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Research Article

Application of T^2 Control Charts and Hidden Markov Models in Condition-Based Maintenance at Thermoelectric Power Plants

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An innovative approach to condition-based maintenance of coal grinding subsystems at thermoelectric power plants is proposed in the paper. Coal mill grinding tables become worn over time and need to be replaced through time-based maintenance, after a certain number of service hours. At times such replacement is necessary earlier or later than prescribed, depending on the quality of the coal and of the grinding table itself. Considerable financial losses are incurred when the entire coal grinding subsystem is shut down and the grinding table found to not actually require replacement. The only way to determine whether replacement is necessary is to shut down and open the entire subsystem for visual inspection. The proposed algorithm supports condition-based maintenance and involves the application of T^2 control charts to distinct acoustic signal parameters in the frequency domain and the construction of Hidden Markov Models whose observations are coded samples from the control charts. In the present research, the acoustic signals were collected by coal mill monitoring at the thermoelectric power plant "Kostolac" in Serbia. The proposed approach provides information about the current condition of the grinding table.

1. Introduction

In today's industry, fault detection and preventive maintenance are the most important tasks in ensuring reliability and safety of automated and highly complex processes. There are two main approaches to fault detection and isolation (FDI), which are referred to in the literature as model-based fault detection methods and data-driven fault detection techniques [1]. The former was initially proposed by Beard [2] and Jones [3]. Rapid development ensued and today this field of study is rather prominent in engineering and control. Being founded upon a model, the model-based approach enables model simulation. A detailed description of various model-based detection techniques is available in Frank [4] and Ding [5].

The data-driven approach constitutes a family of different techniques based on analyzing real process data in different ways, expecting that a fault will be revealed by altered statistical, spectral, or other signal properties. These methods are founded upon rigorous statistical development of process data and are mostly used in cases where the model of the process is either highly complex or unreliable. Many data-driven techniques are described and discussed in the literature, such as univariate statistical process control [6], multivariate statistical process control [7], PCA (Principal Component Analysis) based techniques [8], and PLS (Projection to Latent Structures) based approaches [9].

In order to prevent failure from occurring at all, industries undertake preventive maintenance. The goal of preventive maintenance is to extend the period of time during which the system will function well and at the same time reduce the number of unnecessary delays and failures [10–12]. Preventive maintenance can be conducted in several ways. It can be time-based and carried out at given time intervals, depending on the traveled distance, number of service hours, number of operations, or the like. Time-based maintenance is certainly preferable to simply waiting for failure to occur. Still, it is not the optimal solution, given that the life cycle of the components is shorter than it should be and results in higher costs of replacement and much more frequent maintenance. A good solution is presented in this paper; it is a type of predictive maintenance, or condition-based

maintenance, where maintenance activities are undertaken on the basis of the condition of the parts and the system. Many authors prefer condition-based maintenance to time-based maintenance, for example, Ahmad and Kamaruddin [13] and Yang [14]. Condition-based maintenance actually proposes time-based maintenance in conjunction with numerous condition monitoring techniques [15, 16].

In condition-based maintenance, failure prognostic is one of the main processes as it allows the Remaining Useful Life (RUL) to be predicted before failure occurs [15]. Contrary to fault detection that isolates the probable cause of failure, undertaken after failure has occurred (or *a posteriori*), a failure prognostic predicts the time of failure *a priori*. A number of methods and tools can be used to assess the RUL. The methods can be classified into three main groups: (1) model-based prognostic, (2) data-driven prognostic, and (3) experience-based prognostic [16].

Model-based prognostic techniques rely on a dynamic model of the system. This approach uses a mathematical model of the process to incorporate physical understanding of the system into the diagnostic problem. The outcomes include end-of-life (EOL) and RUL predictions [17, 18]. The resulting behavioral models are used to predict future evolution or degradation [19, 20]. The main advantage of this method is the precision of the results, given that predictions are derived from a mathematical model of degradation. Its shortcoming is that it is not always easy to construct an accurate model.

The data-driven prognostic approach involves the conversion of collected process data into reliable models of degradation patterns. The collected data are first analyzed to extract important features then used to learn behavioral model parameters, and finally tools like neural networks, hidden Markov models [21], dynamic Bayesian networks, and trend analyses are applied. If the system in question is well monitored, the advantage of this approach is that the future evolution of degradation can be predicted without the need for a prior mathematical model of degradation. Still, the results can be less accurate than those obtained by model-based prognostics [16].

The experience-based prognostic method relies on stochastic models of degradation phenomena, or the life cycle of the components, taking into account the data and knowledge accumulated over the entire service life of the industrial system. Such data are used to adjust the parameters of certain reliability models (Weibull law, exponential law, etc.) [22]. The disadvantages are that the method requires a lot of data and it is rather difficult to construct accurate models if there are variable statistics.

The present paper will focus on the data-driven approach and the application of hidden Markov models (HMMs). Given that condition-based maintenance is in fact comprised of time-based maintenance and condition monitoring techniques, the idea was to apply an HMM through a statistical approach and identify the current condition of the system from observable signals collected while the system was operating. Even though HMMs have primarily been used in speech recognition [23], many applications pertaining to industry and fault detection are described in the literature [24–27]. Also, HMM-based diagnostic models founded upon the condition of the system have been addressed by, among others, Ertunc et al., Wang et al., Li et al., Lee et al., and Tobon-Mejia et al. [21, 24–26, 28].

On the other hand, statistical process control and diverse applications of control charts in industry and fault detection have been under development for years [6–9], including solutions for constraints encountered in practice, such as autocorrelation of collected data [29], design of control charts for data that are not normally distributed [30], and construction of control charts with adaptive limits [31].

