

# CONSISTENT DATA AND DECISION FUSION OF HETEROGENEOUS INFORMATION DENOISING IN COMPLEX SYSTEMS DIAGNOSIS

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**Abstract:** In the diagnosis of complex industrial systems arise a lot of severe problems to solve due to the heterogeneous information sources, a large number of directly unmeasurable variables, which should be replaced by softsensing, big uncertainty of current information, temporal uncoherency of some measurements because of the very different requirements for the spectral window of corresponding signals in the different stages of the FDD (Fault Detection and Diagnosis) procedure. In the paper a hybrid approach of multistep procedure is considered for denoising of diagnostic information in order to achieve more realistic and more effective decision in a comparison with the conventional statistical approaches using some techniques from the Computational Intelligence like Neural Networks and Case- Based Reasoning. The main statements accepted in this investigation are: the different stages of complex diagnosis could require different information, different methods of partial diagnosis and different methods of decision making; the main method of hybridization is accepted to be consistent data and decision fusion; signal processing in particular diagnosis stages should be relevant to the main diagnostic goals in the stage. In the paper the proposed method for consistent fusion of data and decisions is implemented for on-line vibrodiagnosis of mechanical condition of the industrial mill fan of steam boiler in Power plant.

## 1 INTRODUCTION

Modern diagnosis significantly extends the scope of measurements, information and methods used, as traditional techniques themselves turns out unable to work in the case of complex problems [10, 16]. Along with approved approaches based on models, intelligent methods using various techniques of computational intelligence increasingly enter: Neural Networks [16], Case Based Reasoning (CBR) [3,13,15,16], data and decision fusion [3,5,6]. A combination of different intelligent methods is increasingly observed [5,16,8] for using the advantages of each component in the hybrid scheme. Diagnosis of complex technological plants is a key element in the rapidly evolving field of Condition Based Monitoring and Maintenance (CBM) [1,9,10,12,14,16]. The complexity of CBM requires

a new approach in decision making, given the great variety of possible solutions and the significant uncertainty [1,9,12]. The intelligent methods for decision making are an area of intense research in recent years [1,12].

The present work presents a method for intelligent decision making, based on consistent fusion of data and knowledge in conditions of heterogeneous information, large uncertainty and nonlinearity, using some ideas of last achievements in the area of signal denoising some new structures are proposed in order to overcome the drawbacks in complex systems diagnosis.

It is recognized that the methods of hybridization in the field of intelligent decision making are promising approach, but require specific research to expand all its features for at least sufficiently wide class of problems.

## 2 PROBLEM STATEMENT

In the diagnosis tasks of complex technological and mechanical plants emerge a set of difficulties. This paper tries to handle with them using intelligent techniques to obtain more realistic and more effective solutions than the existing conventional technologies.

Some assumptions are stated below:

- The problem of deep diagnosis is decided as multistage procedure.
- The different steps may require a different amount of information, different methods for diagnosis and different methods for decision making.
- As a basic method for hybridization scheme with weighted linear combination of solutions is preferred.
- The weights in fusion are determined by various metrics of closeness.
- The quality of decision-making procedure of diagnostic solution is improved by:
  - Training to optimize the weights;
  - Inclusion of variable number of components in the procedure for decision making;
  - Using different number of information resources.

The task becomes the combining of three different approaches – intelligent filtration with analytical models, logical analysis based on Case Based Reasoning and conventional statistical analysis to achieve better diagnosis decision making quality.

## 3 DATA AND DECISION FUSION

### 3.1 Data fusion

In the case of data alternatives solutions for intelligent data processing include:

- Rejection of corrupted sections of data (non-stationary, with gaps);
- Replacement of data and/or sections of data (strings) to preserve the integrity of the processing sample (training of neural networks, statistical analysis);
- Selection of parameters of the chosen filters with predefined structure (moving average, exponential smoothing);
- Correction of available data sets of synchronized data, incompatible (data

reconciliation) in respect of the fundamental requirements (material balance, heat balance).

Decisions  $DM_{1i}$  are made for particular action in the signals processing process, and in combining several actions  $A_{1i}$ .

### 3.2 Decision fusion at higher diagnosis level

Figure 1 shows a generalized scheme for the proposed multi-stage intelligent decision-making for diagnosis tasks of complex plants and systems. A three-stage procedure for Intelligent Decision Making (IDM) is adopted:

- IDM1: solutions to the basic level, mainly related to faults detection;
- IDM2: solutions to average depth of diagnosis, most often - without specific measurements;
- IDM3: solutions for identification of complex faults or multiple faults.

