Knowledge-based Mill Fan System Technical Condition Prognosis

LYUBKA DOUKOVSKA[1], SVETLA VASSILEVA[2]
[1]Department of Intelligent Systems, Department of Integrated Systems [2]
[1] IICT, [2] ISER –Bulgarian Academy of Sciences
Acad. G. Bonchev str., bl.2, POB 79, 1113 Sofia
BULGARIA
doukovska@iit.bas.bg, svassileva@yahoo.com http://www.iict.bas.bg, http://www.iser.bas.bg

Abstract: The task of diagnosis is to find an explanation for a set of observations and – in the case of prognosis – to forecast the course of events. Diagnosis can be broken down into anomaly detection and failure identification, depending on the desired granularity of information required. Prognosis is concerned with incipient failure detection, margin prediction, or overall performance prediction. The latter can be prediction of efficiency, current system status, etc. The outcome of diagnosis and prognosis processes drives planning and execution.

Fault isolation task can only be realized if the fault to be isolated has been previously taken into account in the model. There are different approaches for the design of diagnostic observers: the geometric methods, algebraic methods, spectral theory-based methods and frequency domain solutions.

In our paper a two-step procedure is commonly employed for data-driven fault detection. A model that represents the normal operation conditions is first developed; then fault detection is carried out according to the residual information or according the differences in the quality parameters of the transient process.

The data-based models, usually black-box models, lie in the core of a modular diagnosis system concept which has been chosen as separate fault detection systems. Each of these systems is handling only partial information on the process. This is similar to different persons analyzing the same situation with different methods and/or different sources of information.

In the paper are presented the studied industrial mill fan, models of the studied systems and corresponding controller design by implementing conventional and fuzzy logic-based approaches. Simulation results – transient processes in the closed loop are implemented for the knowledge-based fault detection and prognosis.

*Key-Words: K*nowledge-based Fault Detection, Fault Diagnostic, Fault prognosis, Mill fan, Fuzzy Logic Controller design

1 Introduction

The mill fans are a main part of the fuel preparation in the coal fired power plants. They are a part of the power units' equipment which is most often repaired due to intensive erosion of the wheel blades in the grinding of low-calorific lignite coal with high percentage of dust. The possibility to predict eventual damage or wearing out without switching off the device is significant for providing faultless and reliable work avoiding the losses caused by planned maintenance [16].

The mill fans are used to mill, dry and feed the coal to the burners of the furnace chamber. They are together milling and transporting devices. Mill fans are most often used for power plants' burning brown and lignite coal. The mill fans are of critical importance for the automation of the power unit supply, so their technical state is an object of strict monitoring, repair and on-line duty according to the operative dispatcher schedule. The control range of the 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 fans. The principal graph of a MF is shown in Fig. 1 and in detail is described in paper [14].

In the presented paper we have chosen to analyze a mill fan device from Maritsa East 2 Thermal Power Plant (TPP). After reconstructions and modernizations installed capacity in this TPP at the moment reaches 1556 MW as in the end of 2009 block 6 was cut off for the purpose of modernization and increasing its capacity to 230 MW. The Maritsa East 2 TPP being the largest thermal power plant on the Balkan Peninsula and the choice of the given power plant is not occasional. There are 8 power units in the complex - four units of 175MW and four units of 210MW each. The boiler, which milling system is studied, is a Benson type once-though sub-critical boiler. There are four mills per boiler,

[16]. Each mill fan system has four radial bearings – two in the mill and two in the motor.

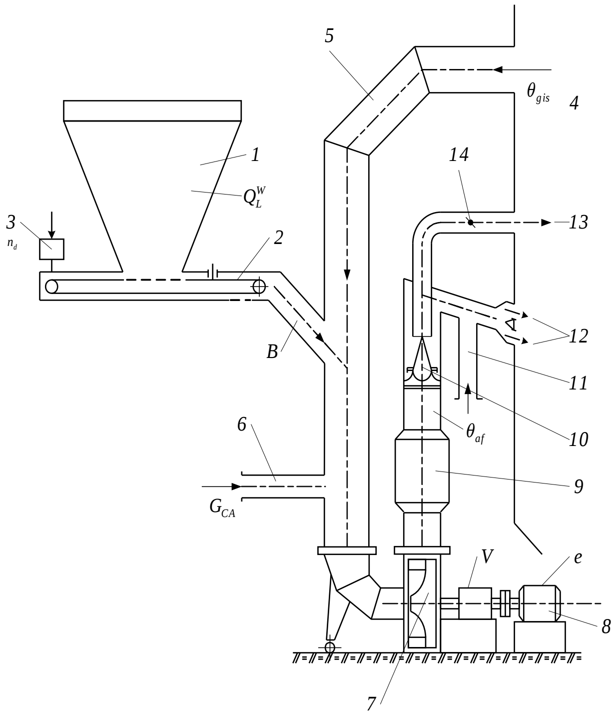

Fig. 1. Structure scheme, where 1 – Row fuel bunker, 2 – Row fuel feeder, 3 – Controller of row fuel feeder, 4 – Upper side of the furnace chamber, 5 – Gas intake shaft, 6 – Added cold air, 7 – Mill fan, 8 – Electric motor, 9 – Separator, 10 – Dust concentrator, 11 – Hot secondary air, 12 – Main burners, 13 – Discharge burner, 14 – Synchronized valves of discharge burners, $_{af}$ – Temperature of air-fuel mixture, $_{gis}$ – 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.