The approach proposed in this paper is new because it offers compromises that exceed existing solutions. It is based on the data-driven method since it does not require knowledge of the model, while the nonstationary state of the model is addressed through the introduction of an HMM. By defining different states, the HMM involves both a dynamic model and nonstationary observations. On the other hand, the observations entering the HMM are not raw measured data from the system but parameterized statistics from control charts. In other words, the proposed procedure extracts the best features of the existing approaches and incorporates them into an innovative algorithm.

The proposed algorithm was applied to a process that takes place at the Kostolac Thermoelectric Power Plant (Kostolac TPP), where the coal grinding subsystem is one of the key subsystems. The grinding table of the coal mill becomes worn over time and needs to be replaced after a certain number of service hours, through time-based maintenance. Depending on the quality of the coal and of the grinding table itself, sometimes replacement needs to be made before or after the specified time, resulting in considerable losses if the entire subsystem was shut down even though replacement was not necessary, or if failure occurs before replacement. The only way to ascertain the condition of the grinding table is to shut down the entire subsystem and open it for visual inspection of the mill. The goal of applying the algorithm was to improve energy efficiency at the Kostolac TPP through condition-based maintenance, by providing information about the current condition of the grinding tables.

The paper proposes an algorithm that uses process data collected while the process was taking place, applying statistical process control or T^2 multivariate control charts [32] to extracted acoustic signal parameters in the frequency domain. The acoustic signals were acquired from monitoring of a coal mill at the Kostolac TPP, while the mill was operating. Then an HMM was constructed with coded samples from the control charts as observations, to arrive at information about the condition of the subsystem or the probability that the grinding table has become worn. Reports of other researches dealing with the detection of certain types of failures at thermoelectric power plants can be found in the literature [33, 34]. The condition-based maintenance approach proposed in this paper differs from the solutions described in the literature in that it is a specific combination of control charts and an HMM, aimed at determining the condition of the system in order to

implement condition-based maintenance. Namely, one of the references describes an application of control charts whose construction is based on spectral analysis of signals by Tiplica et al. [35]. The present research proposes the application of T^2 control charts to the spectral components of the signals, which was demonstrated as highly efficient. The literature also describes an application of control charts and HMM [27, 28], but there the standard p-chart and the Hotelling T^2 control chart were used. However, the present research proposes that first the control chart is applied to the spectral components of the signals and then coded samples from the control charts are taken as HMM observations. Also, the proposed algorithm has been implemented at the Kostolac TPP and demonstrated as highly efficient from the condition information gathering perspective. The advantage of the method is that it is noninvasive; it is not necessary to shut down the entire subsystem in order to inspect the mill.

The paper is organized as follows: Section 2 describes the system and parameter extraction from acoustic signals. A detailed presentation of the proposed algorithm for condition-based maintenance, along with the general theoretical background of T^2 control charts, HMMs, and vector quantization, is provided in Section 3. Section 4 contains the results. Section 5 is the conclusion, which highlights the advantages and shortcomings of the proposed method.

2. Description of the System and Data Acquisition

Thermoelectric power plants are the largest generators of electricity in Serbia, contributing more than 65% to the overall power supply. To ensure their steady and efficient operation, the main subsystems and individual components need to be monitored in order to detect any performance variation or fault and thus improve energy efficiency and reduce potential financial losses incurred by the national electric power industry.

One of the key TPP components is the coal grinding subsystem. Its physical layout is shown in Figure 1. Raw coal enters the subsystem through a feeder and goes down a chute to the grinding table that rotates at a constant speed. The coal is then moved outward by centrifugal force and goes under three stationary rollers where it is ground. The outgoing coal moves forward to the mill throat where it is mixed with hot primary air. The heavier coal particles immediately move back to the grinding table for additional grinding, while lighter particles are carried by the air flow to the separator. The separator contains a large amount of particles suspended in the powerful air flow. Additionally, some of the particles drawn into the primary air-and-coal mix lose their velocity and fall onto the grinding table (as shown) for further grinding, while the particles that are fast enough enter the classifier zone. These particles are swirled by deflector plates. Lighter particles are removed as classified fuel in the form of fine powder that goes to burners, while heavier particles bounce off the classifier cone and fall back onto the grinding table for additional grinding. Both the separator and the classifier contain a significant amount of coal. These coal masses, along with the coal on the grinding table and the three recirculating loads (primary, secondary, and tertiary), play a key role in the dynamic performance of the mill [36].

The paper analyzes one such system at the Kostolac TPP. As previously described, the coal inside the mill is ground by impact and friction against the grinding table that rotates around the mill centerline. The only way to ascertain the current condition of the grinding table is to shut down the entire subsystem and open it for visual inspection. This time-based maintenance method guarantees that grinding tables will be replaced before they become dysfunctional; otherwise, the cost of frequent shutdowns has to be paid. If inspection shows that grinding table replacement is not yet necessary, Serbia's electric power industry will incur a significant financial loss.

The proposed solution to this problem relies on condition-based maintenance following the data-driven prognostic approach. This approach was selected because the model-based method requires an accurate model of the system, which is highly complex. Maffezzoni [37] presents a useful physical model of the mill, a mass-balance model with 76 ODEs (Ordinary Differential Equations), better known as a knowledge-based model. Other models are also available, but the main challenge is to verify model accuracy with real data that are not readily obtainable. On the other hand, the experience-based prognostic approach was not considered due to variable data statistics and an insufficient amount of data. For all these reasons the data-driven approach was selected.

The first step of the data-driven prognostic approach is to collect data. In the present research, acoustic signals recorded in the vicinity of the mill were used to detect the condition of the mill.

