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Intelligent Methods for Process Control and Diagnostics of a Mill Fan System

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Abstract: *The intelligent methods for process control and diagnostics of the mill fan system is an established field of scientific and applied investigations. In the present paper several types of process control approaches with different structures are considered. In order to choose the most efficient one, comparative analysis is carried out. The mill fans are a basic element of the dust-preparing systems of steam generators with direct breathing of the coal dust in the furnace chamber. Such generators in Bulgaria are the ones in Maritsa East 2 Thermal Power Plant, in Maritsa East 3 Thermal Power Plant and also in Bobov Dol Thermal Power Plant. The subject of this research is a device from Maritsa East 2 Thermal Power Plant. This is the largest thermal power plant on the Balkan Peninsula. Standard statistical and probabilistic (Bayesian) approaches for diagnostics are inapplicable to estimate the mill fan technical state due to non-stationarity, non-ergodicity and the significant noise level. The possibility to predict eventual damages or wearing out without switching off the device is significant for providing faultless and reliable work, avoiding the losses caused by planned maintenance.*

Keywords: *Internal model control, intelligent process control, mill fan system, intelligent methods for fault detection, maintenance.*

1. Introduction

The mill fans are a basic element of the dust-preparing systems of steam generators with direct breathing of the coal dust in the furnace chamber. The possibility to predict eventual damages or wearing out without switching off the device is significant for providing faultless and reliable work avoiding the losses caused by planned maintenance.

The following mill fan system characteristics provide the necessary information for fault analysis connected with the process control and monitoring of machinery [1]: vibration responses caused by process changes in the technological temperature and pressure; vibratory forces due to the misalignments, mass unbalances and reciprocating masses; fault responses connected with changes in operating conditions and loads of the motors, pumps, fans; undesired effects of mass unbalances, distortions and other malfunction, as well as defect excitations on the vibration response; instability in components, such as fluid film bearings and seals attributable to wearing and clearance; shaft rotational speeds, bearing defect frequencies, number of teeth in gears, number of vanes and blades in pumps and fans, number of motor poles, and number of stator slots and rotor bars.

A significant part of all operating costs in most processing and manufacturing operations may be attributed to the maintenance, which can be considered in some groups: periodic preventive maintenance; predictive maintenance; proactive maintenance; reactive maintenance.

Condition monitoring is used in conjunction with predictive maintenance, i.e., maintenance of machinery based on an indication that a problem is about to occur. In many plants predictive maintenance is replacing run-to-break down maintenance and preventive maintenance [2]. Condition monitoring systems are of two types: periodic and permanent.

In a periodic monitoring system (also called an off-line condition monitoring system), machinery vibration is measured (or recorded and later analyzed) at selected time intervals in the field; then an analysis is made either in the field or in the laboratory.

In a permanent monitoring system (also called an on-line condition monitoring system), machinery vibration is measured continuously at selected points of the machine and it is constantly compared with acceptable levels of vibration. The principal function of a permanent condition monitoring system is to protect one or more machines by providing a warning that the machine is operating improperly and/or to shut the machine down when a preset safety limit is exceeded, thereby avoiding catastrophic failure and destruction.

The detail analysis of the mill fan system is presented in [25]. In this paper only the principal graph of this system is shown in Fig. 1.