Generalized scheme for intelligent decision making diagnosis tasks for complex plants is shown in Figure 2. In addition to her local feedback, the main feedback from the plant itself is shown ( Figure 1) to improve the quality of decisions making. Thus, assessing both the procedure of decision making and the actions realizing it ( $A_{1i}$ ).

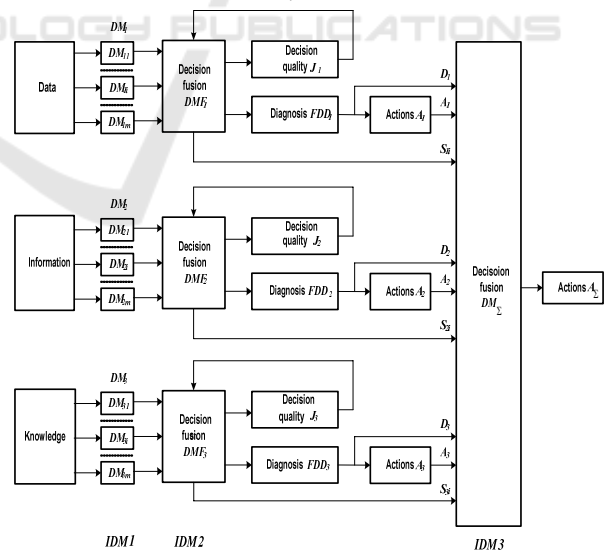


Figure 1: Intelligent Decision Making

Combining the solutions multi alternative for each level of IDM. The quality of decisions is measured by assessing the effectiveness of diagnosis and is improved by training based on modifying the

methods of decision making at the basic level  $IDM_{ij}$ , their number, as well as the fusion weights.

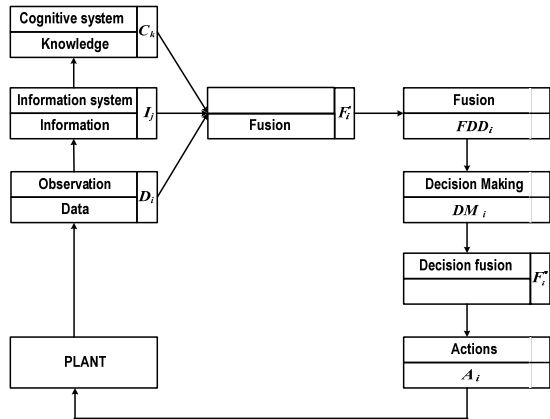


Figure 2: Generalized scheme of IDM

### 3.3 Intelligent diagnosis decision making by fusion of data, information and knowledge.

A scheme for consecutive diagnosis through fusion is shown in Figure 3.

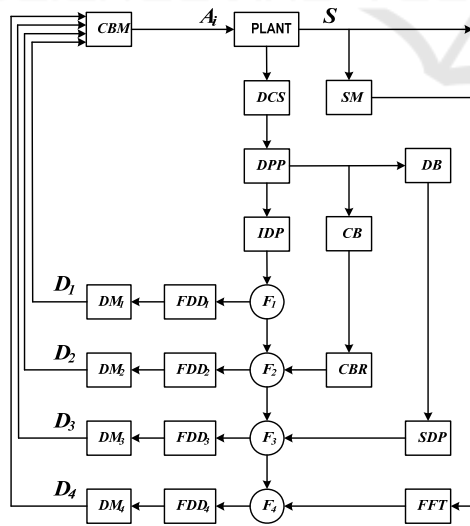


Figure 3: Consistent data and decision fusion

With minor modifications, this scheme retains its validity in diagnosis of a broad class of complex plants from similar class.

## 4 APPLICATION OF THE PROPOSED METHOD FOR DIAGNOSIS OF MILL FAN

### 4.1 Characteristics of mill fans as objects of diagnosis

Mill fans (MF) are key element in ensuring the reliable functioning of energy boilers burning low-grade lignite. The structural scheme of MF with the necessary signage is shown in Figure 4, but details are given in [7, 8, 9].

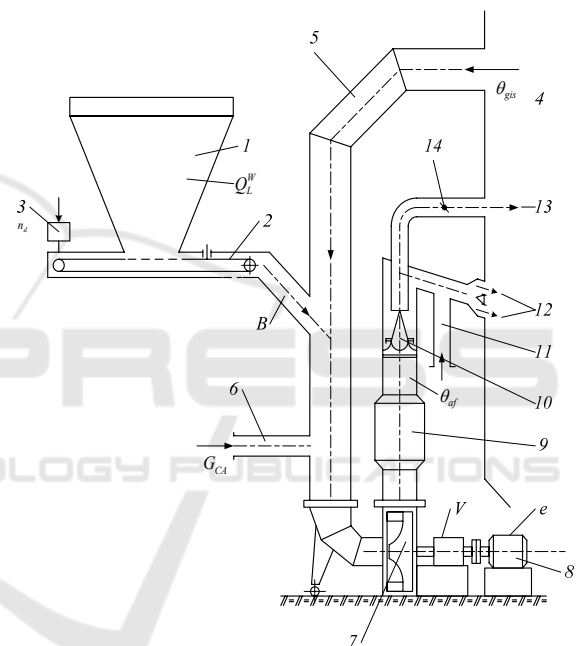


Figure 4: Structure scheme,

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,  $\theta_{af}$  - temperature of air-fuel mixture,  $\theta_{gis}$  - 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 calorificity of working mass.