The acoustic signals were acquired from a coal mill at the Kostolac TPP, while it was operational. The main mill rotation frequency was about 12.5 Hz and the mill from which the signals were acquired had ten impact plates. Namely, certain references claim that rotary component condition and failure information is hidden in the spectral characteristics of vibration signals [38], but it has been demonstrated that in some cases acoustic signals are equally informative.

In 2001, Baydar and Ball [39] conducted a parallel analysis of the frequency characteristics of vibration signals and acoustic signals to detect various types of failures of rotary components, concluding that both signals can be used equally effectively. The present research uses acoustic signals because they are simpler and less costly to record than vibration signals. They can also be acquired without interfering with mill operation because they are recorded externally.

The acoustic signals were acquired by means of a directional microphone at a distance of several millimeters, while the coal grinding subsystem was operational. The sampling frequency was 48 kHz. Data acquisition was conducted every two weeks on average, and it lasted for several minutes. Table 1 shows the dates of recording, the dates of grinding table replacement, and the duration of each signal.

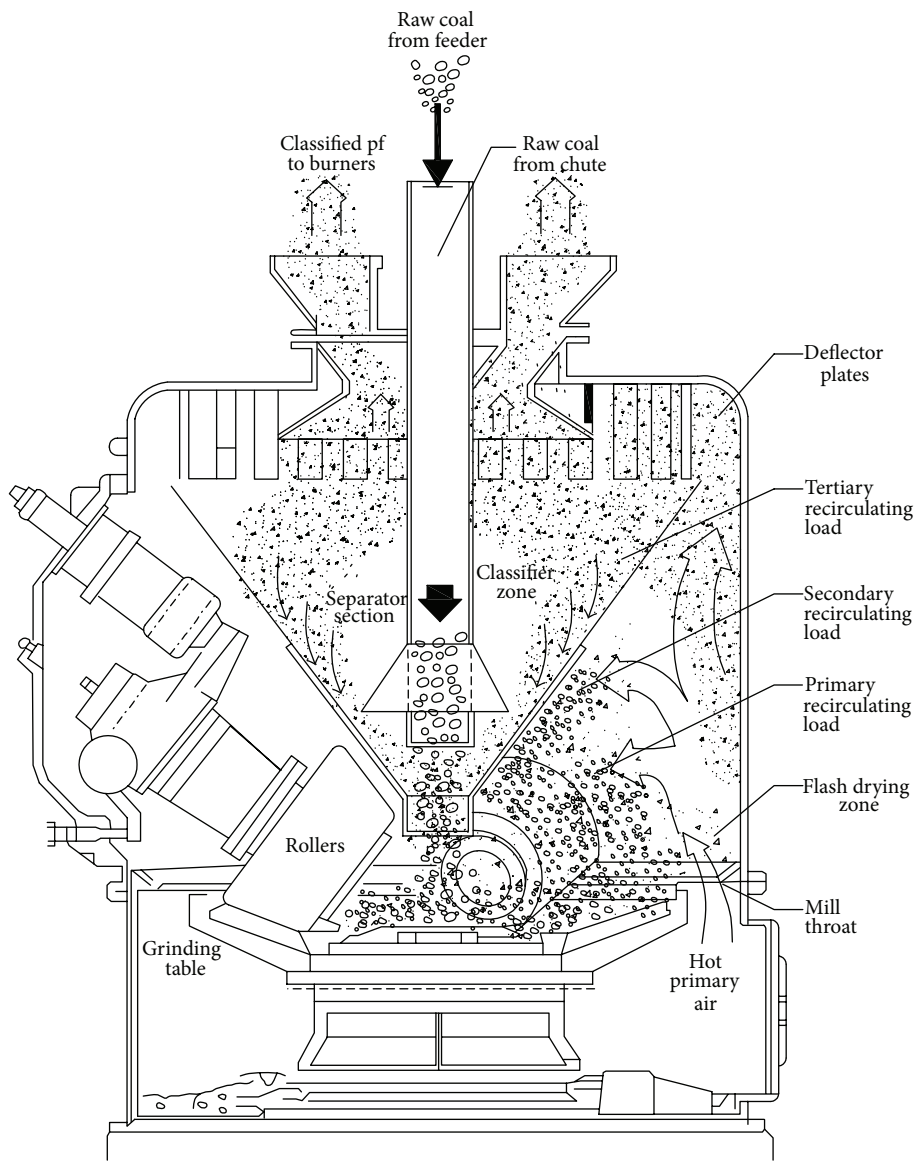


Figure 1: Configuration of the coal grinding subsystem.

For faster implementation of the algorithm, the sampling frequency was decimated from 48 kHz to 4.8 kHz, and the duration of the analyzed signals was one minute.

A spectrogram was used to assess the acoustic signals in the frequency domain, which represented very well the spectral components of the signals in three dimensions: time information along the horizontal axis, frequency information along the vertical axis, and amplitude depicted by a color-coded scale. Color intensity illustrated the strength of the spectral components. Figure 2 shows the spectrogram of an acoustic signal recorded on March 30, 2012, six days after grinding table replacement.

Figure 2 clearly shows the dominant frequencies and indicates that they are the high harmonics of the basic frequency of mill rotation, which was $f_0 = 12.5$ Hz. Also, the dominant peaks in the spectrum occurred at frequencies $10f_0$, $20f_0$, and so forth, attributable to the fact that there were ten impact plates inside the mill, such that the basic

Table 1: Acquired acoustic signals.