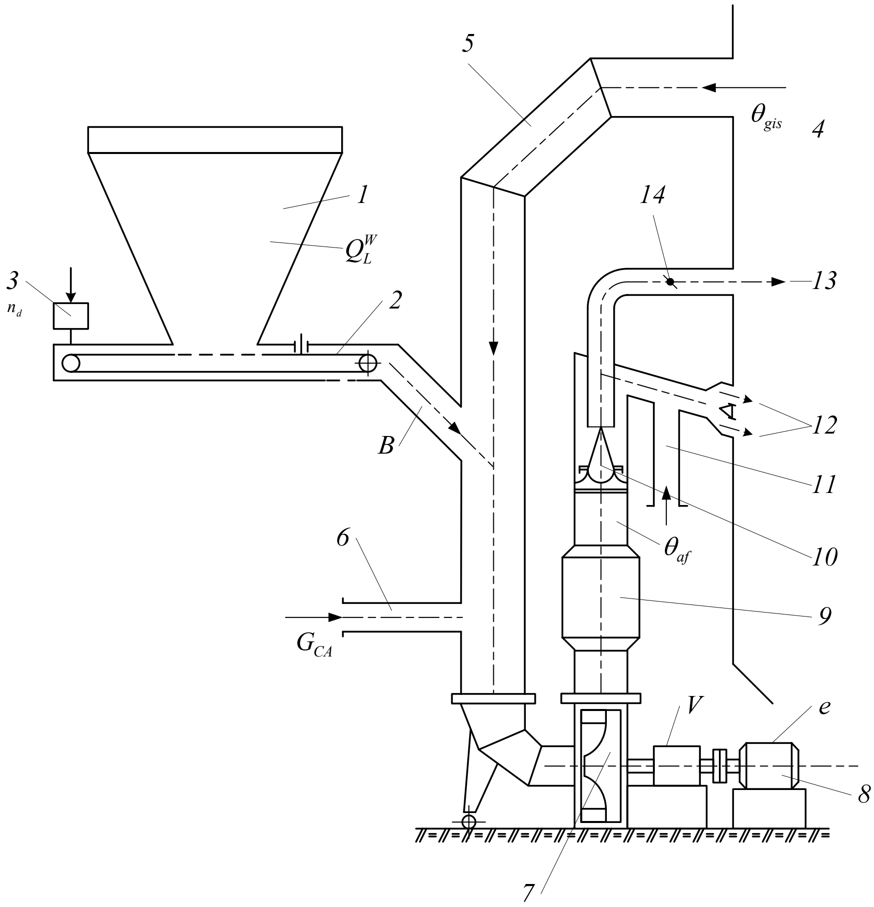

Fig. 1. Mill fan system structure scheme

In Fig. 1, θ_{af} is the 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

In the paper we presented analyze a device from Maritsa East 2 Power Plant. The plant has built up eight blocks – four double blocks with once trough boilers 175 MW each and four monoblocks with drum boilers 210 MW each. For 210 MW power units the milling rotor has diameter D = 3.4 m, width b = 0.9 m and rotation speed n = 490 rpm. There is also a system for drying agent temperature control. Such mill fan is shown on Fig. 2, where 1 is the rotor; 2 – body; 3 – separator; 4 – internal circulation duct; 5 – maintenance and control flap; 6 – duct for bigger fraction recirculation; 7 – dust quality control flap [3].

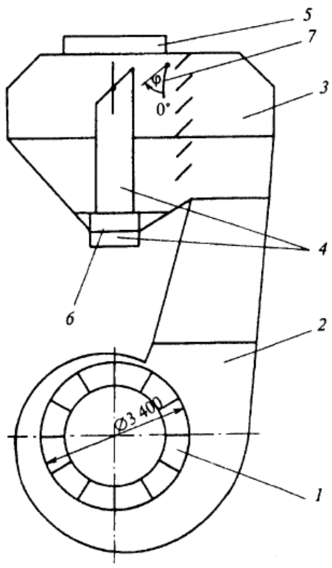

Fig. 2. Mill fan system

Coal milling systems with mill fans are widely used in the fossil fired power plants, due to their possibility to simultaneously dry, mill and transport the coal to boiler's furnace chamber. As drying agents hot flue gases from the furnace chamber with low oxygen content are used, which makes the process explosion safe for very high temperatures. This process also diminishes the nitrogen oxides emissions. These features make the mill fan system suitable for boilers firing low caloricity lignite.

2. Intelligent methods for industrial monitoring, processes control, diagnostics and predictive maintenance

Monitoring methods include monitoring of various processes or machinery factors, such as vibration, thermal, chemical, acoustic, etc. The vibrational components, which are related to the frequency of the power line or variable frequency drive, or to the difference between the synchronous frequency and the rotational speed, occur in electric machines, such as induction motors or generators. These vibrations are due to electromagnetically induced forces.

Fault diagnoses of stochastic systems contain fault detection and fault estimation of the stochastic systems. Two kinds of approaches can be used to deal with the related Fault Detection and Diagnosis (FDD) problem. The ratio of likelihood and the Bayesian methods are used to estimate the abrupt changes of the parameters states.

The FDD algorithms are obtained by using numeral computation methods, such as Monte Carlo or particle filtering methods [4-6]. For example, in [6] an FDD approach was presented for the fault of a parameter-biased type in a class of non-linear time-varying stochastic systems, where a fast fault detection algorithm is obtained by using the extended Kalman filtering and the residual weighted sum of the squares algorithm.

Two approaches are outlined for formulation of the metrics for evaluation [7]. One of them is connected with the risk assessment of a forecast. The other is defined based on the quality of the action taken for preventive or corrective maintenance.

Observers or filters are used to generate residuals, which can be analyzed and dealt with to detect and diagnose faults mainly where the min-max optimization techniques have been applied to the estimation error systems, in order to guarantee some of the required performances [7-10].

In order to achieve high performance and efficiency of the 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 [12].

