate stopping at the first opportunity (stop the unit).

The mill fan state is multidimensional. The basic components are grinding productiveness B [t/h], fan productiveness W [m^3/h] and vibration state S_{MF}^{V} [amplitude of vibrations A (or velocity/acceleration of vibrations)].

Exemplary limits for the workability of the Maritsa East 2 thermal power plant monoblocks of 8 MW each are shown in Table 1.

Table 1 Exemplary limits for the workability

Component (S, dimension)	B (t/h)	W (m^3/h)	A (mm)
S_1	55	200,000	6
S_2	48	180,000	7
S_3	<40	<140,000	>8

3 Mill Fan Vibrations Model

The results from the few references for research of the nature of MF vibrations [16, 17] and also of similar systems [18], our observations included and show that there are enough reasons to treat these vibrations as nonlinear.

Representing the model of vibrations of the mill fan corpse as an object with lumped parameters by the classical equation of linear vibrations [19],

$$\frac{d^2y}{dt^2} + 2\xi\frac{dy}{dt} + \omega_0^2 y = f_0 \cos \omega t \tag{1}$$

does not reflect vibration behavior of MF.

Nonlinear vibrations may be represented in many ways [20]:

$$\frac{d^2y}{dt^2} + 2\xi\frac{dy}{dt} + F(y,t) = f(t) \tag{2}$$

The disturbances in the right side of Eq. (2) may be presented as a function of exciting mechanical disturbances (damaged bearings, unbalanceness due to wear, etc.) q_M and due to mode disturbances (loading, hydrodynamic instability) q_p, i.e.:

$$f(t) = f(q_M(t), q_P(t)) \tag{3}$$

Under certain assumptions without big limitations the function $f(t)$ may be treated as additive:

$$f(t) = f_1(q_M(t)) + f_2(q_P(t)) \tag{4}$$

Equation (2) becomes:

$$\frac{d^2y}{dt^2} + 2\xi\frac{dy}{dt} + F(y,t) = f_1(q_M(t)) + f_2(q_P(t)) \tag{5}$$

The principle of superposition is not applicable to nonlinear vibrations [20]. Therefore the exciting effect of the mode disturbances $q_P(t)$ must be eliminated or it must be rebuked substantially at the stage of analysis. The exciting disturbance $f_1(.)$ is of a deterministic nature and it is possible to be nonstationary if the fault develops (e.g. most often progressive wear leading to debalance). The mode disturbance $f_2(.)$ is of a cumulative nature (due to the co-effect of a variable loading, a change in the coal composition, hydrodynamic instability), it is stochastic. This may be used for processing of measured vibration signal to separate the effect from the mechanical excitement $f_1(.)$ of the observed vibrations.

The measurements for estimation of the MF vibration state—fault isolation (*I*) or diagnostics-in-depth (*D*)—require quite different frequency of discretization of the vibration signal $y(t)$ which is a solution of the nonlinear differential Eq. (5).

1. The fault isolation (case *I*) requires just the usage of discretization of the analog vibrosignal with a big quantization slice (e.g. $T_0 = 1$ [min], as it is accepted in DCS of Maritsa East 2 TPP). Signal $y(kT_0)$ is random, uncorrelated and for the purpose of our research it is characterized by two non-random characteristics.

Mathematical expectation:

$$Y_m(kT_0) = M[Y(kT_0)] \tag{6}$$

Mathematical deviance:

$$\sigma_Y(kT_0) = \sqrt{D[Y(kT_0)]} \tag{7}$$

Both values are functions of the discrete time $t = kT_0$. The signal with rare measurements $y(kT_0)$ (Fig. 4) is accepted in Maritsa East 2 TPP to avoid the excessive memory in the records' base for the process history, because the vibration signal is not at all used for diagnostic purposes and just for the purpose of additional control of the current technical state of the MF.

The performed by us research shows that the measured by a "regular" apparatus of DCS signal $y(kT_0)$ may be successfully used to detect faults (*I*) and it is an integral indicator for the vibration state of the MF. This may be realized only on condition that the effect of technological disturbances $f_2(q_p(kT_0))$ is reduced significantly in the summary vibrosignal $y(kT_0)$. In the case of MF, the problem of eliminating the technological disturbances is different and it is much more complicated than the predefined by some researchers of vibration problem for

