Working Regimes Classification for Predictive Maintenance of Mill Fan Systems
Neural networks and fuzzy sets approaches

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Abstract—In the present paper, the subject of analysis 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 of the equipment avoiding incidents. Standard statistical and probabilistic (Bayesian) approaches for diagnostics are inapplicable to estimate mill fan vibration state due to non-stationarity, non-ergodicity and the significant noise level of the monitored vibrations. Promising results are obtained only using computational intelligence methods (fuzzy logic, neural and neuro-fuzzy networks). In the present paper, two neuro-fuzzy approaches are applied for classification of a mill fan system working regimes based on analysis of data available from its control system.

Keywords—component; fuzzy sets, neural networks, classification, predictive maintenance

I. INTRODUCTION

According to the International Standardization Organization (ISO) “Prognostics is time for estimation of damage and risk for one or several future damages”, [1]. 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 mill fans (MF) are a basic element of dust-preparing systems (DPS) of steam generators (SG) with direct breathing of coal dust in the furnace chamber furnace chamber. Such SG in Bulgaria is the ones in the Maritsa East power plant, in the Maritsa East 3 power plant and also in the Bobov Dol power plant. Mill fans are a part of the equipment of power units that are most often repaired due to intensive erosion of the operative wheel blades in the process of grinding of low-calorific lignite coal from the Trayanovo 1 and Trayanovo 2 mines with high percentage of dust (28%-45% of the dry mass).

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 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.

Honeywell’s Experion control system is installed on Units 1, 3 and 4 in Maritsa East 2 thermal power plant. Using standard engineering tools computer models of the controlled units are created and entered in real-time database. Each parameter is collected and shown in control system’s database in real time. It can be shown in different formats and appearance depending of the user needs- operator, shift engineer, maintenance personal, management etc.

Experion Process Knowledge System (PKS) [2] 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 in the following high-level view of the architecture. 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; Accelerate improvement and innovation. The Experion 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.

Data gathering and collection of as much as possible data is the fundamental of decision support. It is not practical to measure all parameters in a typical power plant, so we can
judge about them by other parameters and overall parameters trends. Data gathering for long period can give good indication how process was developed during the time – for example we can judge if overhaul improved or not equipment operation. In other words, system provides additional information for additional analysis. Depending on the significance and skills needed, conclusion can be made by operator, shift supervisor or other manager depending on duties and responsibilities.

The symptoms in a diagnostic problem are always indirect and they are of stochastic nature (changes of temperature of the dust-air mixture (DAM) at the separator output related to the average one for the DPS, the flame position (horizontal, vertical), the relative power consumption for grinding, corrected rotating frequency for the raw fuel feeders (RFF)) [3-8].

Vibrodiagnostics did not prove to be a serious diagnostic method for MF because regular measurements of their vibration state of the new DCS and SCADA turn out to be quite insufficient for a detailed diagnostics.

In the present work two intelligent approaches that combine neural networks and fuzzy logic methods are applied for classification of the mill fan working regimes. One of them is based on the widely used Jang’s ANFIS [9, 10] that uses gradient learning algorithm adopted from neural networks. This approach however needs to collect expert information about the mill fan working regimes classification in dependence on the on-line measurable variables in order to train a Sugeno-type rule base as fuzzy classifier of the mill fan state. The other approach, developed recently in [11] uses Echo state network (ESN) [12] and subtractive clustering [13, 14] in combination and makes “blind” clustering of available data. The obtained classification of working regimes is then used to train another Sugeno-type fuzzy classifier of the mill fan state. The obtained two fuzzy classifiers are compared using available data from the mill fan control system and advantages and shortcomings of both approaches are discussed.

II. MILL FAN SYSTEM

The mill fans (MF) are centrifugal fans of the simplest type with flat radial blades adapted for simultaneous operation both like fans and also like mills. The basic components of a mill fan are (Fig. 1): steel body V, covered by bar shield plates 2 thick 70—80 mm, and a rotor, consisting of a mill wheel 3 with twelve blades 6. The rotor is fixed by a console to a shaft 4, located upon two roll bearings [15].