Stochastic Distribution Control systems (SDC systems) defined in W a n g [11] serve the feedback control by the measured output Probability Density Function (PDF). Therefore, 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 a high level of sophistication and incorporate monitoring, fault detection, decision making, possible preventive or corrective actions and execution monitoring [14]. Support service of the equipment requires generating of models that can analyze the equipment data, interpreting their past behaviour and predicting the 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 anomality detection and identification, diagnostics, prognostics, estimation and control, have been reported in [15, 16, 17].

The approaches based on regression or AI-models of input-output relations of multifactorial objects are nowadays very popular. For example, a correlation between the 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 the spring loading system [13]. In coal flow–air flow coordinates, the operating window represents the mill performance limits, which can vary with the heating value and composition of the raw coal, temperature and relative humidity of the ambient air, leakage in air-gas preheaters and number of operating mills. The diagnosis system checks the current coal flow-air flow point of each mill, therefore allowing an efficient evaluation of the present conditions, present drifts and future problems.

During the last two years series of papers are published that offer alternative approaches to mill fan system diagnostics and predictive maintenance, which use different intelligent approaches. In paper [19], a fuzzy rule-based classifier of a mill fan system working regimes was created based on the analysis of data available from its control system. Analysis of the available on-line monitoring data from the mill fan system has revealed the tendencies of key observed variables, presented in [20]. In [21] an online monitoring system is studied 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 [22] the aim is to compare a newly developed kind of Recurrent Neural Networks with historical Elman Recurrent Neural Networks architecture. Two Sugeno-type fuzzy rule bases – one with a linear function of the input mill fan variables and one with a constant consecutive part of the rules are trained in [23]. Several types of intelligent mill fan diagnostics approaches with different structures are considered in [25]. In [24] the initial results are described about applying the Case Based Reasoning (CBR) approach for intelligent diagnostic of the mill fan working capacity using its vibration state. In [26] the problem of using the CBR designed to operate in the field of technical mill fan diagnostics is also considered. The obtained results may be successfully applied for development of diagnostics model aimed at fault mill fan system detection.

3. Experimental results

The experimental research is done in the national Maritsa East 2 Thermal Power Plant. The plant has four double blocks with once trough 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 Troyanovo 1 and Troyanovo 2 mines with caloricity of 1200-1600 kcal/kg. This lignite coal is of extremely low quality with very high contents of moisture up to 55%, and ash content up to 40%. The problems related to coal drying and milling determine the efficiency and the static and dynamic performance of the mill fan system.

Analysis of the process control and diagnostics of the mill fan system is considered in the paper. For this purpose, data archived by the installed on the site DCS – Honeywell Experion® PKS R301 is used. The Experion® Process Knowledge System (PKS) is a cost-effective open control and safety system that expands the role of distributed control. This platform is well suited for both small and large systems. It provides the power and flexibility required to handle the full spectrum of process control and safety applications.

The boiler-turbine unit coordinated control strategy is presented in Fig. 3. The figure shows the realized block scheme of the strategy.

