**Course Title:**

***Predictive Maintenance Based on Control Charts Applied at Thermoelectric Power Plant***

Chapter 3

# Predictive Maintenance Based on Control Charts Applied at Thermoelectric Power Plant

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Additional information is available at the end of the chapter

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**Abstract**

In this chapter, innovative predictive maintenance technique is described with the aim of highlighting the benefits of predictive maintenance compared to time-based maintenance. The proposed technique is applied to a specific problem that occurs when time-based maintenance is applied on grinding tables of the coal mill, in coal-grinding subsystem at the thermoelectric power plant 'TEKO', Kostolac, Serbia. Time-based maintenance provides replacement of grinding tables after certain number of working hours, but depending on the quality of the coal and grinding table itself, this replacement sometimes needs to be made before or after planned replacement. The consequences of such maintenance are great material losses incurred because of frequent shutdowns of the entire coal-grinding subsystem, as well as the possibility that the failure occurs before replacement. Innovative predictive maintenance technique described in the chapter is used for solution of this problem.

**Keywords:** predictive maintenance, $T^2$ control chart, hidden Markov model, thermoelectric power plant, statistical process control

## 1. Introduction

In today's industry, application of the best maintenance strategies is a very important task in ensuring stability and reliability of technical systems. Numerous papers and books about different maintenance strategies can be found in literature, and almost everywhere the merits of predictive maintenance in regard to time-based maintenance are emphasized [1]. Predictive maintenance extends the period of time during which the system functions well, decreases unnecessary shutdowns, reduces material losses and prevents catastrophic failures. Although this field of research is very much advanced with the development of highly sophisticated technologies, there is still a lot of room for improvement of the existing techniques and the development of new ones.

In this research, an innovative technique of predictive maintenance is proposed and applied to a specific problem that occurs at the thermoelectric power plant 'TEKO', Kostolac, Serbia. Namely, one of the key thermoelectric power plant components is the coal-grinding subsystem. When time-based maintenance is applied on grinding tables of the coal mill, grinding tables are replaced after certain number of working hours. Depending on the quality of the coal and grinding table itself, this replacement sometimes needs to be made before or after planned replacement. The only way to determine the condition of the grinding table is visual inspection, which implies the shutting down of the whole subsystem. Consequences of grinding table replacement after fixed time intervals are great material losses incurred because of frequent shutdowns of the entire coal-grinding subsystem. Also, there is a possibility that the failure will occur before replacement.

There is an 'urban legend' that experienced operators in industrial plants, such as thermoelectric power plants, can 'hear' the sounds in sound content from operational drives. Based on these sounds, they can recognize the detritions of specific elements that can wear out, such as mill-grinding tables. Also, in literature one can find that 99% of mechanical failures are foregone by some very noticeable indicators [2]. Because of these facts, the idea came up for the recording of acoustic signals while coal-grinding subsystem is operational. In this way, it is easy to obtain condition-monitoring data which can be applied for predictive maintenance, and there is no need for shutting down the whole subsystem for obtaining the information about grinding table condition.

The proposed method is a trade-off between solutions already offered in the literature, and originality of the proposed algorithm is based on the selection of failure prognostic technique. The main goal of the proposed algorithm is the increase of energy efficiency at the thermoelectric power plant.

This chapter is organized as follows: In the next section, we describe the concept of predictive maintenance in detail. In Section 3, a description of the coal-grinding subsystem in thermoelectric power plant will be given. In Section 4, we present a new predictive maintenance technique. Section 5 contains the results. The last section is the conclusion, with the discussion about gain results.

## 2. Predictive maintenance

Nowadays, industrial processes are very complex and cannot be imagined without modern technologies, so highly sophisticated and very expensive maintenance strategies are needed. Consequences of inefficient maintenance are large material losses, and because of that it is necessary to constantly develop and improve the existing maintenance programmes.

