Signal Processing Symposium

SPS 2011

Jachranka Village
June 8-10, 2011
SPS 2011 Technical Committee

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Krzysztof Wesolowski  Poznan University of Technology, Poznan, Poland
Felix Yanovsky  National Aviation University, Kiev, Ukraine
Nonlinear Trend Analysis for Diagnostics and Predictive Maintenance

Mincho B. Hadjiski1, Lyubka A. Doukovska2, Stefan L. Kojnov2, Dimitar I. Kamenov2

1University of Chemical Technology and Metallurgy – Sofia
Bulv. St. Kliment Ohridski 8, 1756 Sofia, Bulgaria

2Institute of Information and Communication Technologies, Bulgarian Academy of Sciences
Acad. G. Bonchev str., bl. 2, 1113 Sofia, Bulgaria

hadjiski@uctm.edu, l.doukovska@mail.bg, skojnov@yahoo.com, dikamenov@gmail.com

ABSTRACT

Present paper considers nonlinear trend analysis for diagnostics and predictive maintenance. The subject is a device from Maritsa East 2 thermal power plant - a mill fan. The choice of the given power plant is not occasional. This is the largest thermal power plant on the Balkan Peninsula. Mill fans are main part of the fuel preparation in the coal fired power plants. The possibility to predict eventual damages or wear out without switching off the device is significant for providing faultless and reliable work avoiding the losses caused by planned maintenance. This paper addresses the needs of the Maritsa East 2 Complex aiming to improve the ecological parameters of the electro energy production process.

Keywords: Technical Diagnosis, Fault diagnosis, Predictive Maintenance, Manufacturing Execution System (MES), Enterprise Resource Planning (ERP)

1. INTRODUCTION

The predictive maintenance includes four stages: predictive diagnosis, estimation of potential losses, decision making for device maintenance and maintenance schedule arrangement. Technological diagnosis as the basis for predictive maintenance is established field of scientific and applied investigations. Top-managers of leading factories in the chemical, petrochemical, silicate industry, energy, metallurgy, mining industry in Europe and around the world have adopted in their current practice that economic success and competitiveness depend heavily on the security of technological facilities and low cost of maintenance them. Predictive maintenance based on diagnosis, prolongs the life of machines and aggregates, reducing downtime, maintain optimal level of production, ensure compliance with the precise timing of delivery of production (raw materials, energy), allows for effective management of maintenance of facilities, using the least staff and costs, planning and repairs according to actual conditions of machines and in the most appropriate time in accordance with the tasks of the subsystems of Enterprise Resource Planning (ERP). The results of the system to predictive maintenance are critical for a number of user groups from industry and engineering specialists maintenance and repair, operators and dispatchers, designers of industrial systems with great complexity, so as to ensure high reliability, fault tolerance and availability. One of the study tasks is evaluation the probability of failure of element, machine or center as a time function. This is important from engineering point of view in order to adjust the machine inspection policy.

According to the International Standardization Organization (ISO) “Prognostics is time for estimation of damage and risk for one or several future damages”, [3]. Thus technological diagnosis can be understood as a process of estimation of Remaining Useful Life (RUL) before damage occurs, which is estimated based on the current status of the facility and last operating mode.

The current state can be considered as the degree of implementation of the specified functionality. The diagnostics it is not classified in only two or three classes, but is conceived as a continuous process of degradation. Quantitative evaluation of the degree of degradation is the result of applying the diagnostic methods on the current measurement data from sensors and Supervisory Control And Data Acquisition (SCADA) or Decentralized Control System (DCS) measurements with special diagnostic equipment. Thus predictive maintenance should be seen as a process of prediction and evaluation of future behavior [2, 5]. Critical stage is forecasting the development of degradation of the facility. Highly debatable issue is the assessment of the accuracy of the forecast. Two approaches are outlined for formulation of
the metrics for evaluation [2, 6]. One of them is connected to risk assessment of a forecast. The other is defined based on the quality of the action taken for preventive or corrective maintenance.