Date of acquisition	Signal duration	Time since last maintenance
Grinding table replaced on January 19, 2012		
February 2, 2012	10 min 51 s	14 days
February 24, 2012	8 min 8 s	36 days
March 1, 2012	8 min 8 s	42 days
March 15, 2012	7 min 3 s	54 days
Grinding table replaced on March 24, 2012		
March 30, 2012	6 min	6 days
April 5, 2012	5 min	12 days
April 19, 2012	6 min	26 days

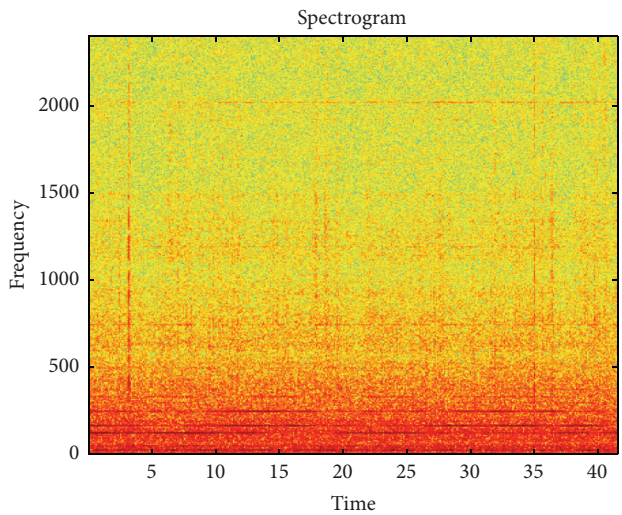


Figure 2: Spectrogram of acoustic signal.

frequency of grinding table travel alongside the microphone was $10f_0$.

Given that the microphone was positioned so as to be as close as possible to the grinding table, these spectral components were much more pronounced than the other components.

3. Structure of Proposed Algorithm for Condition-Based Maintenance

Following data acquisition, the next step was to extract proper characteristics of the recorded acoustic signals in the frequency domain, in order to obtain vector of observations for analysis with T^2 control charts. A spectrogram was used for acoustic signal representation. If recorded acoustic signal is denoted as $y[n]$, spectrogram of acoustic signal S_p is often denoted as Short Time Fast Fourier Transform (STFFT) in literature [40] and computed as FFT (Fast Fourier Transform) on sliding window data. Therefore, spectrogram represents a function of time and frequency arguments:

$$S_p = \text{STFFT}\{y[n]\} = S_p[f, n], \tag{1}$$

where f denotes the frequency and n the time argument of spectrogram.

The extracted quality characteristics in the frequency domain are the values of S_p across the time at the frequencies which represents the values around the high harmonics or the high harmonics themselves. Fourteen selected frequencies are shown in vector f_p:

$$f_p = [14 \quad 18.7 \quad 23.4 \quad 28.1 \quad 32.8 \quad 60.93 \quad 126.5 \quad 178.1 \quad 187.5 \quad 262.5 \quad 346.8 \quad 754.6 \quad 1200 \quad 2025]. \tag{2}$$

Accordingly, 14-dimensional vector of observations is formed at each time point:

$$X[n] = [x_1[n] \quad x_2[n] \quad \cdots \quad x_{14}[n]]^T, \tag{3}$$

whose coordinates are calculated as follows:

$$x_i[n] = \sum_{j=n-L_w}^{n} S_p[f_i, j], \tag{4}$$

where f_i represents the ith coordinate of frequency vector f_p and L_w is the length of window function. This is a procedure for generation of initial observation vectors.

After obtaining the vector of observations, T^2 control charts were constructed. Generally speaking, a control chart is a statistical tool used to detect failure. Control charts make a clear distinction between ubiquitous, indeterminate disturbances (i.e., the so-called common causes of variations in the process), and failures of the system. A system affected by such common causes of variation is deemed to be under statistical control.

A control chart generally comprises a center line (CL), upper control limit (UCL), and lower control limit (LCL). The center line represents the mean value of the quality characteristic of interest, detected while the process is under statistical control. The control limits are selected such that while the process is under statistical control, nearly all the points in the control chart will fall between these two lines.

The first step in constructing control charts requires an analysis of preliminary data, which are under statistical control. This step is called Phase I and data used in this phase are called historical data set. In Phase II, the control chart is used to monitor the process by comparing the sample statistic for each successive sample as it is drawn from the process to the control limits established in Phase I.

If only one quality characteristic of interest is monitored, univariate control charts are used. Many types of control charts are available and selection can be made depending on the type of process. When several correlated quality characteristics are monitored, multivariate control charts, which take the correlation into account, are used. For example, T^2, MEWMA, and CUSUM charts are described in the literature [6]. A multivariate analysis with T^2 control charts was undertaken in the present research.

The most familiar multivariate control procedure is the Hotelling T^2 control chart, for monitoring the mean vector of a process. Hotelling was the first to propose a multivariate control chart based on statistical distance.

Based on observation vectors, T^2 sequence of values may be calculated according to the following equation:

$$T^2[n] = \left(X[n] - \overline{X}\right)^T S^{-1} \left(X[n] - \overline{X}\right), \tag{5}$$

where $\overline{X}$ and S denote the sample estimators of mean value vector and the covariance matrix, respectively. Assuming that, during the data acquisition sequence of N observations $\{X[0], X[1], \ldots, X[N-1]\}$ is generated, simple estimations of vector of mean values and covariance matrix can be carried out:

$$\overline{X} = \frac{1}{N}\sum_{i=0}^{N-1} X[i],$$
$$S = \frac{1}{N-1}\sum_{i=0}^{N-1}\left(X[i]-\overline{X}\right)\left(X[i]-\overline{X}\right)^T. \tag{6}$$