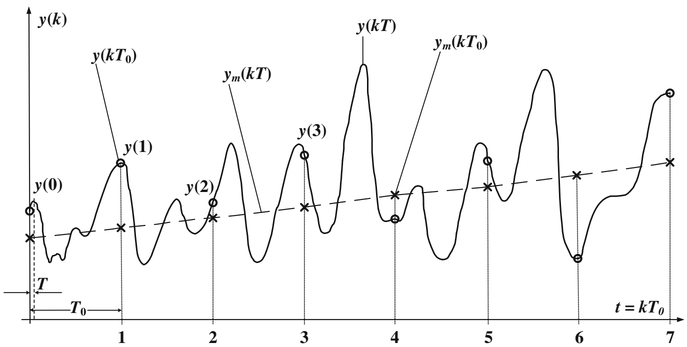

Fig. 4 The vibration signal (1 min sampling time)

de-noising of the signal [21, 22]. The basic reasons for this situation follow from the fact that there is no direct sensor information for the technological impacts and also because they are not only coordinate influences [the right side of Eq. (5)] but also parametric impacts influencing also parameters in the left part of Eq. (5). The uncertainty is substantially bigger, too. This imposed the elaboration of new methods for intelligent filtering of the technological impacts.

2. The in-depth vibrodiagnostics requires a spectral, wavelet and/or temporal-frequency analysis of the vibrosignal $y(t)$ (and its derivatives) and also to estimate the change(s) of its phase characteristics in the harmonic components. This is possible if the temporal analog signal of the vibrations ($y(t)$, $\frac{dy(t)}{dt}$ or $\frac{d^2y(t)}{dt^2}$) is quantized with a discretization interval satisfying the fundamental relation of Shannon-Kotelnikov. It requires in the case of MF a discretization interval T less than 1 [s] (Fig. 5). The obtained discrete signal $y(kT)$ is correlated and it may be used for spectral analyses together with the fast Fourier transform (FFT) for the purposes of a combined temporal-frequency analysis [22, 23], a wavelet analysis [19, 23] and other contemporary techniques for vibrodiagnostics [17, 19, 23]. It is possible to obtain a vibrosignal with a small discretization interval T via two approaches.

1. Apply frequent quantization in DCS with an interval of 300–500 [ms]. This approach requires adding a program code in the overall information system; this is a complex task and in the concrete case there is no agreement with the power plant managers. The drawback of the approach is the measurement just of the "overall vibration" which lacks information about the symptom in various places in the MF.
2. Include special diagnostic apparatus of the producing company that is applicable for routine vibrodiagnostics. The obtained signal $y(kT)$ then must be processed with original algorithms due to the peculiarities of MF vibrations and their multidimensionality [17, 19, 23].

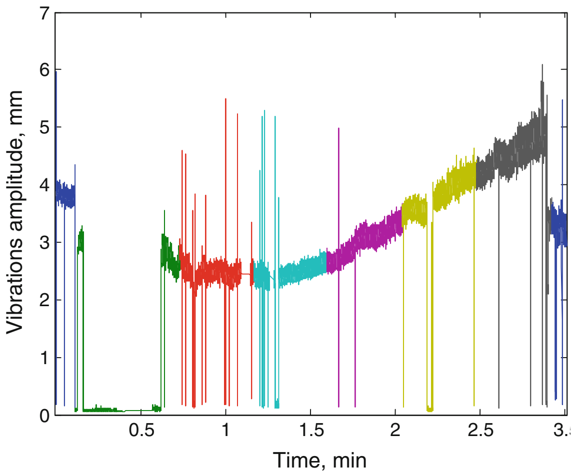

Fig. 5 Vibrations amplitude for entire period of observations

A great deal of the mode disturbances $q_p(t)$ over the vibration state S_{MF}^V of the MF are formed during the co-operation of the whole assembly of all operative MF. Such are: the drying gases temperature in the gas intake shaft, the torch position, the amount of the fuel that is synchronously distributed between the operative MF, the superheated steam. The differentiation between the individual part of the general impact $q_p^i(t)$ from the total one $q_p(t)$ is rather complex and it may be realized satisfactorily only applying intelligent techniques from computational intelligence [fuzzy logic, neural networks, support vector machines (SVM)] and processing knowledge (case-based reasoning (CBR), training) [4, 5, 10, 12, 16, 19].

4 Experimental Research

The experimental research is done in the national Maritsa East 2 thermal power plant. The plant has four double blocks with direct-current boilers 175 MW each and four monoblocks with drum boilers 210 MW each. The fuel for both types of blocks is one and the same: low-quality Bulgarian lignite coal from the Trayanovo 1 and Trayanovo 2 mines with caloricity of 1200–1600 kkal/kg (5000–6700 kkal/kg). The basic data are obtained from steam generator 6 of block 3. The steam generator has four MF. There is a decentralized control system (DCS) mounted over the steam generator: Experion PKS R301 Process of Honeywell. All used data are recorded in the Historian system of DCS. The duration of the observations is 8 months in 2010. Two types of data are used for the research—vibrosignals from MF and data about the basic mode parameters related to MF.