The second approach is based on measurements and data-driven. There are numerous other approaches, but all can refer to two types of techniques - artificial intelligence (AI) and the theory of probability and mathematical statistics. Between the artificial intelligence techniques have become particularly popular the methods of artificial neural networks and neuro-fuzzy networks. These are flexible and general approaches for predictive maintenance [7]. It is shown that their effective will be improved if is using different techniques such as: radial-based recurrent neural networks [8], wavelet neural networks [9], and robust neural networks [10]. The results are illustrated by different examples using machines with rotating parts [11].

In last few years is increasing interest in the diagnosis based on the method of precedents (Case-Based Reasoning - CBR) [12]. This method is effective in the absence of sufficient measurements and especially for analysis and retrieval of precedents with their attributes and relationships. The adaptation procedure is implemented the base of rules derived from experts. The results in paper [1] show that it is appropriate to combine the diagnostic method based on the precedents with neural network or fuzzy logic, which will mitigate the disadvantages of the method. Similar results are contained in [13].

The predictive maintenance, as a complex interdisciplinary field of science, technology and economy is far from completion. Its application in the industry faces a number of complexities. They are related to problems of technological diagnostics (limited opportunities for application of active diagnosis, lack of repeatability in testing objects, extremely large complex of facilities, equipment variability in their life cycle, inevitably a high degree of uncertainty), procedures for decision making for proactive or corrective actions to maintain, the methods for the scheduling of the action, integration into Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP) systems.

From industrial application viewpoint, the maximal number of fault diagnostic applications in process industries are based on process history based approaches. This is due to the fact that process history-based approaches are implement modeling an a priori knowledge. Further, even for processes for which models are available, the models are usually steady-state models. It would require considerable effort to develop dynamic models specialized towards fault diagnosis applications. The scope of the process history based systems as applied in the industry is mainly restricted to sensor failures. There are very few industrial applications in published literature that deal with parametric failures. Among the process history based approaches, statistical approaches seem to have been well studied and applied. The reason for this might be that with the current state-of-the-art in applications, detection seems to be a bigger concern than detailed diagnosis. Hence, statistical approaches that are easy to build and which do very well on fast detection of abnormal situations have been successful in industrial applications. Chemical processes are inherently nonlinear in nature. While the theory of linear quantitative model-based approaches is quite mature, the design and implementation for nonlinear models is still an open issue.

Fault diagnosis shares with other process operations the realization that with powerful knowledge representation schemes, one can capture the expertise of operators and control engineers that was gained over years of experience with process plants. Process specific knowledge can be used to improve general purpose methodologies. There is a close coupling between diagnosis and process operations design of chemical plants. The proper design of a chemical plant can reduce the burden on the task of diagnosis. Also, the information from diagnosis can be used to continuously improve the performance of process operations. The information from fault diagnosis can be incorporated into the traditional solution paradigms of other process operations. The aim of this paper is to provide a brief overview of various methods and operations modules that would particularly share information with the fault diagnosis module and also outline the nature of interaction that one can expect.

2. PROBLEM FORMULATION

In the presented paper we have chosen to analyze a device from Maritsa East 2 power plant - a mill fan. Maritsa East 2 thermal power plant (TPP) has built up eight blocks - 4x175 MW and 4x210 MW. In historic plan in 1962 a decision has been taken for building up Maritsa East 2 TPP, and since 1970 the electro energy of least price cost for the country is produced in Maritsa East 2 TPP. In the end of 1995 8th energy block has been connected in parallel to the energy system of the country by which the second stage of Maritsa East 2 TPP enlargement was completed. Achieved installed capacity is 1450 MW. This turns Maritsa East 2 TPP into the biggest thermal power plant in the Balkans. After following reconstructions and modernizations installed capacity 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 Marita East 2 TPP being the largest thermal power plant on the Balkan Peninsula and the choice of the given power plant is not occasional.