In general mill fans are large centrifugal fans which suck flue gases with temperature around 800-1000℃ from the top of the furnace chamber. In the same pipe the coal is feed, thus diminishing the drying agent temperature and drying the coal prior entering the fan. The coal is being milled by the fast rotating rotor of the fan and turn into coal dust. This dust is transferred to separator which returns the bigger particles to the fan. The separator can be tuned for a desired dust granulometric size. One of the most important parameters to control is the discharge temperature of the dust-air mixture. For the considered mill-fan it should be between 145-195℃. Lower than 145 ℃ may cause clogging of the mill and higher than 195℃ may cause the dust to be fired in the ducts prior the burners. This temperature is also a measurement for the load of the mill. The lower the temperature the higher the load is – more coal is fed to the mill. The part which suffers the most and should be taken care of is the rotor of the mill fan. Because of the abrasive effect of the coal it wears out and should be repaired by welding to add more metal to the worn out blades.

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 mono-blocks 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.

All the data used in the present research are obtained from the Distributed Control System (DCS) historian system. The DCS installed on the site is Honeywell Experion R301 Process. This is a cost-effective open control and safety system that expands the role of distributed control. It addresses critical manufacturing objectives to facilitate sharing knowledge and managing workflow. Experion provides a safe, robust, scalable, plant-wide system with unprecedented connectivity through all levels of the plant as illustrated. The Experion unified architecture combines DCS functionality and a plant-wide infrastructure that unifies business, process, and asset management to: facilitate knowledge capture, promote knowledge sharing, optimize work processes and accelerate improvement and innovation.

The traditional approaches to fault detection and diagnosis (FDD) involve the limit checking of some variables or the application of redundant sensors. More advanced approaches are based on data-driven multi-factorial processes monitoring, mostly used in chemical and manufacturing industries [3,6,14-16,26,32,35-40,42,43].

The data-based models, usually black-box models, lie in the core of a modular diagnosis system concept which has been chosen as separate fault detection systems. Each of these systems is handling only partial information on the process.

This is similar to different persons analyzing the same situation with different methods and/or different sources of information [26].

Other methods use comparison of the actual plant behavior to that expected on the basis of a mathematical model. These methods implements correctly trained ANN-dynamic model of the detected system. Often, further insights is required as to the explicit behavior of the model involved and is here that fuzzy and hybrid intelligent methods come into their own in FDD application [24].

In our paper a two-step procedure is commonly employed for data-driven fault detection. A model that represents the normal operation conditions is first developed in part 3; then controller design and comparison is presented in part 5 and after that intelligent fault detection system is presented in part 6 by the structure, functions and some results, obtained according to the residual information [18] or differences in the quality parameters of the transient process.

2 Specific Features of the Mill Fan System Process Control

The mill fans are basic part of the boiler and have a direct influence on its behavior as a part of the power grid. Due to the specifics of the milling system it is always difficult to develop an optimal and effective control strategy. It is a system containing few similar devices with a big number of mutual links, so each device influences the dynamic behavior of the others.

Worldwide mill fans are not commonly used because there are more efficient ways for preparation of high quality coal – roller, hammer, ball mills, which are studied in details and there are a lot of publications on the topic. At the other hand low caloric lignite coal happen to be effectively milled only in mills of centrifugal fan type, but unfortunately there are too less studies related to modeling of these devices. The coal mined in Maritsa East basin has too variable characteristics - different content of ash and non burnable particles. The common practice shows that there is a correlation between the moisture and ash content, which allows the quality disturbance to be a function of a single variable only – the moisture [33].

The classic papers [2,4,5,43] are further developed in [1,4] where analytical approach in description of the separate elements is used creating a very complicated structure. In papers [41,42] are included more than 70 separate elements each containing three or higher number of parameters. It is plain to see that experimental approach to estimate more than 200 constants is not an easy task and due to this the analytical approach is not popular. Recently in papers [9,12] instead of analytical, an experimental approach for mill-fans dynamic characteristics estimation is proposed. The paper [9] shows that depending on the current condition the mill-fan can have up to 300% deviation in its dynamic behavior, so there is a huge parameter ambiguity area which makes the control more difficult.

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The lack of serious studies on mill-fan system modeling leads to a significant in volume experimental research for obtaining input information necessary for designing an efficient control strategy. This has to be done during the normal operation of the mills in their full load range and during the whole period - just after maintenance and before it.

Among the variety of techniques and methods available in the contemporary control achievements, for that particular case the most suitable are the multi-connected control system approaches in conditions of nonlinearity and high level of ambiguity. Belonging to this group on the first place are the methods for controlling similar multi-connected objects [23]. On the second place is the multi-connected diagonal dominant control.

3 Description of the Experimental Set-up and Measurements

Mill-fan system control is a kind of a task which is determined by the specifics of the separate devices which build it. Presented paper contains the results of the analysis of two control techniques. In the first one the interconnection are not taken into account. In this case we just determine the set point values for the temperature of the coal air mixture after the mill. The responses of each mill are shown on the next figure.

As it is shown on the figure the responses for each mill are different, which is due to: different running time of each mill rotor; disturbances over the control channel – different coal moisture.

Another input disturbance is the torch center in the furnace chamber. If it is not in the middle the temperature of the drying agent for the mills will be different thus the mills having higher drying agent temperature will have a bigger milling capacity. At the other hand having the torch close to the walls leads to slag formation which is lead to a plug formed on the gas shaft and thus disabling the milling process of the given mill.

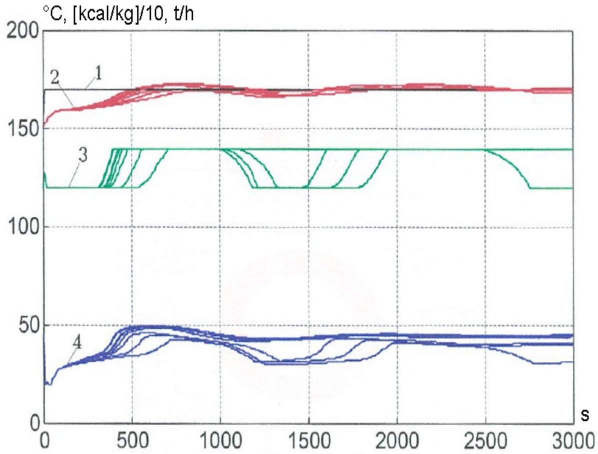

Fig. 2. Responses, 1 – Set points, 2 – process values – coal air mixture temperature, 3 – Estimated initial coal caloricity, 4 – Coal quantity – output of each mill controller.