Figure 5 shows lines of discretized data about the MF vibration amplitude for a discretization time slice $T_0 = 1$ [min] and presents raw measurement data from the DCS for vibrations amplitude of the nearest to the mill fan motor bearing block.

The period of observations starts 7 days before mill fan rotor replacement; next are the data for the following 6 months exploitation period and at the end are measurements from the 7 days period after mill fan rotor replacement. The data are collected with 1 min interval. As can be seen from the figure, there are observed long stopping periods (when vibrations amplitude approaches zero) as well as different working regimes of the mill fan during its exploitation cycle.

The entire observations period is divided into sub-periods of 12 h each. Figure 6 present maximal density values of vibrations amplitude at each sub-period.

The following corollaries may be drawn from these data:

- The discretization time slice of the recorded data in the Historian files is $T_0 = 1$ [min]. These data belong to uncorrelated (due to the big values of T_0) random processes. Therefore according to the discussion above these temporal series may be used to isolate events in the MF vibration state but not for the detailed MF bearings' diagnostics because it is impossible to determine spectra of MF vibrations in successive time intervals due to the general non-stationarity of the process as a result of the wearing-out of the working wheel.

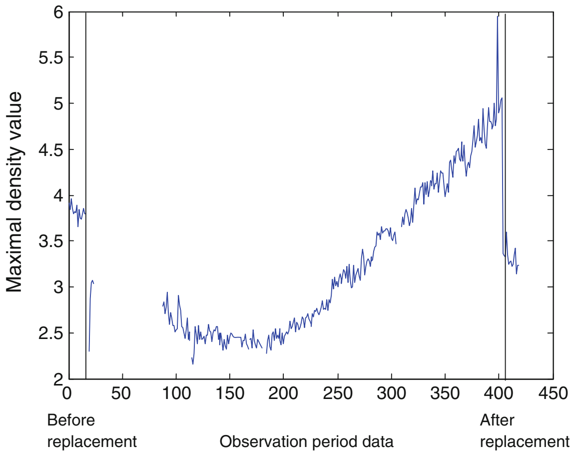

Fig. 6 Maximal density values of vibrations amplitude

- Vibrosignals demonstrate significant unstability of the MF oscillations due to series of random exciting powers q_p (Eq. 5)—a change in the fuel composition, non-homogeneous filling of sectors in the working wheel, hydrodynamic instability due to a change in the flow for the input and output cross sections of the MF. This instability is also due to often interrupts and load changes, provoked by corrections of the RFF rev regulator which is jointed in a cascade or due to a redistribution of the load of the main regulator for thermal block loading.
- Two exploitation periods are obviously formed—right after a repair (E_1) and after a normal exploitation (E_2). In the first case (E_1) there is a random change in the vibrations with different tendencies. In the second case (E_2) there is observed non-monotonous rise of vibrations due to the joint action of leading factors—erosive wearing-out of the blades leading to a debalance of the working wheel and a random combined influence of the enumerated above exciting the oscillations mode factors (B_{MF}—Throughput capacity of fuel, Q_L^W—Low fuel caloricity of working mass, θ_{af}—Temperature of air-fuel mixture, θ_{gis}—Temperature of intake drying gases, n_d—Position of discharge duct valve). These two periods must be analyzed apart.
- The root mean square deviation of the vibration amplitude σ_V is changed during the cycle of the working wheel from one repair to another (Fig. 6) and it is an additional symptom for an isolation of an abnormity and also for a forecast.
- Vibrosignals must be analyzed synchronously together with the extracts for the mode parameters (θ_{af}, θ_{gis}, n_d) due to the high level of the noise in the causal-effective relations.

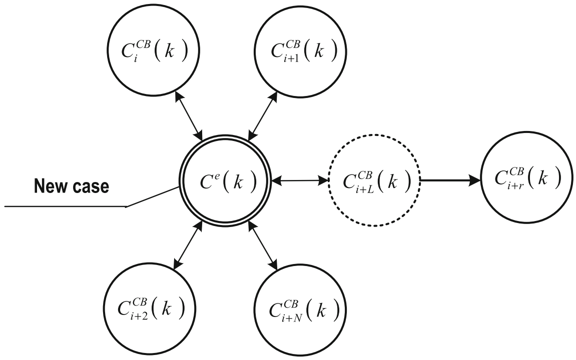

Fig. 7 Case-based reasoning model

5 Case-Based Reasoning Analysis

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 [24–27] (Fig. 7).