Maintenance strategies were evolving during time. The first maintenance strategy was the *unplanned maintenance* or *run-to-failure* maintenance which implies waiting for failure to occur. It is obvious that with this maintenance strategy catastrophic failures are unavoidable, so very rare this kind of maintenance is sustainable and profitable. Later, *preventive maintenance* was introduced. Preventive maintenance can be conducted as *planned maintenance* or

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*time-based maintenance*, which is implemented at fixed time intervals, or it can be conducted as *predictive maintenance* or *condition-based maintenance* where maintenance activities are realized based on the condition of the system. Although with time-based maintenance equipment failures sometimes can be reduced, it does not eliminate catastrophic failures and causes unnecessary maintenance. In literature, it can be found that in the USA, because of ineffective maintenance, more than 60 billion of dollars are spent every year [3]. Similar situation is in other countries. Namely, the biggest shortcoming of time-based maintenance is too often replacement of system's parts, as well as premature stopping of the system while it is operational, which leads to great material losses. In most situations, predictive maintenance is the best choice, especially when maintenance is very expensive and occurring of failure is unacceptable. The main goal of predictive maintenance is extension of time in which system functions well and at the same time reduction of unnecessary stoppages and failures. Also, the aim of predictive maintenance is to prevent the occurring of catastrophic failures which can produce not only material costs but also loss of lives and environment pollution. List of this kind of accidents is not small and can be found in Ref. [4]. Because of these catastrophic failures which occasionally occur in modern industries, more attention is paid to the improvement of the existing predictive maintenance strategies, as well as to introducing the new ones. If it is regularly established and effectively implemented, predictive maintenance can significantly reduce maintenance expenses through cutting down of unnecessary time-based maintenance operations [5].

Diagnostics and prognostics are two very important aspects in predictive maintenance programme. Diagnostics deals with fault detection, isolation and identification after occurring of the fault. Fault detection indicates when something goes wrong in a monitored system, that is, it detects that failure has occurred. Fault isolation has a task to locate faulty component, whereas fault identification has a task to determine the nature of the fault when the fault is detected. Diagnostics has been developed for years, and today it presents very important area in engineering and automatic control [6, 7].

Prognostics deals with fault prediction, before the fault will occur. In other words, diagnostics is the posterior analysis of events, while prognostic is a priori analysis of events. Prognostics is more efficient in regard to diagnostics for achieving zero-downtime performances. On the other hand, diagnostics is necessary when failure prediction within prognostic fails and fault occurs. References about prognostics can be found in Refs. [8, 9]. Predictive maintenance can be used for diagnostics and prognostics, or both. Some newer references about predictive maintenance can be found in Refs. [10–12]. No matter what is the goal of predictive maintenance, three key steps must be followed for its implementation: (1) data acquisition, (2) data processing and (3) maintenance decision-making.

Data acquisition is the process of data collection from specific physical resources in order to implement predictive maintenance properly. This process is the key step in applying predictive maintenance, both for diagnostics and for prognostics. Collected data can be classified into two major categories: *event data* and *condition-monitoring data*. Event data include information about what happened (faults, repairs, what were the causes, etc.). Condition-monitoring data are the measurements about physical resource 'health condition'.

The first step in data processing is data cleaning. This step is very important, because data (especially event data), which are entered manually always, have some mistakes. Without data cleaning, it is possible that diagnostics and prognostics will be inaccurate. The next step in data processing is data analysis. Different models, algorithms and tools for data analysis depend mostly from data type [5]. Condition-monitoring data can be classified into three categories: (1) value type, (2) waveform type and (3) multidimensional type.

The last step in predictive maintenance programme is decision-making. Techniques for decision-making can be divided into two categories: *diagnostics* and *prognostics*. It is obvious that prognostics is superior in regard to diagnostics, because it can prevent failure to occur, and if it is possible it provides spare parts and planned human resources for problems that will occur. In this way, it is possible to reduce material losses and avoid catastrophic failures. However, prognostics cannot replace diagnostics completely, because in practice there will be always some unpredictable faults.

Here, we focus on prognostics. There are two types of prediction when we talk about *failure prognostic*. The first type is the prediction of how much time is left before failure will occur (one or more failures) depending on the current state of the machine and past operation profile. Time that is left before the fault is noticed is called *remaining useful life* (*RUL*). In some situations, especially when failure is catastrophic (e.g. nuclear plant), it is much a preferable second type of failure prognostic, that is, prediction of probability that the machine will work until some future time (e.g. until next interval when inspection is needed) depending on the current state of the machine and past operation profile. Actually, in any situation, it is good to know the probability that a machine will work without failure until the next inspection or condition monitoring. Most papers deal with the first type of failure prognostic, that is, with *RUL* estimation [13, 14]. Only few papers can be found that deal with the second type of prognostic [15]. According to Ref. [8], failure prediction can be divided into three different categories:

1. Traditional reliability approaches—prediction based on event data (experience) [16]
2. Prognostics approaches—prediction based on condition-monitoring data [17, 18]
3. Integrated approaches—prediction based on event data and condition-monitoring data [19].