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The torch position in the furnace chamber is shown on the next figure. In this case there is no danger of slag formation.

The second approach is based on similar multi-connected objects control. In this strategy the systems is considered as and aggregation of several equal separate systems connected with links between each other. So the main feature that distinguishes these systems of the multi-connected ones is that the main control channels are the same. This happens when we have same aggregates working in parallel, but having different parameters.

The links between the separate systems can act inside the whole object, as well as in the multi-connected controller. In the first case they express the existing mutual influence among the separate systems. In the second case they coordinate the performance of the separate aggregates.

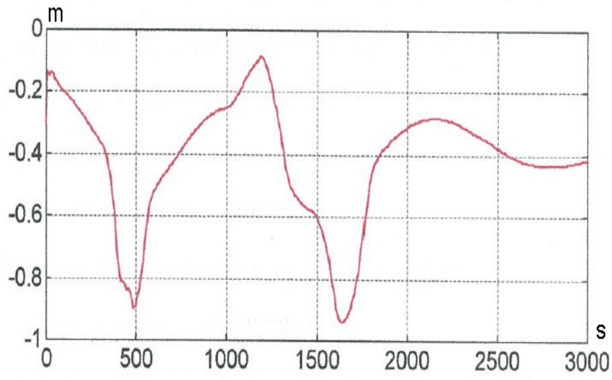

Fig. 3. Torch position in the furnace chamber

The structure of the milling system allows for considering it as an aggregation of multi-connected similar systems. Based on Sobolev's results [23] in the present paper the system of 8 mills is presented as 4 groups, each containing 2 mills. Each group is presented by the transfer function of each 2 diametrically opposite mills.

The responses obtained using the reduced models are shown on the next figure.

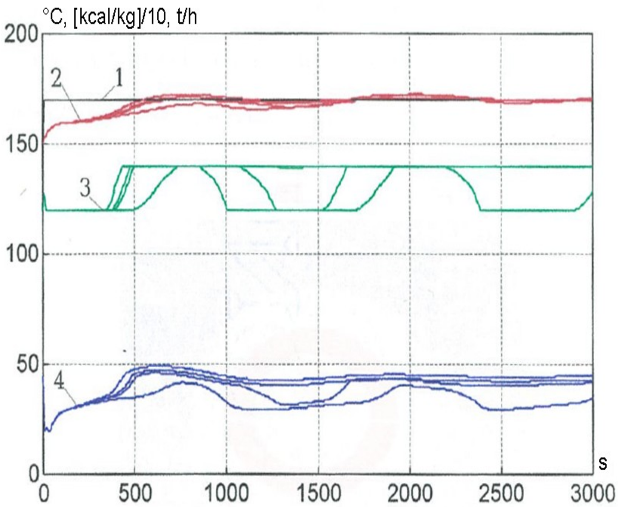

Fig. 4. Responses, 1 – Set points, 2 – process values – coal air mixture temperature, 3 – Estimated initial coal caloricity, 4 – Coal quantity – output of each mill controller.

The torch position in the furnace chamber is shown on the next figure.

The difference in the responses using the whole and the reduced models in insignificant and can be ignored. The torch position using the reduced model deviate about 0.25 m compared to the whole model, which also can be ignored.

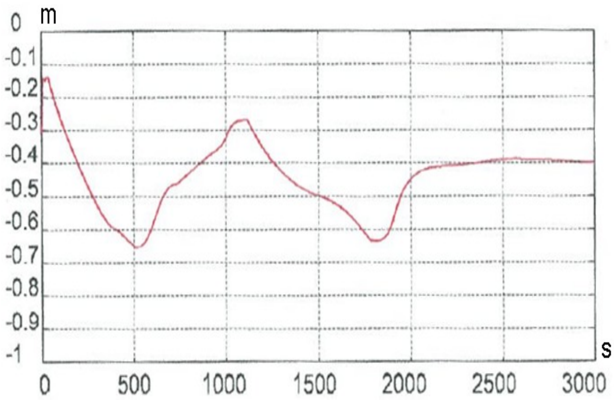

Fig. 5. Torch position in the furnace chamber

Based on the above, we can accept that the reduced model is very close the real one and can be successfully used to control the mill system.

4 Intelligent Mill Fan Control Systems

In order to achieve high performance and efficiency of coal-fired power plants, it is highly important to control the coal flow into the boiler in the power plant. This means suppression of disturbances and forces the coal mill to deliver the required coal flow, as well as monitor the coal mill in order to detect faults in the coal mill when they emerge. This paper deals with the second objective. Based on a simple dynamic model of the energy balance a residual is formed for the coal mill. An optimal unknown input observer is designed to estimate this residual. The estimated residual is following tested by measured data of a fault in a coal mill, it can hereby be concluded that this residual is very useful for detecting faults in the coal mill, [27].

Stochastic distribution control systems (SDC systems), defined in Wang [6], aims to control the shape of the output probability density functions (PDFs) for non-Gaussian and dynamic stochastic systems. This differs from traditional stochastic control where only the output mean and variance are considered. Specific feature of the recent stochastic distribution control methodologies is that the control objective is concerned with the PDF and in addition the driven information for feedback control is also characterized by PDF or the statistical information. The objective of FDD is to use the input and the output PDF to detect and diagnose the faults.