The mill wheel blades 1 (Fig. 2) [15] bear shield beats 2 thick 30-40 mm, directly beating the coal particles. The fuel entering the mill is sucked to the beating elements of the mill-fan rotor together with the drying agent (usually hot gases with a temperature of 950-1100°C). The located before the mill fan descending mine is the place for intensive drying of the fuel where a good deal of the external moisture is reduced; in the milling zone, i.e. between the shield bars -blades an additional drying takes place and also an effective milling of the dried fuel.

The ground product with the cooled drying agent is forced by the dozing rotor of the aggregate into a centrifugal or inertial separator 3 from where the big particles return to the mill and the small ones are carried out by the gas stream through the dust pipes to the burners. At the output end of the pipe for returning big particles from the separator a cone valve is set to regulate the amount of recycling gas from the separator downwards to the bottom of the fuel-delivering drying mine to induce into the mill fan.

Fig. 1. Mill fan

Fig. 2. Mill fan rotor

Whenever it is necessary to reduce the intensiveness of drying, the recirculation of the cooled drying agent is intensified (increased). Metallic parts and the trioxide are caught in a specific box 10 in the down section of the corpse. The higher the productiveness of the mill fan, the greater its diameter; this is accompanied by a deterioration of the even fuel distribution along the blades, by an intensified local wearing-out of the blades, also of the trioxide disc and a decrease of the milling effectiveness.

The drying-agent temperature after the drying mine, i.e. before the very mill fan, must not exceed 450-500°C. The percentage of CO₂ in the damp mixture before the mill can reach 2.5% and the part of O₂ together with the moist evaporation in the drying mine is reduced to less than 15-16%; this ensures the installation against explosions this makes the installation explosion-proof.

The total pressure developed by the mill fan equals to 1-2 kPa (100-200 mm water column) and it is directed to overcoming the resistance of the drying path which is under pressure and also of the resistance of the separator, the dust piping and the burners.
In this paper are analyzed real data available from the mill fan control system in TPP Maritsa East 2. For this purpose data archived by the installed on the site DCS – Honeywell Experion PKS R301 are used. The observation period is 01.06.2010–06.11.2010. The period chosen allows for process analyzes before (period 01.06–31.10.2010) and after (period 01–06.11.2010) the replacement. All measurements are taken with 1min intervals.

III. FUZZY CLASSIFIERS

A. Using ANFIS to train Sugeno classification rule base

In [16, 17] looking at all the significant variables tendencies before and after replacement we derived the following major working regimes:

- **Case 1 – starting regime**: The maximum density distribution of rotor vibrations is around 2.5mm, the maximum density distribution of dust-air mixture temperature – around 170-190degC, while the maximum density distribution of control action – around 60-75%.

- **Case 2 – stable working regime**: The maximum density distribution of vibrations is around 2.5-3.5mm, the maximum density distribution of dust-air mixture temperature – around 170-180degC, while the maximum density distribution of control action – around 75%.

- **Case 3 – deterioration regime**: The maximum density distribution of vibrations is around 3.5-4.5mm, the maximum density distribution of dust-air mixture temperature – around 150-170degC, while the maximum density distribution of control action – around 75-90%.

- **Case 0 – stop or manual control regime**: The maximum density distribution of control action falls below 50%.

Based on such defined four cases we define the following three linguistic variables as fuzzy classifier inputs: maximum density distribution of dust-air mixture temperature – \( T_{mix} \); maximum density distribution of mill rotor bearing block vibrations – \( V \); maximum density distribution of control action – \( C \). The linguistic variable of the output will be called case and will represent current case state of the mill fan.

Here we trained a Sugeno-type fuzzy rule base with linear function of input variables. The fuzzy rules have the following form:

\[
If T_{mix} \text{ is } c_i \text{ and } V \text{ is } c_j \text{ and } C \text{ is } c_k \text{ then case is } Out_i, i=1\div6
\]

Here \( Out_i \) is linear combination of crisp values of the input variables as follows:

\[
Out_i = a_i T_{mix} + b_i V + d_i C + e_i
\]

Here \( a_i, b_i, d_i \) and \( e_i \) are constants corresponding to \( i \)-th fuzzy rule. The training data were generated using crisp version of initial rule-base defined from expert knowledge. However the crisp logic not always allows obtaining decision about intermediate cases. Hence when the case is not clear, we accepted the case to be the same as the case during previous 12 hour period implying that serious changes in the systems state didn’t happened.