Every one of these approaches has some advantages and limitations. Combinations of these approaches are different according to their applicability, price, precision and complexity [20].

## 3. Description of the coal-grinding subsystem in thermoelectric power plant

Thermoelectric power plants are the largest producers of electricity in Serbia, contributing with more than 65% of the total electricity supply. In order to ensure their stability and operational efficiency, it is necessary to monitor their major subsystems and individual components. In this way, it is possible to detect any change in behaviour, or failure on time, which leads to the increase of energy efficiency and the reduction of the financial losses of the electric power industry.

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One of the key thermoelectric power plant 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

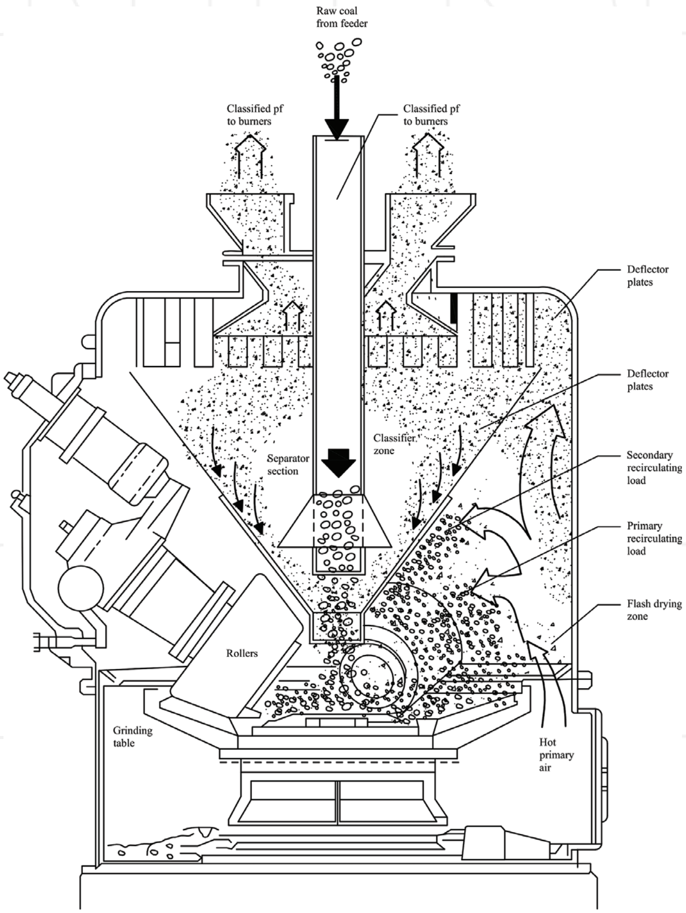


**Figure 1.** Configuration of the coal-grinding subsystem.

and fall back onto the grinding table for additional grinding. Both the separator and 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 [21, 22].

In this research, one such system at the thermoelectric power plant 'TEKO' (Serbia) is analysed. As it is previously described, the coal inside the mill is ground by impact and friction against the grinding table that rotates around the mill centre line (CL). The only way to determine 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, but at a cost of frequent shutdowns. If inspection shows that grinding table replacement is not yet necessary, then significant material losses will incur. In **Figure 2**, two grinding tables are shown. On the left figure is a new grinding table, immediately after replacement, and on the right figure is a worn grinding table, straight before replacement.


**Figure 2.** New grinding table (left) and worn grinding table (right).

In practice which is common on plant A1, at thermoelectric power plant 'TEKO', Kostolac, grinding tables are replaced every 1800 h. However, it often happens that because of the increased presence of limestone, sand and other impurities in coal, grinding tables become deteriorated already after 1400 h, or even shorter. In that case, weaker effectiveness of the mill is noticeable, it is 'chocked', and serious problem with regulation occurs in an attempt to regulate the temperature of air mixture and pressure of fresh steam in front of the turbine. This appearance has for consequence significant misbalance of temperature distribution inside the firebox, which has negative influence on increased water injection in fresh steam, knockdown of coefficient of boiler efficiency and so on. In such conditions, usually, mill must be stopped unplanned for grinding table replacement and that incurs financial losses. Because of that, system which offers predictive maintenance is of great importance.