Process Equipment Service can be optimized to prevent failures and maximize uptime while avoiding superfluous maintenance. Some of these objectives can be accomplished by using tools that measure the system state and indicate arising failures. Such tools ask for high level of sophistication and incorporate monitoring, fault detection, decision making, possible preventive or corrective actions and execution monitoring [8]. Support service of equipment requires generating of models that can analyze the equipment data, interpreting their past behavior and predicting their future one. These problems pose a challenge to traditional modeling techniques and represent a great opportunity for the application of AI-based methodologies.

Because of the complexity of these tasks, AI-methods have been forced in the implementation of fault detection and isolation tools. Some application of AI-based techniques in support of service tasks, such as anomaly detection and identification, diagnostics, prognostics, estimation and control, have been reported in [25,26,31].

Approaches based on regression or AI-models of input-output relations of multifactor objects are nowadays very popular. For example, a correlation between mill energy consumption and mill performance characteristics may help in the prediction of mill malfunctions, such as pulverized coal too coarse or too fine, grinding pieces wearing higher than expected and bad adjustment of spring loading system [7]. In coal flow–air flow coordinates, the operating window represents the mill performance limits, which can vary with heating value and composition of raw coal, temperature and relative humidity of ambient air, leakage in air-gas pre-heaters and number of operating mills. The diagnosis system checks the current coal flow-air flow point of each mill, therefore allowing an effective evaluation of present conditions, present drifts and future problems.

During the last two years are published series of papers that offer alternative approaches to mill fan system diagnostics and predictive maintenance, which used different intelligent approaches. In paper [28], fuzzy rule-based classifier of a mill fan system working regimes was created based on analysis of data available from its control system. Analysis of the available on-line monitoring data from the mill fan system is revealed the tendencies of key observed variables are presented in [11]. In [38] is studied online monitoring system for predictive maintenance based on sensor automated inputs. The main sensor information is based on the vibration of the nearest to the mill rotor bearing block. In paper [29] the aim is to compare newly developed kind of Recurrent Neural Networks with historical Elman Recurrent Neural Networks architecture. Two Sugeno-type fuzzy rule bases – one with linear function of input mill fan variables and one with constant consecutive part of the rules are trained in [28]. Several types of intelligent mill fan diagnostics approaches with different structures are considered in [20]. In paper [18], it is described initial results on applying the Case Based Reasoning (CBR) approach for intelligent diagnostic of the mill fan working capacity using its vibration state. Also in paper [17], the problem of using the CBR designed to operate in field of technical mill fan diagnostics is considered. The obtained results may be successfully applied for development of diagnostics model aimed at fault mill fan system detection.

5 Mill fan controller design

5.1. Validating the Estimated Model to Experimental Output

The step response of the model estimated may also be compared with a step response that is directly computed from the data in a non-parametric way. The simplest way to get started on a parametric estimation routine is to build a state-space model where the model-order is automatically determined, using a prediction error method.

The connected in series closed mill fan control system and steam generating system are approximated with the following transfer function:

$$W(p) = \frac{k}{(Tp+1)^r}$$

where: $k = 0.7kW/kg, T = 105.4s, r = 4$

To determine its parameters optimization procedure based on the Nelder-Mead simplex algorithm is used, [28].

The model structure of the mill fan systems is as follows:

System 1:

$$W(s) = \frac{0.7}{(1+30s)(1+60s)(1+200s)} e^{-s\tau},$$

System 2:

$$W(s) = \frac{K}{(1+sT_1)} .e^{-s\tau}$$

where τ = 0 [ms], s-Laplace transformation symbol, time constants of System 1 are T1 = 30, T2 = 60 and T3 = 200 [s].

5.2. Conventional controller design

Parameters of controller are determined by the execution of procedure for optimal tuning with implementation of four known methods of Naslin, Optimal magnitude, Graham-Lathrop and Butterworth. The aim of optimization process is achieving a minimal diversion from the given value. Obtained parameters of the controller for the both models are shown in Table 1 and Table 2. Corresponding transient processes for System 1 with PID-controllers according Naslin and Optimal magnitude are shown in Fig.6.

Table 1. Controllers design about the System 1

№	Design Method	$R(s) = r_o + \frac{r1}{s} + r2.s$	$R(s) = P\left(1 + \frac{1}{T_i s} + T_d s\right)$
1	Naslin	r_0 = 9.2669 r_1 = 7.3532E-002 r_2 = 363.57	P = 9.2669 T_i = 126.0266 T_d = 39.233
2	Graham-Lathrop	r_0 = 23.5173 r_1 = 0.24198 r_2 = 785.1313	P = 23.5173 T_i = 97.1872 T_d = 33.3853
3	Optimal magnitude	r_0 = 7.4417 r_1 = 2.8124E-002 r_2 = 363.5714	P = 7.4417 T_i = 264.6024 T_d = 48.8558
4	Butter-w or th	r_0 = 11.2289 r_1 = 0.10298 r_2 = 368.17419	P = 11.2289 T_i = 109.038 T_d = 32.7882

Table 2. Controllers design about the System 2

№	Design Method	$R(s) = r_o + \frac{r1}{s} + r2.s$	$R(s) = P\left(1 + \frac{1}{T_i s} + T_d s\right)$
1	Naslin	r_0 = 1 r_1 = 1.9585E-002 r_2 = 0	P = 1 T_i = 51.0588 T_d = 0
2	Graham-Lathrop	r_0 = 19.6514 r_1 = 1.5057 r_2 = 0	P = 19.65 T_i = 13.051 T_d = 0
3	Butter-w or th	r_0 = 19.6514 r_1 = 1.5057 r_2 = 0	P = 19.65 T_i = 13.051 T_d = 0