The MF diagnosis is embarrassed due to certain circumstances:

- A lot of diagnostic parameters are hardly or are impossible to be measured fuel consumption, granulometric composition, coefficient of grindability, coal quality.
- Real operation shows asymmetric wear of operative wheel blades, variable fan and grinding capacity between two successive repairs.
- The measurements of abig number mill fan variables in the DCS or SCADA system are rather inaccurate due to the significant changeability of the conditions for measurements (wear, slagging, sensor pollution) and the great amount of external disturbances (dust and humidity of fuel, imprecise of coal, stohasticity of temperature of the intake oven gases due to non-stationarity of the flame position)
- The mill fan state is multidimensional. The basic components are grinding productiveness  $B$  [t/h], fan productiveness  $W$  [m<sup>3</sup>/h] and vibration state.

Because of listed circumstances the vibrations of MF could be considered as nonlinear and extremely noised with very low relation vibrosignal/noise under certain assumptions. The MF nonlinear vibration could be represented with the next equation [9]:

$$\frac{d^2y}{dt^2} + 2\xi \frac{dy}{dt} + F(y,t) = f_1(q_M(t)) + f_2(q_P(t)) \quad (1)$$

where  $y$  is amplitude of vibration, the disturbances in the right side of the equation may be presented as a function of exciting mechanical disturbances (damaged bearings, unbalanceness due to wear, etc.)  $q_M$  and due to operational disturbances (loading, hydrodynamic instability)  $q_P$ .

The exciting effect of the mode disturbances  $q_P(t)$  must be eliminated or to be reduced substantially at the stage of analysis. The exciting disturbance  $f_1(\cdot)$  is of a deterministic nature and it is possible to be nonstationary if the fault evolves (e.g. most often progressive wear leading to debalance). The operational disturbance  $f_2(\cdot)$  is of a cumulative nature (due to the co-effect of a variable loading, change in the coal composition, hydrodynamic instability) and stochastic. This may be used for processing of measured vibration signal to separate the effect from the mechanical excitement  $f_1(\cdot)$  of the observed vibrations.

## 4.2 Experimental investigations

To verify the effectiveness of the proposed above method of cascade data and decision fusion historical data for 8 months work of MF are used.

The Fig.5 presents raw measurement data from the Experion DCS system for vibrations amplitude of the mill fan motor bearing block. The data are collected with 1 minute interval.

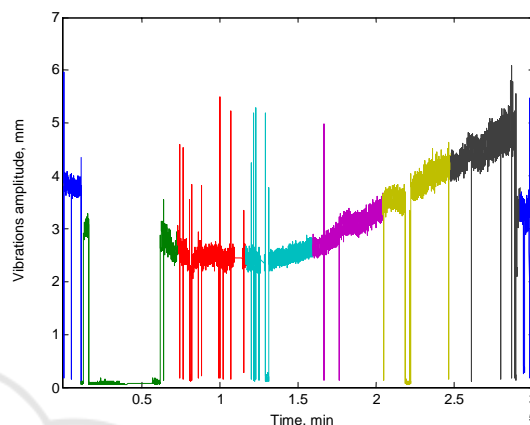


Figure 5: Vibrations amplitude for entire period of observations

The following conclusions may be drawn from these data:

- Because of the large discretization time  $T_0 = 1$  min these data belong to uncorrelated (due to the big values of  $T_0$ ) random processes. Therefore 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.
- Vibrosignals demonstrate significant instability of the MF oscillations due to series of random exciting powers  $q_P$  (equation (1)) – 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.
- 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 calorificity of working mass,  $\theta_{af}$  – Temperature of air-fuel mixture,  $\theta_{gis}$  – Temperature of intake drying gases,  $n_d$  – Position of discharge duct valve).

- The root mean square deviation of the vibration amplitude  $\sigma_V$  is changed during the cycle of the working wheel from one repair to another. This could be used as an additional symptom for an isolation of an abnormality and also for a forecast.
- Vibrosignals must be analyzed synchronously together with the extracts for the operational

parameters ( $\theta_{af}$ ,  $\theta_{gis}$ ,  $n_d$ ) due to the high level of the noise in the causal-effective relations.