## 4. Proposed new predictive maintenance technique

The proposed solution to described problem is based on predictive maintenance. In this research, for the last step in predictive maintenance, the condition-monitoring data approach

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is chosen. This approach can be divided into two main categories: *model-based* prognostic technique and *data-driven* prognostic technique. Here, data-driven technique is chosen, because condition-monitoring data were available. Model-based method requires an accurate model of the system, which is highly complex. Maffezoni presents a useful physical model of the mill, the so-called *mass-balance model* with 76 *ordinary differential equations* (*ODE*), better known as a *knowledge-based model* [21]. It is obvious that it is very hard to make accurate model of the system, so this approach was not considered. On the other hand, the experience-based prognostic approach could not be used, because of the variable data statistics and an insufficient amount of data. For all these reasons, the data-driven approach was selected.

As it is described earlier, the first step in predictive maintenance programme is data acquisition. In this 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 'TEKO' thermoelectric power plant, while it was operational. The main mill rotation frequency was about 12.5 Hz and the mill from which the signals were acquired had 10 impact plates.

Namely, in the literature it can be found that failure information is hidden in the spectral characteristics of vibration signals [23], but it has been demonstrated that in some cases acoustic signals are equally informative. In 2001, Baydar 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 [24]. 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 millimetres, while the coal-grinding subsystem was operational. Recording of these signals is performed at the low altitude in thermoelectric power plant, where acoustic contamination is highly expressed. Because of that, special system for microphone fixation is projected, at a distance of several millimetres from the walls of analysed mill, so the power of useful signal could be multiple higher than the power of contaminating acoustic sources as neighbouring mills, feed pumps, surrounding valves and so on. The sampling frequency of recorded acoustic signals was 48 kHz. Data acquisition was conducted every 2 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. For faster implementation of the algorithm, the sampling frequency was decimated from 48 to 4.8 kHz, and the duration of the analysed signals was 1 min.

We can see from **Table 1** that the whole time period from the moment of grinding table replacement until the moment when grinding tables are worn is covered. After the first cycle of acoustic signal recording, three more recordings were performed after grinding table replacement. In this way, based on recorded acoustic signals, coal-grinding subsystem data are collected in different states. A large base of condition-monitoring data is obtained (without disturbing coal-grinding subsystem while it is operational) which can be further processed.

The second step in predictive maintenance is data processing. Given that collected data are acoustic signals, they are classified as waveform type of data. In order to overcome disadvantages encountered when such data are analysed in time domain and frequency domain [25], these data are analysed in time-frequency domain. A spectrogram was used to assess the acoustic signals in

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

**Table 1.** Recorded acoustic signals.

the time-frequency domain, which represented the spectral components of the signals in three dimensions very well: time information along the horizontal axis, frequency information along the vertical axis and amplitude depicted by a colour-coded scale. Colour intensity illustrated the strength of the spectral components. **Figure 3** [26] shows the spectrogram of an acoustic signal recorded on 30 March 2012, 6 days after grinding table replacement.

**Figure 3** 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 on, according to the fact that there were 10 impact plates inside the mill, such that the basic frequency of grinding table travelling 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.