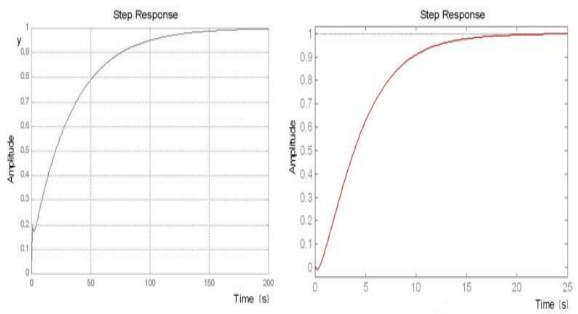

Fig.6. Simulation results: Transient processes for System 1 with PID-controllers designed according Naslin and Optimal magnitude

5.3. Fuzzy logic controller design

Fuzzy logic control is a control strategy based on linguistic knowledge processing [23, 34,36,37,40]. In a fuzzy controller (Fig.7a) the data passes through a preprocessing block, a controller (with fuzzyfier, inference engine, rule base and defuzzyfier), and a post-processing block. Preprocessing consists of a linear or non-linear scaling as well as a quantization in case the membership functions are discretised; if not, the membership of the input can just be looked up in an appropriate function. When designing the rule base, the designer needs to consider the number of term sets, their shape, and their overlap. The rules themselves must be determined by the designer, unless more advanced means like self-organization or neural networks are available. There is a choice between multiplication and minimum in the activation. There is also a choice regarding defuzzification; centre of gravity (COG) is probably most widely used. The post-processing consists in a scaling of the output. In case the controller is incremental, post-processing also includes integration. The following is a checklist of design choices that have to be made:

- Rule Base related choices. Number of inputs and outputs, universes, continuous/discrete, the number of membership functions, their overlap and width, singleton output;
- Inference Engine related choices. Connectives, modifiers, activation operation, aggregation operation, and accumulation operation.
- Defuzzyfication method. COG, COGS, BOA, MOM, LM, and RM.
- Pre- and Post-processing. Scaling, gain factors, quantization, and sampling time.

Some of these items must always be considered others may not play a role in the particular design.

The input-output mappings provide an intuitive insight which may not be relevant from a theoretical viewpoint, but in practice they are well worth using.

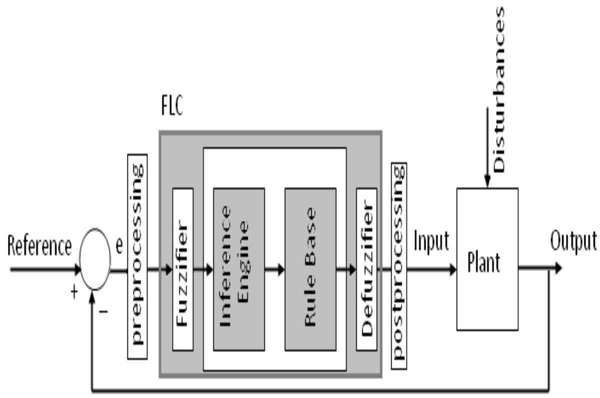

Fig. 7a) Structure of fuzzy logic controller

There are at least four main sources for finding control rules:

- Expert experience and control engineering knowledge. The most common approach to establishing such a collection of rules of thumb is to question experts or operators using a carefully organized questionnaire.
- Based on the operators' control actions. Fuzzy *If-Then* rules can be deduced from observations of an operator's control actions or a log book. The rules express input-output relationships.
- Based on a fuzzy model of the process. A linguistic Rule Base may be viewed as an inverse model of the controlled process. Thus the fuzzy control rules might be obtained by inverting a fuzzy model of the process. This method is restricted to relatively low order systems, but it provides an explicit solution assuming that fuzzy models of the open and closed loop systems are available. Another approach is fuzzy identification or fuzzy model-based control.
- Based on learning. The self-organizing controller is an example of a controller that finds the rules itself. Neural networks are another possibility.

There is no design procedure in fuzzy control such as root-locus design, frequency response design, pole placement design, or stability margins, because the rules are often nonlinear.

Therefore we will settle for describing the basic components and functions of fuzzy controllers, in order to recognize and understand the various options in commercial software packages for fuzzy controller design.

In our case a PI-FLC was designed. For this reason in Fig. 7b) a nonlinear PI-like fuzzy control rule base is depicted. The table shows the rate of change in control action as a function of the error and its derivative. The linguistic values are NL, negative large, NS, negative small, ZE, zero, PS, positive small, PL, positive large, which are being represented by fuzzy sets.

$\dot{e}/e$	NL	NS	ZE	PS	PL
NL	PL	PL	PS	ZE	ZE
NS	PL	PL	ZE	ZE	NS
ZE	PS	ZE	ZE	NS	NS
PS	ZE	ZE	ZE	NL	NL
PL	ZE	NS	NS	NL	NL

Fig. 7b) PI-like fuzzy control rules

In our case different working regimes are distinguished based on the observed changes of trends of vibrations, dust-air mixture temperature, load, and control action. Also in our research study used membership functions are simple triangular and singletons. In the first step the fuzzifier converts numerical information into a fuzzy set that the fuzzy inference mechanism can take as input. Uncertainty in the numerical information (such as measurement noise) can naturally be represented. In Fig.7c) is shown fuzzy classification of observed variables with constants in rules consecutive parts [20].