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. In general these are large centrifugal fans which suck flue gases with temperature around 800-1000 degC 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 degC. Lower than 145 degC may cause clogging of the mill and higher than 195 degC 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.

![Figure 1. Mill Fan](image)

Coal milling systems with mill fans are widely used in the fossil fired power plants, due their possibility to simultaneously dry, mill and transport the coal to boiler’s furnace chamber.

As drying agent are used hot flue gases from the furnace chamber with low oxygen content which makes the process explosion proof 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.

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 Figure 1.

Drying agent flow depends on the amount of coal to be milled. Thus if the mill gets loaded the discharge temperature decreases and vice versa.

Coal and flue gases enter the mill through a special duct taking gases from the top of the furnace chamber. The rotor works as fan and a mill. After milling the coal dust gets into a separator, where the milled fractions are directed to the burners or back for additional milling depending on their size.
The boiler which milling system is studied is a Benson type once-through sub-critical boiler. There are four mills per boiler. Each mill fan system has four radial bearings – two in the mill and two in the motor. The DCS installed on the site is Honeywell Experion PKS R301 Process. All the data used in the present research are obtained from the historian system of the Distributed Control System (DCS).

3. EXPERIMENTAL RESULTS

Prognostic maintenance of a mill fan is considered in the presented paper. It is based on the vibration of the nearest to the mill rotor bearing block. In the present paper the analysis is done using data archived by the installed on the site DCS – Honeywell Experion PKS R301. The observation period is 16.12.2010 – 16.01.2011. On 31.12.2010 the rotor of the mill fan is changed. After the replacement it has been working for 378 hours. The period chosen allows for vibrations analyzes before and after the replacement. On Figure 2 are shown the vibration values in millimeters as a function of the mill’s rotor working hours.

![Figure 2. Raw Signal Data](image2)

Presented data show working and idle states of the device before and after replacing the rotor. Next figure shows vibration rates before rotor replacement.

![Figure 3. Vibrations before the rotor replacement](image3)

Due to higher nonlinearity of the device a nonlinear trend analysis for diagnostics and predictive maintenance is done. Regression analysis is done in Matlab environment. It was found that a polynomial of degree 7 fits the data best. Results are presented on the next figure. From industrial application viewpoint, the maximal number of fault diagnostic
applications in process industries are based on process historian based approaches. This is due to the fact that process history-based approaches are implementing modeling an a priori knowledge.

![Figure 4. Vibrations analysis before the rotor replacement](image)

It is observed that after the replacement the vibrations with new rotor have higher amplitudes than with the worn out one. This is because of the abrasive wear out of the rotor – the blades become thinner and the rotor becomes lighter. The new rotor is heavier so the vibrations are more intensive even though the rotor has been carefully balanced.

![Figure 5. Vibrations after the rotor replacement](image)

After preliminary data processing including idle periods removal on Figure 5 are shown the vibration rates after rotor replacement. It is plain to see the vibration rate is higher. Taking into account the observed trend before rotor replacement it is possible to prognosticate the next planned device maintenance shutdown.

4. CONCLUSIONS

This paper proposes a nonlinear trend analysis for diagnostics and predictive maintenance. Vibration rates of a mill fan system for Maritza East 2 power plant have been analyzed. The obtained results show that nonlinear trend analysis may be successfully applied to estimate and predict changes of the mill rotor state. Because of the chosen device features it is important to mention the necessity of additional information regarding the exploitation rates. In the considered example this is expressed in knowledge about the planned maintenance and rotor replacement shutdowns. To increase the usability of the proposed diagnostic procedures it is also necessary to take into account the efficiency rates of the process, which would allow for a better picture about the necessity of effective and in time prognostic maintenance of the plant devices.
ACKNOWLEDGMENT

This work is supported by the European Social Fund and Bulgarian Ministry of Education, Youth and Science under Operative Program “Human Resources Development”, Grant BG051PO001-3.3.04/40/28.08.2009.

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