In order to define number of Sugeno fuzzy rules we applied subtractive clustering [13, 14] to such generated input/output data vectors. Six overlapping clusters \( c_i \) with membership functions presented on Figure 3 below are obtained. For training of Sugeno-type fuzzy rule base Matlab ANFIS procedure with hybrid training (backpropagation and least squares methods) was used. The training and testing mean square errors were about 0.5 and the classification results are similar to the experts’ opinion about current system state.
The classification of the de-noised data is presented on the Figures 4. The green lines represent raw data while the red – de-noised data. De-noising was done using wavelet decomposition as in [18]. We used soft heuristic thresholding of the wavelet coefficients using symlets for wavelet decomposition at level 5.

B. “Blind” clustering procedure

Since generation of the training data in previous section was subjective and besides crisp rules don’t allow to generate correct class number in all cases, here we apply a clustering procedure that don’t need to know correct classification of the mill fan state. There are known numerous methods to solve such problem [19] but with increase of characteristic data set dimensions it becomes hard to solve the task easily.

Here we apply a recently developed especially for multi-dimensional data sets procedure [11]. It explores the equilibrium states of the neurons in the reservoir of an Echo state network (ESN) that result from pre-training of the network using Intrinsic Plasticity (IP) improvement algorithm [20]. After pre-training of the ESN using data available from the mill fan control system, these equilibrium states are used to obtain numerous two-dimensional projections of the original multi-dimensional data. The best one among the projections is chosen based on the number of maxima in its probability density distribution [11]. Then selected projection is subject of subtractive clustering [13, 14] to determine the number and centers of data clusters. Finally, the original data are classified based on their distance from the cluster centers.

Figure 5 presents the processed data and the corresponding to them cluster (case) numbers obtained from the “blind” clustering procedure.

C. Comparative analysis of the two approaches

From the obtained number and position of the input variables membership function (see Figures 3 and 6) we can conclude that while in the first case the input space is divided into more fuzzy levels, in the second we have only three levels for each input variable. But on the Figure 3 it is clear that in fact some of the membership functions are overlapping and it will be more natural to “merge” them. Moreover, the bigger is the number of fuzzy clusters, the bigger becomes the number of tuning parameters of the corresponding fuzzy rule base. Hence in the second case we obtained simpler classifier which rules can be interpreted by human experts in more natural way.
Looking at the Figures 4 and 7 it is clear that the obtained results are very similar. Both classifiers are able to discover “case 0”, i.e. stopping regime relatively correct. They also follow the logical change of cases starting with “start” (case 1) regime, following the “normal operation mode” (case 2) and reaching the “deterioration” phase (case 3) shortly before the planned mill fan maintenance. But the classification of the data after the maintenance (that happens shortly before the end of the data on both pictures) is more logically done by the second fuzzy classifier since it is expected that the mill fan will work in “starting” mode again rather than to reach immediately its “normal” mode as it is shown by the first classifier.

Our further aim will be to integrate into real-time measurement system the best obtained fuzzy classifier together with on-line training procedure that will allow its refinement in order to serve as operators assisting unit. We’ll also incorporate into each cluster fuzzy rule a separate RNN predictive model in order to serve as operators assisting unit. We’ll also incorporate into each cluster fuzzy rule a separate RNN predictive model in order to predict given period in the future possible changes (deterioration) in the mill fan working regime.

IV. CONCLUSIONS

The both created here fuzzy classifiers are based only on available on-line monitoring data analysis. The second one that is created using “blind” clustering appears to be better with respect to the simplicity and correctness of the mill fan state interpretation. Further refinement of the classifier can be done by collecting more expert information from the control engineers working with this mill fan to clarify and refine the fuzzy rule bases. Fine-tuning of membership functions shapes and parameters as well as of logical operations can be done further during on-line application and real time training. The next aim of our work will be development of diagnostics model aimed at fault detection of the mill fan system.

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