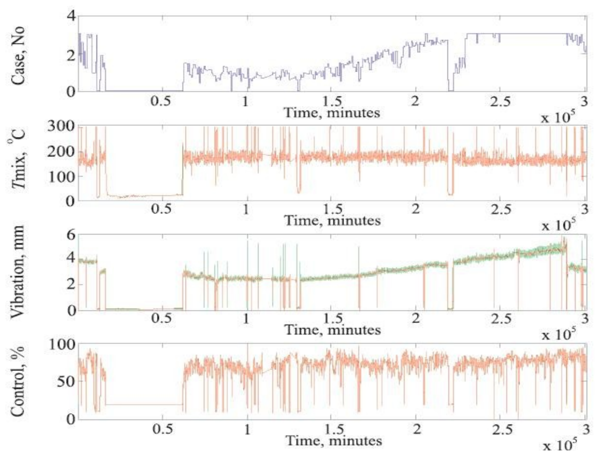

Fig.7c) Fuzzy classification of observed variables with constants in rules consecutive parts

The control rules in the rule base relate operating conditions (or the state) to control actions, such as rule IF e is positive small (PS) AND ė is negative large (NL) THEN u is zero (Z).

The premise part of such control rules corresponds to a set of states that can be viewed as an operating regime, and the knowledge base can often be visualised and interpreted as being based on a fuzzy partitioning of the system's operating range.

The inference mechanism combines the fuzzy set representation of the measurements with the rule base, and infers a fuzzy set representation of the control action. The defuzzification converts this fuzzy set into numerical information such as a command to the actuator.

In Fig.7d) is presented optimal PI-FLC surface regarding error e and change of the error Δe.

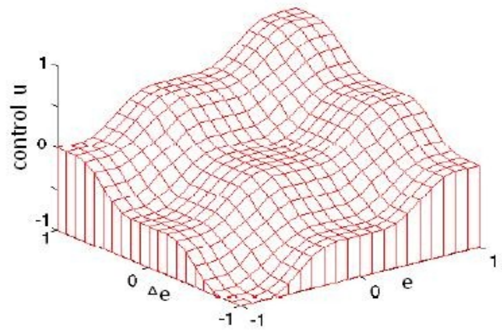

Fig.7d) optimal PI-FLC surface regarding error e and change of the error Δe

Simulation results - the transient characteristics of the system by implementing designed FLC for the output variable control of the closed loop for preliminary determined overregulation of 5% and 20% are depicted in Fig.8.

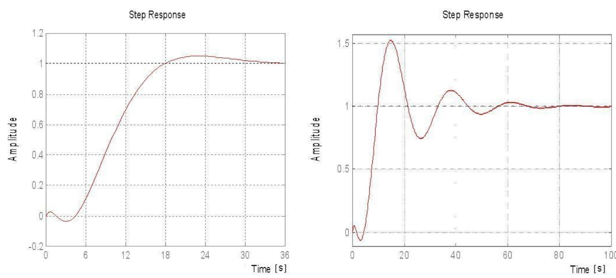

Fig.8. Simulation investigations: Transient characteristics of the system by using Fuzzy Logic Controllers for 5% overregulation (left) and 20% overregulation (right)

Methods from linear and nonlinear control theory can be adopted for the Fuzzy Knowledge-Based Controller (FKBC) design if a good crisp model of the process exists. System of IF-THEN rules can be transformed into a non-linear transfer element with scaling factors in a crisp manner. Thus qualitative or symbolic control design will be completed by qualitative (numerical) design phase. This way a FKBS can be identified as a highly specialized knowledge-based system for performing specific tasks for control of multifactor processes.

6 Structure and Functions of Mill Fan Knowledge-based Fault Detection and Prognosis System (KBFDPS)

6.1. Structure and function of KBFDPS

KB-FDDP system architecture is presented in Fig.8. The data from the plant are preprocessed for Data Base needs, FNN-model design and FDD. After obtaining necessary information in Knowledge Base, Inference engine is deciding about the faults, Interpreter sends messages about it and fault is eliminated or minimized by using man-machine interface and manipulation procedures, which can be selected from the KB manipulation in accordance with the detected fault.

6.2. Knowledge-Base Formation for Fault Symptoms Detection

The data-based models, usually black-box models, lie in the core of a modular diagnosis system concept which has been chosen as separate fault detection systems. Each of these systems is handling only partial information on the process. This is similar to different persons analyzing the same situation with different methods and/or different sources of information.

Since the early work of [8], system models common in control theory, which represent the dynamical behaviour between the system inputs and outputs (or states), have been taken for the design of FDI systems, although it is well known, that different kinds of applications require different types of models. For control system analysis and design, the system model has to represent the dynamical input-output behaviour of the system and should be as simple as possible. Hence, the model used is often simplified or linearized by ignoring many of the attributes of the physical nature of the system and only retaining the attributes that are deemed relevant for the behaviour of the resulting control system. Not so in FDI: here one needs a representative model of high fidelity and in some cases high preciseness which is in general of higher complexity than the one for control. But under certain circumstances, models for FDI can also be simpler than those for control, which has often been overseen in the FDI society [34].

6.3. Inference Engine

Fault isolation task can only be realized if the fault to be isolated has been previously taken into account in the model. There are different approaches for the design of diagnostic observers: the geometric methods, algebraic methods, spectral theory-based methods and frequency domain solutions.

In our paper a two-step procedure is commonly employed for data-driven fault detection. A model that represents the normal operation conditions is first developed; then fault detection is carried out according to the residual information or according the differences in the quality parameters of the transient process.

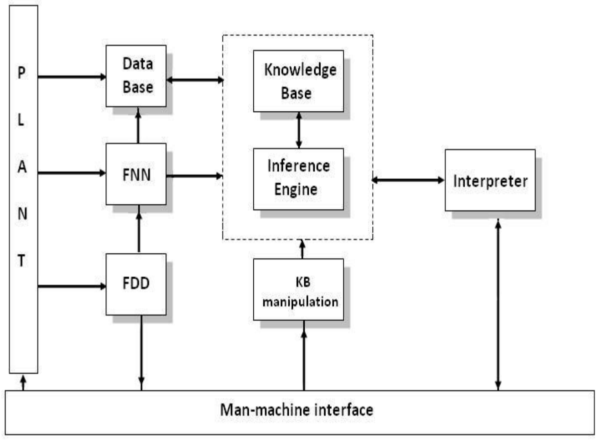

Fig. 8. KB-FDDP system architecture

Obtained results are demonstrated in Fig.9.