### 4.3 Implementation of the proposed method

In order to make denoising of heterogeneous information from vibrosensors and a various regime parameters a consistent data and decision fusion is accomplished according the Fig. 6.

fusion in Mill Fan state estimation  
As a main approach for data fusion Neural Networks (NN) are accepted. The intermediate result of the proposed intelligent filtration is illustrated in the Fig.7.

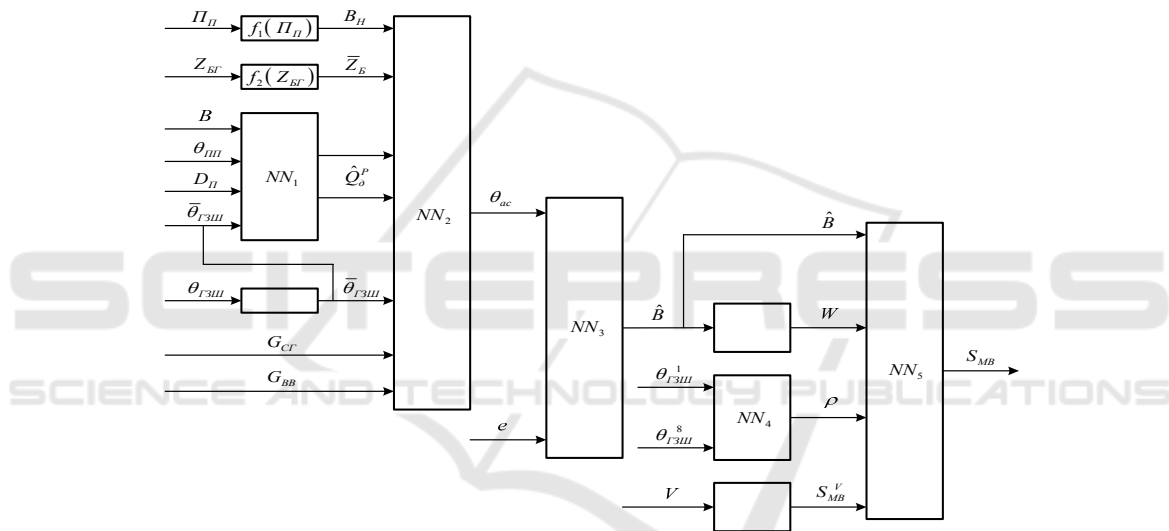


Figure 6: Scheme of sequential data and decision

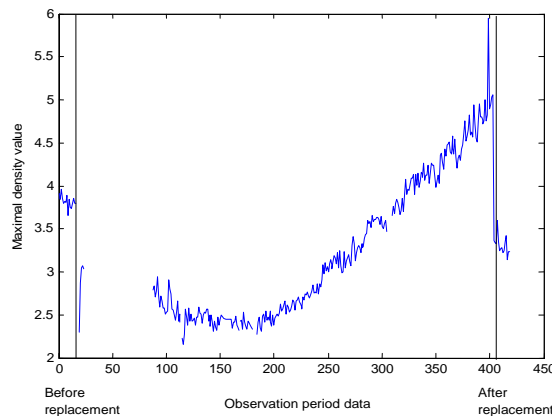


Figure 7: Maximal density values of vibrations amplitude

#### 4.4. Application for Condition Based Maintenance of MF

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).

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.

$$S_j(k) = (G, H(k)) \quad (i = 1, 2, 3) \quad (2)$$

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  $R_{i_s}$  for  $(i=1, N)$ .

According the proposed above method (Fig.3) a multistage procedure is accepted to estimate the mill fan vibrational state –  $S'_{MB}$ , where the defined limits  $h_i'$  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 represented as a multiset:

$$M = (M_1, M_2, M_3, M_4) \quad (3)$$

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 present 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  $M$  (13)) 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.

Independently on the presented significant difficulties during the determination of the vibration state of MF -  $S'_{MB}$ , 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. The mill fan vibration state ( $S'_{MB}$ ) 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.

## 5 CONCLUSIONS

1. The proposed method allows resolving complex diagnostic tasks in multistage hierarchical sequence, which cannot be done in single stage procedure.

2. Heterogeneous data from different resources could be used – direct and indirect measurements, data bases, case bases and knowledge bases.

3. At each stage of decision making process the most appropriate method for fusion, FFD and decision making could be used. This allows improvement of decision making quality, based on the specific characteristics of the considered diagnostic problem.

4. The method allows the fusion of particular procedures of decision making, which have different time evaluation scope, because of the different time characteristics.

5. This method allows estimation of the decision quality at each hierarchical level, and based on this to improve the particular and the common procedure of decision making.

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