The control limits in Phase II are

$$\mathrm{UCL} = \frac{p(n+1)(n-1)}{n^2 np}F_{\alpha,p,n-p},$$
$$\mathrm{LCL} = 0, \tag{7}$$

where $F_{\alpha,p,n-p}$ is the upper α percentage point of the F distribution with parameters p and $n-p$ (p represents number of variables which is in our case 14). When the number of preliminary samples n is large ($n > 100$), approximated control limits are generally used in practice, such as

$$\mathrm{UCL} = \frac{p(n-1)}{n-p}F_{\alpha,p,n-p}, \tag{8}$$

or

$$\mathrm{UCL} = \chi^2_{\alpha,p}, \tag{9}$$

where $\chi^2_{\alpha,p}$ is the upper α percentage point of the chi-square distribution with p degrees of freedom. For $n > 100$, (9) is a reasonable approximation. In Phase I, the limits are based on beta distribution:

$$\mathrm{UCL} = \frac{(n-1)^2}{n}\beta_{\alpha,p/2,(n-p-1)/2}, \tag{10}$$

where $\beta_{\alpha,p/2,(n-p-1)/2}$ is the upper α percentile of beta distribution with parameters $p/2$ and $(n-p-1)/2$.

As apparent from (5), the T^2 statistic is a scalar. Consequently, the values of the T^2 statistic can be plotted at different points in time and, with appropriate control limits, a T^2 control chart is produced. Each point on this chart represents information obtained from all p variables [6].

According to the relation (5) the time sequence of T^2 values is formed, denoted as $\{T^2[0], T^2[1], \ldots, T^2[n]\}$, where n denotes sequence number of sliding window data. After analysis of Figure 8 which shows the estimated probability density functions of the T^2 control chart samples for the signals recorded two, five, and eight weeks after grinding table replacement, it is apparent that the T^2 statistics change over time and that they are a function of the condition of the grinding table (i.e., they change as the condition of the grinding table changes). In order to account for system dynamics, instead of the very last control chart sample, the last ten samples were used for characterization of the actual state of grinding tables. In other words, vector

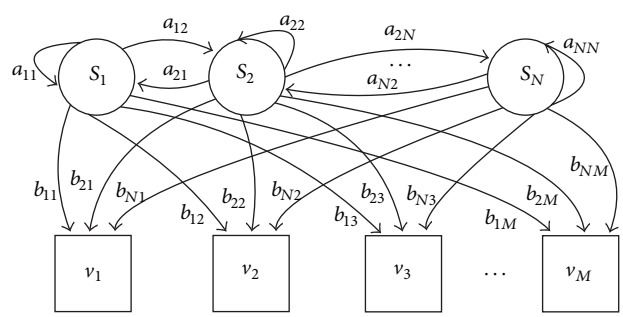


Figure 3: Hidden Markov Model.

$$O[n] = \left[T^2[n-9] \;\; T^2[n-8] \;\; \cdots \;\; T^2[n]\right]^T \tag{11}$$

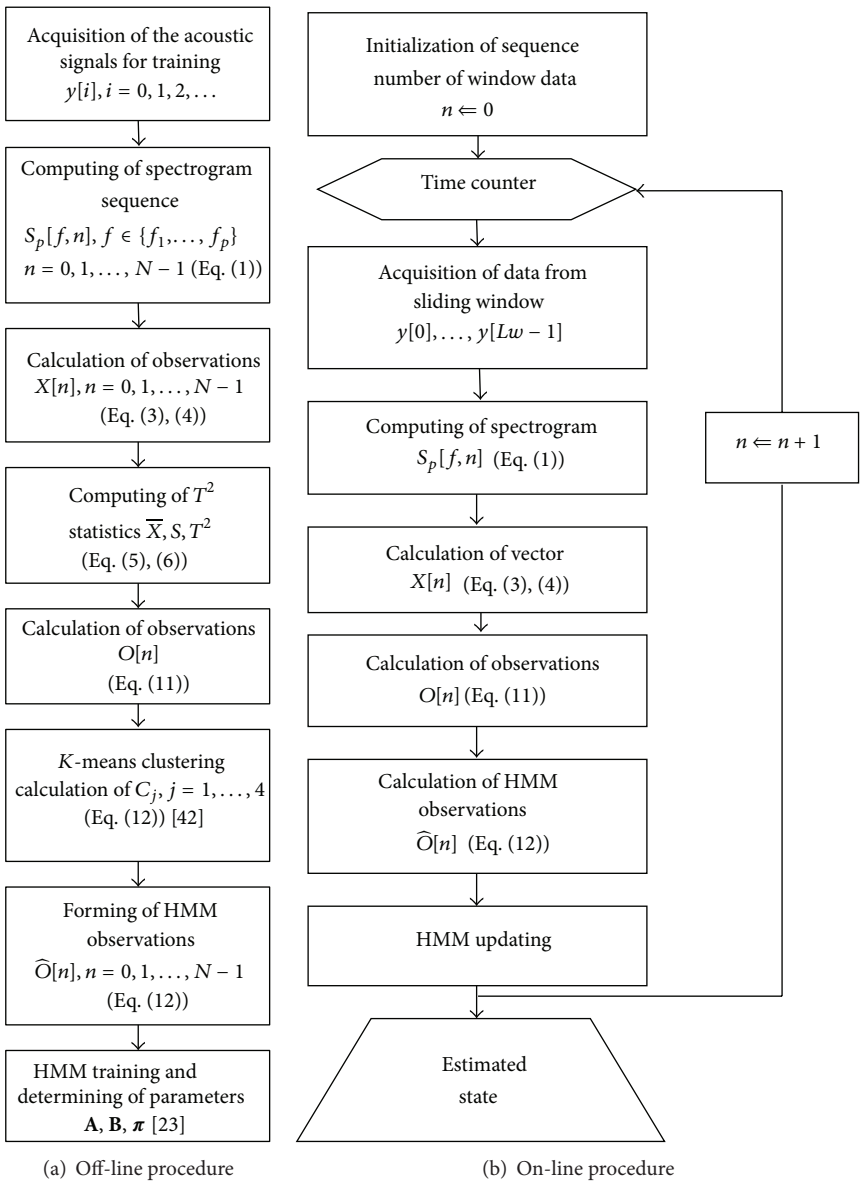
will be used for further estimation of system states. However, if this vector had been introduced as observation in HMM, it would be necessary to estimate joint probability function for this tenth dimensional vector. In order to avoid this complex numerical problem, it has been decided, as it is usual in the literature, to apply the procedure of vector quantization. In this purpose, the method of k-means clustering is used [41, 42]. The result of k-means clustering is sequence of k cluster centers (centroids). In our case, based on try-and-error approach, it turned out that for $k = 4$ satisfying results and cluster centers (C_i, $i = 1, 2, 3, 4$) are obtained. Accordingly, the final vectors of observations $\widehat{O}[n]$ are formed and forwarded to HMM in the following way:

$$\min_j \left\|O[n]-C_j\right\|^2 = \left\|O[n]-C_k\right\| \Rightarrow \widehat{O}[n] = C_k. \tag{12}$$

After the samples were coded as described above, the next step was to construct the HMM. An HMM (Hidden Markov Model) is a statistical model used to describe the transition of a system between states. It is an extension of the ordinary Markov chains with nonobservable or partially observable states. The general organization of a discrete HMM with N states, $S = (s_1, s_2, \ldots, s_N)$ and M observation symbols $V = (v_1, v_2, \ldots, v_M)$, is shown in Figure 3. The states are connected in such a way that it is possible to move from any one to the other. The hidden state at time t is denoted by q_t, and the move from one state to the other is subject to Markov's rule (that state q_t depends solely on state q_{t-1}). In addition to the number of states, N, and the number of observation symbols, M, several other HMM characteristics need to be defined.

The transition matrix $\mathbf{A} = \{a_{ij}\}$ represents the probability of moving from state i to state j. The coefficients a_{ij} are nonnegative in the general case and equal to zero if there is no direct switching from one state to another. The sum of probabilities in each matrix of type $\mathbf{A}$ needs to be equal to 1. The observation matrix (also called emission matrix), $\mathbf{B} = \{b_j(k)\}$, shows the probability that observation k was produced by the jth state.

The sequence of initial states $\boldsymbol{\pi} = \{\pi_i\}$ carries information about initial probabilities, indicating the likelihood that



(a) Off-line procedure (b) On-line procedure

Figure 4: Flow diagram of the proposed algorithm.

a new input sequence will move from a given state. Finally, the HMM can be defined by the triplet:

$$\lambda = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi}). \tag{13}$$

There are three fundamental problems that can be solved by means of HMMs. The first is the so-called evaluation problem, where the probability of a sequence of observations $O = \{O_1, \ldots, O_T\}$ needs to be determined for the given model. The solution to this problem is of the form of a forward algorithm, which sums up all model pathways. In this way the probability of a given sequence $P(O \mid \lambda)$ will be computed. The second problem is to determine the most probable sequence of states for the given model (13) and sequence O. The Viterbi algorithm has been proposed as a solution. The third problem is HMM training. Namely, a model (13) that maximizes the probability of O needs to be found for a given sequence of observations O and model dimensions N and M. The Baum-Welch algorithm or forward-backward algorithm is commonly used to reestimate model parameters. A detailed description of HMMs and the solutions to these three problems are available in [23]. A combination of the problems can facilitate solutions to many other, more complicated formulations. It is for this reason that HMMs are so popular.

Figure 4 shows how the proposed algorithm for condition-based maintenance is organized. For the purpose of the practical implementation of the proposed method it should be clarified that certain activities are realized only once (like off-line procedure) in order to determine the necessary statistics and HMM training. On the other hand, once the off-line

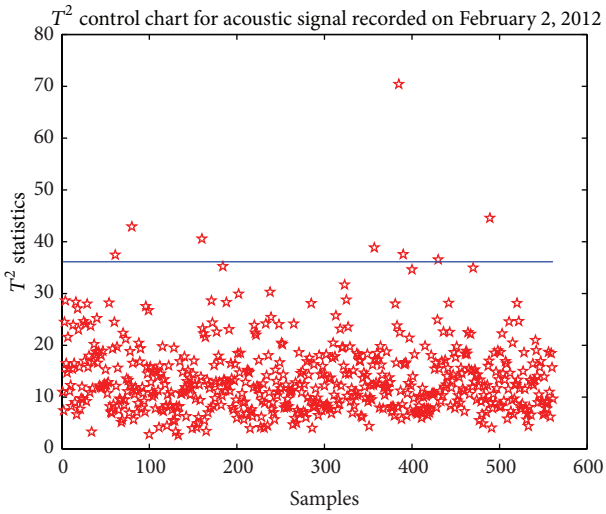


FIGURE 5: T^2 control chart for acoustic signal recorded two weeks after grinding table replacement.