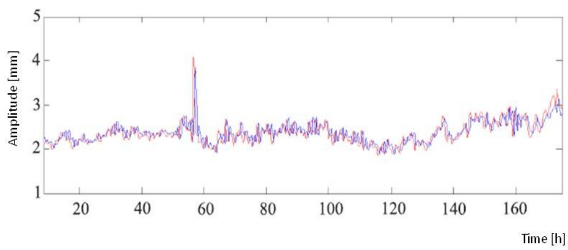

Fig.9. Simulation results: Training data matching

7 Results and Discussion

The knowledge-based controller's application is a suitable approach for complicated nonlinear plants with high level of uncertainty, where mathematical models building are difficult or impossible. The traditional algorithmic approaches ignore significant amount of information necessary for the control.

This ends up with very big efforts for tuning and adapting the originally accepted algorithms for the specific cases.

The intelligent control rationally makes use of the complete available information – basic and auxiliary, obtained by measuring, literature sources or heuristic. The auxiliary information related to specific plant features may be obtained during the control strategy design. One of the best approaches is to combine conventional and intelligent control algorithms.

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References:

[1] A. Obtulowicz, *Badanie Dinamiki Mlyna Wentilatorowego*, Energetica, Praha, 1971.

[2] A. Schneider, *Das Regeldynamishe Verhalten von Kohlenstaubfeuerungen*, Diss. THStuttgart, Germany, 1959.

[3] D. Driankov, Hellendoorn, H. and Reinfrank, M. *An Introduction to fuzzy control*. Springer-Verlag, Berlin, 1996.

[4] D. Spalding, A. Smith, Verbrennung Faster Brenstoffe als Grenzschichtproblem, *BMK 10*, Germany, 6, 1958, pp. 271-273.

[5] H. Kayser, Verbrenung und Vergasungsvorgan-geaus der Sicht des Ingenieurs, *BMK 11*, Germany, 6, 1957, pp. 259-265.

[6] H. Wang, *Bounded, Dynamic Stochastic Systems: Modelling and Control*, Springer, London, 2000.

[7] I.Arauzo, C. Cortés, *Proc. of 30th Intersociety Energy Conversion Engineering Conference* Vol. 2, Orlando Fl., USA, 1995, pp. 397-402.

[8] J. Wünnenberg, *Observer-based fault detection in dynamic system*, Fortschrittsber, VDI-Verlag, Reihe 8, № 222, Düsseldorf, Germany, 1990.

[9] K. Bollinger, H. Snowden, Field Test Results for Multi-Variable Control of a Coal-Mill, *IEEE Trans. on Power Systems*, Vol. PWES-1, 1986.

[10] K. Robenack, Nicolas D. Observer Based Current Estimation for Coupled Neurons *WSEAS Trans. on Systems, Special issue "Modeling and Control of the Integrated Bio-systems"*, 11(7), 2012, pp.268-281.

[11] L. Doukovska, P. Koprinkova-Hristova, S. Beloreshki, Analysis of Mill Fan System for Predictive Maintenance, *Proc. of the Int. Conf. Automatics and Informatics*, Sofia, Bulgaria, 2011, pp. 331-335.

[12] L.Corti, A. de Marco, A. Radice, A. Zizzo, Control and Modeling of Coal Mills, *Proc. of 2nd IFAC Workshop in Modeling and Control of Electric Power Plants*, Philadelphia, USA, 1986.

[13] M. Angelova, Pedro Melo-Pinto, Pencheva T. Modified Simple Genetic Algorithms Improving Convergence Time. *WSEAS Trans. on Systems, Special issue "Modeling and Control of the Integrated Bio-systems"*, 11(7), 2012, pp.256-267.

[14] M. Basseville, Model-based statistical signal processing for change and damage detection, In: *Encyclopedia of Structural Health Monitoring*, C. Boller, F.-K. Chang, Y. Fujino (Eds.), pp. 677-696, John Wiley & Sons, Chichester, GB, 2009.

[15] M. Basseville, Nikiforov I., *Detection of Abrupt Changes – Theory and Applications*, Prentice Hall Series in Information and System Sciences, Englewood Cliffs, NJ, 1993.

[16] M. Basseville, On fault detectability and isolability. *European Journal of Control*, Vol. 7(6), 2001, pp. 625-638.

[17] M. Hadjiski, L. Doukovska, CBR approach for Technical Diagnostics of Mill Fan System, *Comptes rendus de l'Academie bulgare des Sciences*, Vol. 66(1), 2013, pp. 93-100.

[18] M. Hadjiski, L. Doukovska, P. Koprinkova-Hristova, Intelligent Diagnostic on Mill Fan System, *Proc. of 6th IEEE Int. Conf. on Intelligent Systems – IS'12*, Sofia, Bulgaria, 2012, pp. 341-346.

[19] M. Hadjiski, L. Doukovska, St. Kojnov, Nonlinear Trend Analysis of Mill Fan System Vibrations for Predictive Maintenance and Diagnostics, *Int. J. of Electronics and Telecommunications (JET)*, Versita, Warsaw, Poland, Vol. 58(4), 2012, pp. 351-356.

[20] M. Hadjiski, L. Doukovska, Technical Diagnostics of Mill Fan System, *Comptes rendus de l'Academie bulgare des Sciences*, Vol. 65(12), 2012, pp. 1731-1738.