In accordance with the settled tradition [24, 27] precedents are represented in the form "problem-solution":

$$C_i = (p_i, s_i). \tag{8}$$

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

$$p_i = (a_i, v_i). \tag{9}$$

The attributes vector includes the diagnostic features a_{ij} [28]:

$$a_i = (a_{i1}, a_{i2}, \ldots, a_{ir}). \tag{10}$$

The values $v_i(k)$ are related to the attributes a_i at the moment k and they are defined as creeping average analogical to formula (9). The averaging interval L is as it is known [19] an optimization problem and it is established experimentally.

$$v_i(k) = (v_{i1}(k), v_{i2}(k), \ldots, v_{ir}(k)). \tag{11}$$

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.

$$C_i = C_i(k). \tag{12}$$

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 (9) and the value v_i from the substantiation of the attribute a_i (10) are related to a fixed time moment k.

$$\begin{aligned} p_i &= p_i(k) \\ v_i &= v_i(k) \end{aligned} \tag{13}$$

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

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

$$s(k) = (S, M(k)). \tag{14}$$

According to the already made assumptions three diagnostic states are accepted:

- S_1—operable;
- 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 possesses a structure of the "attribute-value" type.

$$S_j(k) = (G, H(k)) \quad (j = 1, 2, 3). \tag{15}$$

The current state $S_{MB}(k)$ 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 ($i = 1 \div N$).

The set of attributes G consists of elements g_i:

$$G = \ (g_1, g_2, \ldots, g_m). \tag{16}$$

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

$$H(k) = (h_1(k), h_2(k), \ldots, h_m(k)). \tag{17}$$

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 (11).

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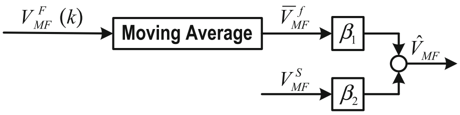

Fig. 8 Moving average structure scheme

$$R_i : IFh_1 < h_1^t uh_2 < h_2^t u \ldots h_5 < h_5^t \quad THEN \quad S \subset S_i. \tag{18}$$

In the present paper, a multistage procedure is accepted to estimate the mill fan vibrostate—S^V_{MB}, 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 (Fig. 8).

In the present paper a multistage procedure is accepted to estimate the mill fan vibration state—S^V_{MB}, 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 multi-set [28]:

$$M = (M_1, M_2, M_3, M_4). \tag{19}$$

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. with 3 elements.
- M_2—current repair, e.g. with 5 elements.
- M_3—replacing elements without big breaks of the mill fan operation, e.g. with 4 elements.
- M_4—stopping for repair, e.g. with 7 elements.

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 for the supporting activities M (19)] 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 an additional knowledge for secondary using of archived results from the mill fan exploitation. There originate certain difficulties to apply the approved procedure in order to follow the principle for local-global proximity [29–31] in cases of current diagnostics with a time attribute k from the beginning of the mill fan exploitation. The n-closest neighbors at the moment k are realized using the weighted proximity measure between two states I and J.

$$Sim(I,J) = \sum_{i=1}^{n} w_i sim_i(I_i, J_i) \quad \sum w_i = 1 \tag{20}$$

Here I_i and J_i denote the values and $w_i > 0$ is the weight of attribute a_i from (10). 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 as a proximity measure sim_i to be normalized for the range [0, 1]; the Euclidean distance is used for the calculation in [31]. At the arrival of new data obtained through an interval of $T_{CBR} = 2$ h in cases of successive usage formula (19) is transformed in the following form.

$$Sim(p(k), p_i(k)) = \sum_{i=1}^{n} w_i sim_i(a(k), a_i(k)) \tag{21}$$

where $p(k)$ is the current "new" problem for the mill fan state, $p_i(k)$ is the existing ith 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 $S_{MB}^{V,CBR}(k)$ and the common S_{MB}^{CBR} diagnostic state is shown at Fig. 9. Block $CBR(n, k)$ is the generally accepted four-stage CBR procedure introduced in [29] and widely used during the following 15 years [19, 23, 30–33]. Estimates of the mill fan diagnostic state may be obtained with a discretization of $T_{CBR} = 2$ h, i.e. this is a slower approach that the one of intelligent filtration where the interval of discretization may be 20 [min].

Independently on the presented significant difficulties during the determination of the vibration state of MF—S_{MB}^{V}, it is advisable to include it as an important component in the assessment of the overall technical state of mill fan. 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 re-covered changes of multimode factors.

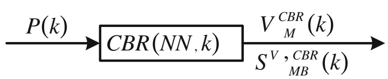

Fig. 9 CBR diagnostic block

The mill fan vibration state (S_{MB}^{V}) is a valuable integral indicator for its working capacity. 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 decentralized control DCS systems.