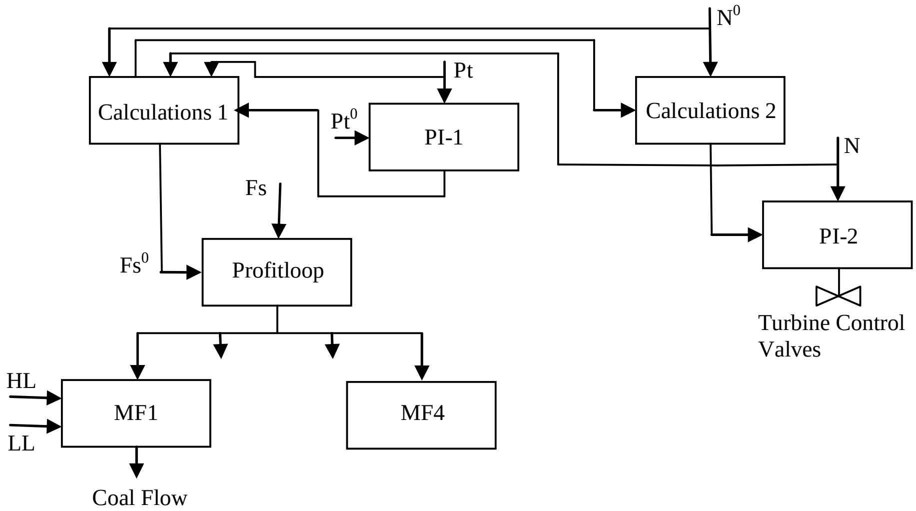

Fig. 3. Boiler-turbine unit coordinated control strategy

In it, Calculations 1 is the moving average filter calculating the steam flow in tons which is necessary to generate one MW. Thus having the power set point, the boilers are immediately set to generate the corresponding steam flow. This block also receives the output of the corrective Inlet Turbine Pressure Proportional-Integral (PI-1) controller which is being added to the calculated steam flow. If the inlet turbine pressure goes out of a specified range, this calculation block increases or decreases the power set point of the Power Output Proportional-Integral (PI-2) controller in order to keep the inlet turbine pressure in safe limits. PI-1 is an inlet turbine pressure PI controller. PI-2 is a power output PI controller acting on turbine control valves. Calculations 2 is frequency correction on the power output set point and coordinated link from the inlet turbine pressure deviation limitation. Profit Loop is Honeywell Robust Model Based Predictive Controller acting on the mill fans loading. The MF1 ... MF4 are calculation blocks limiting the mill loading in order to avoid very low and very high air coal mixture temperatures. The gain of the mill on the channel load-temperature is constantly calculated and a high and low load limit is calculated.

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

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

where: k is the gain, T – lag time constant, r – order.

To determine its parameters optimization procedure, based on Nelder-Mead, a simplex algorithm is used, as presented in paper [18]. The achieved values of these parameters are – k=0.7 kW/kg, T=105.4 s, r=4.

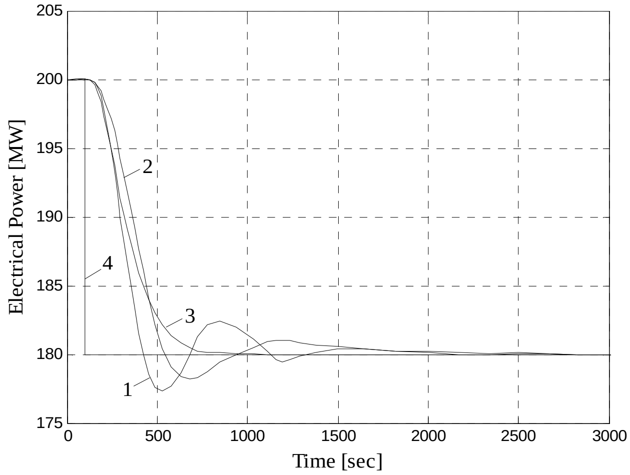

Fig. 4. Electrical power of the unit

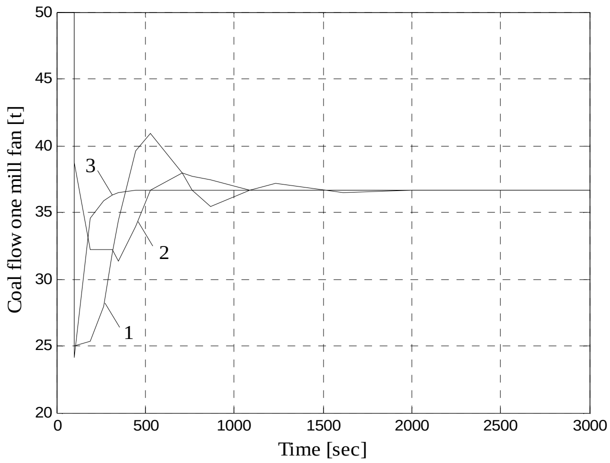

Fig. 5. Mill fan coal quantity

The previous two figures show the results of the comparative analysis between a conventional Proportional Integral Derivative (PID) controller, a control strategy with Internal Model Control (IMC) and a Robust Model Based Predictive controller. Figs 4 and 5 show the system responses on the channel single mill fan coal quantity – the electrical power of the unit. Curve 1 shows the system responses with a PID controller, curve 2 – with a Robust Model Based Predictive controller and curve 3 – with IMC. Curve 4 is the power set point for the unit. For all three algorithms the process reaches a steady state for about 1000 s, where the PID controller is the fastest reaching the set point, but it gives the biggest overshot. The IMC controller gives the smoothest response typical for this strategy. The Robust Model Based Predictive controller response is closer to the PID one, but with a smaller overshot.

Regarding the control output, the smoothest curve is generated by the Robust Model Based Predictive controller, which as a matter of fact is the most important for the flawless and robust operation of the milling system. Considering this, it could be concluded that the most appropriate is the application of the intelligent control strategy.

4. Conclusions

Intelligent controller's application is a suitable approach for complicated nonlinear plants with a high level of uncertainty, where mathematical models construction is difficult or impossible. The traditional algorithmic approaches ignore a significant amount of the 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.

The obtained results can be successfully applied to real mill fan systems control strategies design.

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