[21] M. Hadjiski, S. Dukovski, Adaptive Control of 210 MW Boiler Milling System – Comparative Analysis of Several Approaches, *Proc. of Int. Symp. On Adaptive Control Signal Processing*, Budapest, Hungary, 1995.

[22] N. Dimitrova, Krastanov M. On the Asymptotic Stabilization of an Anaerobic Digestion Model with Unknown Kinetics. *WSEAS Trans. on Systems, Special issue "Modeling and Control of the Integrated Bio-systems"*, 11(7), 2012, pp.244-255.

[23] O. Sobolev, *Однотипние связанние системи регулирования*, (in Russian), Energetika, Moscow, Russia, 1973.

[24] P. Amann, P. Frank, On fuzzy model-building in observers for fault diagnosis, *Proc. of 15th World Congress on Scientific Computations, Modelling and Applied Mathematics IMACS* '97, Berlin, 1997.

[25] P. Bonissone, V. Badami, K. H. Chiang, P. S. Khedkar, K. Marcelle, M. J. Schutten, Industrial Applications of Fuzzy Logic at General Electric, *IEEE Proc.*, 83(3), 1995, pp. 450-465.

[26] P. Bonissone, Y-T. Chen, K. Goebel, P. Khedkar, Hybrid Soft Computing Systems: Industrial and Commercial Applications, *IEEE Proc.*, 87 (9), 1999, pp. 1641-1667.

[27] P. F. Odgaard, B. Mataji, *IFAC Symposium on Power Plants and Power Systems Control Proc.*, Kananaskis, Canada, 2006, pp. 177-182.

[28] P. Koprinkova-Hristova, L. Doukovska, S. Beloreshki, Fuzzy classifier of mill-fan system working regimes, *Proc. of XIX Int. Symposium PCPPS*, Bulgaria, 2011, pp. 25-28.

[29] P. Koprinkova-Hristova, M. Hadjiski, L. Doukovska, S. Beloreshki, Recurrent Neural Networks for Predictive Maintenance of Mill Fan Systems, *Int. J. of Electronics and Telecommunications (JET)*, Versita, Warsaw, Poland, Vol. 57(3), 2011, pp. 401-406.

[30] PM Frank, E. Alcorta Garc´ıa, B. Köppen-Seliger. Modelling for fault detection and isolation versus modelling for control. *Mathematics and Computers in Simulation*, Elsevier, 53, 2000, pp. 259–271.

[31] R. Iserman, *Fault Diagnosis Systems*, Springer, 2006.

[32] R.V. Beard, Failure *Accommodation in Linear Systems through Self-Reorganization*, Ph.D. Dissertation, MIT Press, Cambridge, MA, 1971.

[33] S. Batov, B. Bonev, T. Totev, Problem and Decision of the Use of Bulgarian Low-Rank Lignite Coal for Electric Power Generation, *Proc., STC*, Ohrid, 1995.

[34] S. Vassileva, B. Tzvetkova. ANN-based Software Analyzer Design and Implementation in Processes of Microbial Ecology. *Advanced topics on Neural Networks. Artificial Intelligence Series*, Publ. WSEAS Press, Hon.Ed. L.A.Zadeh and J.Kacprzyk, Ed.D.Dimitrov, S.Jordanova, V.Mladenov and N.Mastorakis, 2008, pp.142-147.

[35] S. Vassileva, F.Neri. An Introduction to the Special Issue: Modeling and Control of Integrated Bio-Systems. *WSEAS Transactions on Systems*, 7(11), 2012, pp. 221- 222.

[36] S. Vassileva, S. Mileva. Intelligent Software Analyzer Design for Biotechnological Processes. *Advanced topics on Neural Networks. Artificial Intelligence Series*, Publ. WSEAS Press, Hon.Ed. L.A.Zadeh and J.Kacprzyk, Ed.D.Dimitrov, S.Jordanova, V.Mladenov and N.Mastorakis, 2008, pp.48-53.

[37] S.Vassileva. Advanced Fuzzy Modeling of Integrated Bio-systems. *WSEAS Transactions on Systems*, 7(11), 2012, pp. 234-243.

[38] T. Balabanov, Koprinkova-Hristova P., L. Doukovska, M. Hadjiski, S. Beloreshki, Neural Network Model of Mill-Fan System Elements Vibration for Predictive Maintenance, *Proc. of Int.Symp. on Innovations in Intelligent SysTems and Applications, INISTA'*11, Istanbul, Turkey, 2011, pp. 410-414.

[39] T. Slavov, Roeva O. Genetic Algorithm Tuning of PID Controller for Glucose Concentration Control using Software Sensor. *WSEAS Trans. on Systems, Special issue "Modeling and Control of the Integrated Bio-systems"*, 11(7), 2012, pp.223-233.

[40] U. Lange, U., S. Vassileva, L. Zipser. Controllable Shock and Vibration Dampers Based on Magnetorheological Fluids. *Electrical and Computer Engineering Series – A Series of Reference Books and Textbooks "Advances in Systems Theory, Mathematical Methods and Applications"*, Ed. Alexander Zemliak and Nikos E.Mastorakis, Publ. WSEAS Press, 2002, pp.245-250.

[41] V. Cerny, Dynamic Properties of Coal Pulverizing System based on Direct Blowing Mill Fans, *Proc. of Int. Symp., Varna*, Bulgaria, 1972.

[42] V. Cerny, *Urcovani Dynamiki Mlecich Okruhus Ventilatorovymi Mlyny na Analogovem Pocitaci*, Energetica, Praha, 1972.

[43] W. Raush, *Widerstande in Feivertalten Stauben und Mehlen im Luftstrom*, BMK 9, Germany, 9, 1957, pp. 437-44.