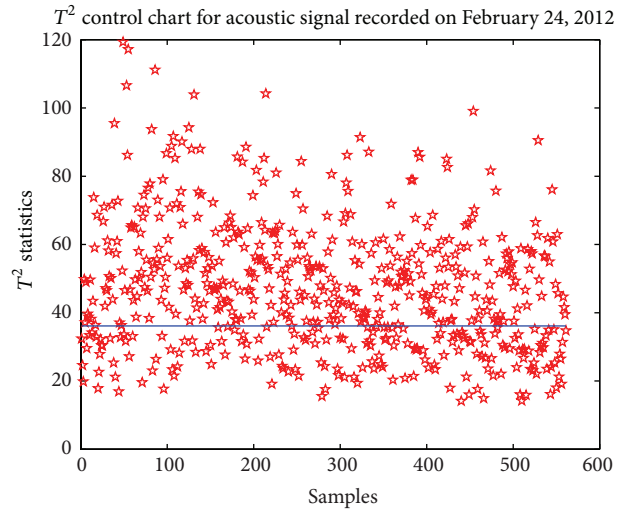


FIGURE 6: T^2 control chart for acoustic signal recorded five weeks after grinding table replacement.

procedure is over, the algorithm can be implemented in real time and thus providing on-line monitoring of the mill grinding plates' states.

To define clearly the order of operations, two flow-chart diagrams have been prepared. Flow chart on Figure 4(a) shows the sequence of activities for the off-line procedure that precedes the real-time application, while flow-chart on Figure 4(b) shows the sequence of activities in the on-line part of the algorithm.

4. Results

The acoustic signal recorded on March 30, 2012, was used for $\overline{X}$ and S estimations in (6), knowing that a new grinding table was operational. In this way, this signal was observed as historical data set. This was in effect Phase I of statistical control, where the entire TPP subsystem was under statistical control. The estimated values of $\overline{X}$ and S in Phase I were to be used in Phase II of the multivariate analysis. The dominant frequencies of the acoustic signal were expected to change over time, or it was expected that the grinding table would gradually become worn and that there will be an increasing number of outliers, until the time of utter wear, when most of the points would be beyond the control lines. The samples from the control charts could be used as HMM observations, to indicate the condition of the grinding table.

The chi-square control limit was taken as the UCL, as in (9). For the 14 quality characteristics, UCL = 36.12 and LCL = 0.

Figure 5 shows the T^2 control chart for the acoustic signal recorded on February 2, 2012, two weeks after grinding table replacement.

Figure 6 shows the T^2 multivariate control chart for the acoustic signal recorded on February 24, 2012, five weeks after grinding table replacement.

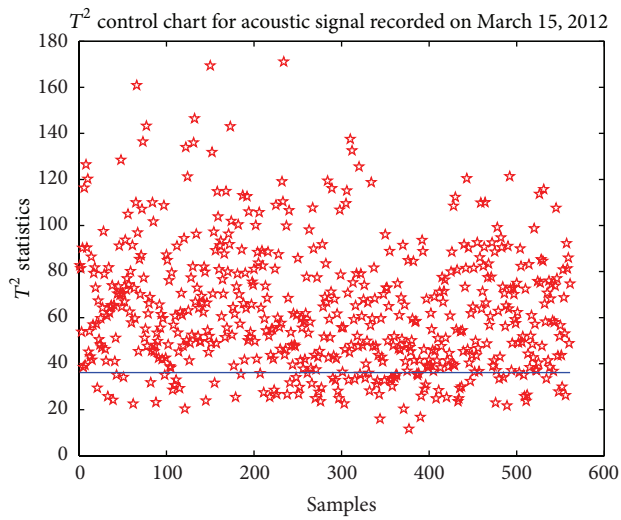


FIGURE 7: T^2 control chart for acoustic signal recorded eight weeks after grinding table replacement.

Figure 7 shows the T^2 control chart for the acoustic signal recorded on March 15, 2012, eight weeks after grinding table replacement.

It is apparent from Figures 5, 6, and 7 that the number of points above the UCL on the T^2 control chart grew as the grinding table became increasingly worn.

Eight weeks after replacement, nearly all the points were beyond the UCL. To corroborate the results, the multivariate analysis was repeated using the signals recorded on 5th and 19th of April 2012. Table 2 shows the exact number of outliers for all the recorded signals.

The difference in the number of points above the UCL for the signals recorded on February 2 and April 19, 2012, can be explained. Namely, both signals were acquired two weeks after grinding table replacement, but the results are different for two reasons: (1) the signal acquisition conditions were not

Table 2: Number of data points above the upper control limit.

Date of signal acquisition	Number of weeks after grinding table replacement	Number of data points above UCL	Data points above UCL [%]
Feb. 2, 2012	2	8	1.43%
Feb. 24, 2012	5	383	68.27%
Mar. 15, 2012	8	476	84.85%
Apr. 5, 2012	2	94	16.75%
Apr. 19, 2012	4	323	57.58%

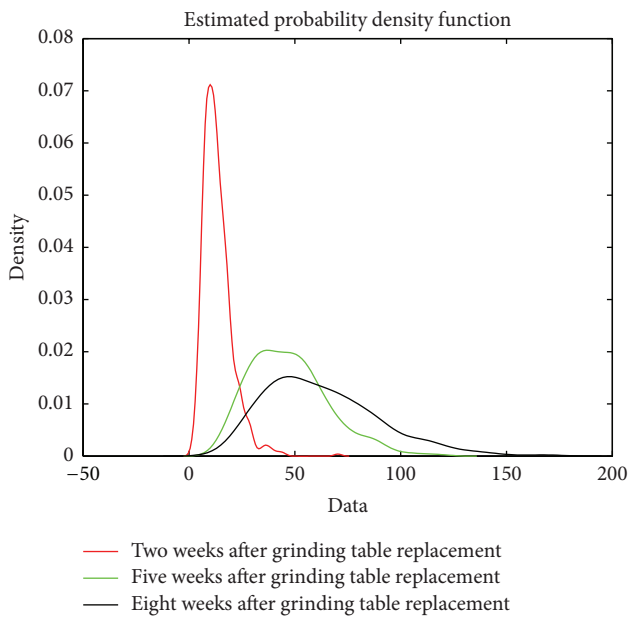


Figure 8: Estimated probability density functions for signals recorded two, five, and eight weeks after grinding table replacement.

ideal in terms of noise. All the recorded signals reflect this noise as well as other disturbances (e.g., when a large chunk of coal or stone hit the mill). The signals were not filtered, so as not to lose information. All this could have influenced the accuracy of the results. (2) Grinding table wear depends on the quality of the coal and of the grinding table itself. It is therefore impossible to ascertain what the right time for grinding table replacement would be, unless the entire subsystem is shut down and opened for visual inspection.