Figures 10, 11, 12, and 13 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 mentioned high non-stationary nature of

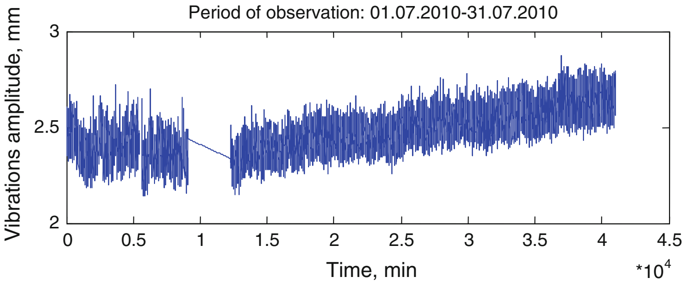

Fig. 10 Processed data for the period of observation 01.07.2010–31.07.2010

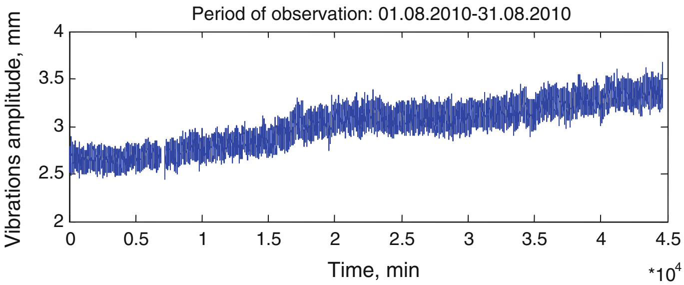

Fig. 11 Processed data for the period of observation 01.08.2010–31.08.2010

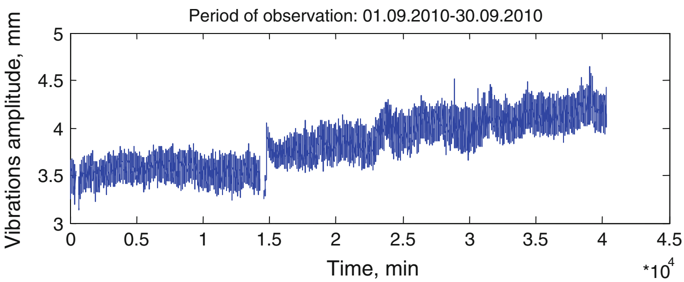

Fig. 12 Processed data for the period of observation 01.09.2010–30.09.2010

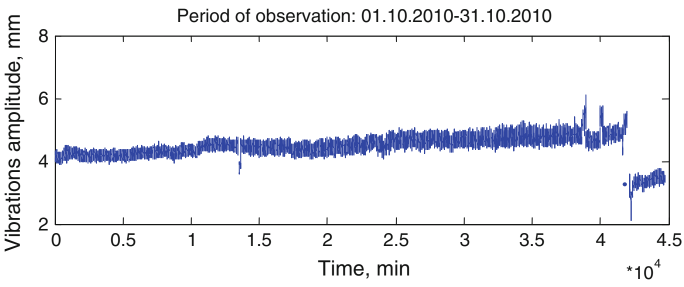

Fig. 13 Processed data for the period of observation 01.10.2010–31.10.2010

these data. Another purpose of this processing was to exclude stopping periods from our investigation.

6 Conclusion

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 MF vibration state is a complex problem due to the exceptionally big uncertainty in the measurements which follows from the temporally re-covered changes of multimode factors. The MF vibration state S^V_{MB} is a valuable integral indicator for its efficiency.

Independently on the discussed significant difficulties during the definition of the vibration state of MF—S^V_{MB}, it is advisable to include it as an important component in the assessment of the overall technical state of MF.

The records from existing DCS (or SCADA) do not allow a frequency (e.g. spectral) analysis but they may be used to isolate and to forecast defects at the stage of "isolation". An increase of the discretization frequency (e.g. 100 times) is unacceptable for DCS due to unforeseen in the computational resources and software.

Separate "short" records as long as 2–3 days (2000–4000 point of data) must be processed due to the non-stationarity of the vibrosignal that are enough as a volume for a representative statistical analysis of the time series at an admissibly low non-stationary change of the mill fan vibrostate.

Standard statistical and probabilistic (Bayesian) approaches for diagnostics are inapplicable to estimate MF 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).

In this paper are presented promising results only using computational intelligence methods. Adequate for the case methods of computational intelligence [fuzzy logic, neural networks and more general AI techniques—the precedents' method (CBR), machine learning (ML)] must be used.

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