After constructing the T^2 control charts, vector quantization was undertaken, as described in the previous section, in order to represent the control chart samples as a sequence of observations for the HMM. Figure 8 shows the estimated probability density functions of the T^2 control chart samples for the signals recorded two, five, and eight weeks after grinding table replacement. As it is pointed out in Section 3, it is apparent that the T^2 statistics change over time and that they are a function of the condition of the grinding table (i.e., they change as the condition of the grinding table changes).

The final step of the proposed algorithm was to construct the HMM. The states of HMM are chosen so as to represent physical condition of mill grinding plates. In order to illustrate the proposed method, it is assumed that HMM has three states. The first state is the condition of the grinding table immediately after replacement (i.e., that of a new grinding table). Having in mind that the average length of mill grinding table duration is 1500 h approximately, the fact that HMM is in the first state could be interpreted as the grinding tables being in the first third of their life. The second state was the "intermediate state," where the grinding table becomes partially worn out, but there is still time before replacement is needed. Consequently, the system staying in second state can be interpreted as the grinding tables entering the second third of their lifetime. The third state means that the condition of the grinding table had deteriorated to the point where replacement is necessary. As shown, research started from the assumption that HMM has only three states; if it is needed that the grinding table conditions are characterized with greater precision, the number of states could be increased. In this way estimating the Remaining Useful Life (RUL) would be much more reliable.

After the sequence of observations was calculated, the third problem (HMM training) needed to be addressed. The Baum-Welch algorithm was applied and then the values of transition matrix A and emission matrix B were obtained as

$$A = \begin{bmatrix} 0.9982 & 0.0018 & 0 \\ 0 & 0.9982 & 0.0018 \\ 0 & 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1.0000 & 0.0000 & 0 & 0 \\ 0 & 0.8167 & 0.1115 & 0.0718 \\ 0 & 0.2776 & 0.3844 & 0.3379 \end{bmatrix}. \tag{14}$$

Following HMM training, the second problem (described in Section 3) was addressed by means of the Viterbi algorithm. Figure 9 shows the sequence of observations and corresponding HMM states.

It is apparent in Figure 9 that the HMM provides information about a change in the condition of the grinding table. It is obvious that the time of HMM entry into the third state (worn out grinding table) coincides with the beginning of observations that correspond to the control chart samples for the signal recorded eight weeks after replacement.

5. Conclusion

The paper puts forward an innovative approach to condition-based maintenance, which was applied to a coal grinding subsystem at the Kostolac TPP in Serbia. The proposed method is a trade-off between solutions already offered in the literature, as it is based on the data-driven approach that does not require knowledge of a model, while an HMM is introduced to account for the fact that the process is nonstationary, where different states are defined to reflect a dynamic system and nonstationary observations. The application of T^2 multivariate control charts to spectral components was

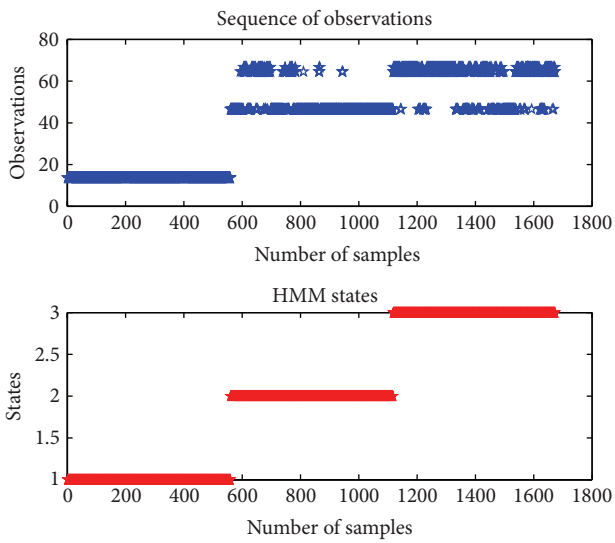


Figure 9: Hidden Markov Model states.

demonstrated as highly efficient. The results were as expected: as the coal mill grinding table became worn over time, the number of outliers (points above the upper control line) increased. After the control charts were constructed, the control chart samples were coded by means of vector quantization and taken as observations for the HMM. The combination of control charts and the HMM was highly effective; based on control chart samples, the HMM provided the needed information about the condition of the grinding table. The goal of the proposed method is to improve energy efficiency at the Kostolac TPP, which is likely achievable if the proposed algorithm is applied to on-line data. The advantage of the method is that it is noninvasive; it does not require the entire coal grinding subsystem to be shut down for inspection and thus prevents significant financial losses. The disadvantage of the method is that acoustic signals are recorded in the presence of unavoidable noise, which can affect the accuracy of the results. Signals need to be acquired by means of a directional microphone, at a distance of several millimeters to minimize the noise effect. Additionally, a large amount of data is needed for proper HMM training. Still, the proposed method is able to improve the operational stability and reliability of one of the key subsystems at thermoelectric power plants.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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