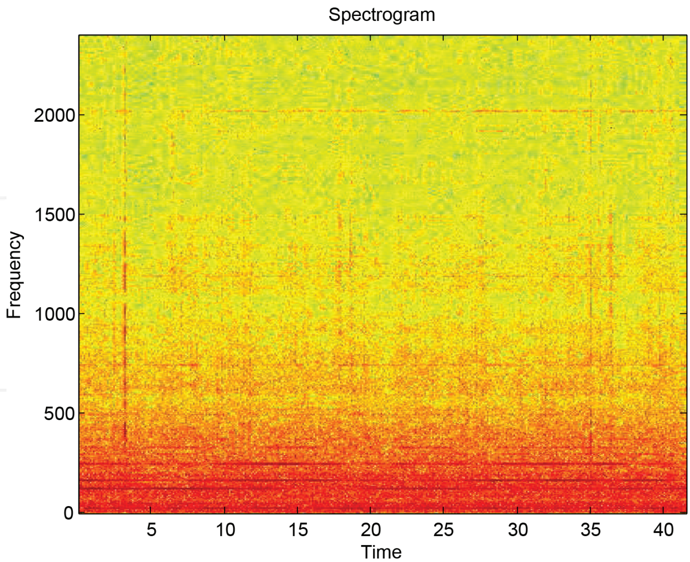


**Figure 3.** Spectrogram of acoustic signal.

After data acquisition, it was necessary 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. As it was mentioned earlier, a spectrogram was used for acoustic signal representation. If recorded acoustic signal is denoted as $y[n]$, the spectrogram of acoustic signal $S_p$ is often denoted as *short time fast Fourier transform* (*STFFT*) in literature [27] and computed as *fast Fourier transform* (*FFT*) on sliding window data. The idea of *STFFT* is dividing of the whole signal on segments with short time window, and applying the *Fourier transform* on each segment. The spectrogram represents a function of time and frequency arguments, which can be written as follows:

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

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 the vector $f_p$:

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

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

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

Coordinates of the vector $X[n]$ 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 $i$th coordinate of the frequency vector $f_p$, and $L_w$ is the length of the window function. This is a procedure for the generation of the initial observation vector. In this way, the data-processing step and feature extraction are completed.

The last step in predictive maintenance programme is maintenance decision-making. As it is described in the beginning of this section, data-driven technique is chosen, that is, it is decided that the input of the sequence of observations be analysed with $T^2$ control charts, and then, outputs of control charts will be the input sequence for *hidden Markov model* (*HMM*). *HMM* should give us the information about the grinding tables condition, that is, are they worn so that their replacement is necessary. This would be the second approach in failure prognostic, because of the prediction that the system will work without failure until some future time, that is, until the next interval when inspection is needed.

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 common causes of variations in the process and failures of the system. For a system where only common causes of variations are present, we say that such a system is under *statistical control*. A control chart generally has a centre line (*CL*), upper control limit (*UCL*) and lower control limit (*LCL*). The centre 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 the 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 the 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 [28, 29].

A multivariate analysis with Hotelling $T^2$ control charts was undertaken in the present research [30]. Based on observation vectors, $T^2$ sequence of values may be calculated according to the following equation:

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

where $\overline{X}$ and $S$ denote the sample estimators of the 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, sample estimators of vector of mean values and covariance matrix can be written as follows:

$$\overline{X} = \frac{1}{N}\sum_{i=0}^{N-1} X[i] \tag{6}$$

$$S = \frac{1}{N-1}\sum_{i=0}^{N-1}(X[i] - \overline{X})(X[i] - \overline{X})^T \tag{7}$$

The control limits in Phase II are

$$UCL = \chi^2_{(\alpha,p)}, LCL = 0 \tag{8}$$

where $\chi^2_{(\alpha,p)}$ is the upper $\alpha$ percentage point of the chi-squared distribution with $p$ degrees of freedom ($p$ represents the number of variables which is in our case 14). When the number of preliminary samples $n$ is large ($n > 100$), using chi-squared control limit in Phase II is reasonable approximation [29]. In Phase I, the limits are based on beta distribution:

$$UCL = \left[\frac{(n-1)^2}{n}\right]\beta_{(\alpha;p/2,(n-p-1)/2)}, LCL = 0 \tag{9}$$

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

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According to 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 the sequence number of sliding window data. In order to account for system dynamics, instead of the very last control chart sample, the last 10 samples were used for the characterization of the actual state of grinding tables. In other words, vector

$$O[n] = \left[\, T^2[n-9] \quad T^2[n-8] \quad \ldots \quad T^2[n] \,\right]^T \tag{10}$$

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 [31]. The result of *k-means* clustering is the sequence of $k$-cluster centres (centroids). In our case, based on *try-and-error* approach, it turned out that for $k = 4$ satisfying results are gain and cluster centres $(C_i, i = 1, 2, 3, 4)$ are obtained. Accordingly, the final vectors of observations $\hat{O}[n]$ are formed and forwarded to *HMM* in the following way:

$$\min_j \|O[n] - C_j\|^2 = \|O[n] - C_k\| \Rightarrow \hat{O}[n] = C_k \tag{11}$$

After the samples were coded as described above, the next step was to construct the *HMM*. An *HMM* is a statistical model used to describe the transition of a system between states. It is an extension of the ordinary Markov chains with non-observable or partially observable states. Generally, *HMM* has $N$ states $S = \{S_1, S_2, \ldots, S_N\}$ and $M$ observation symbols $V = \{v_1, v_2, \ldots, v_M\}$. *HMM* with three states is shown in **Figure 4**. 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

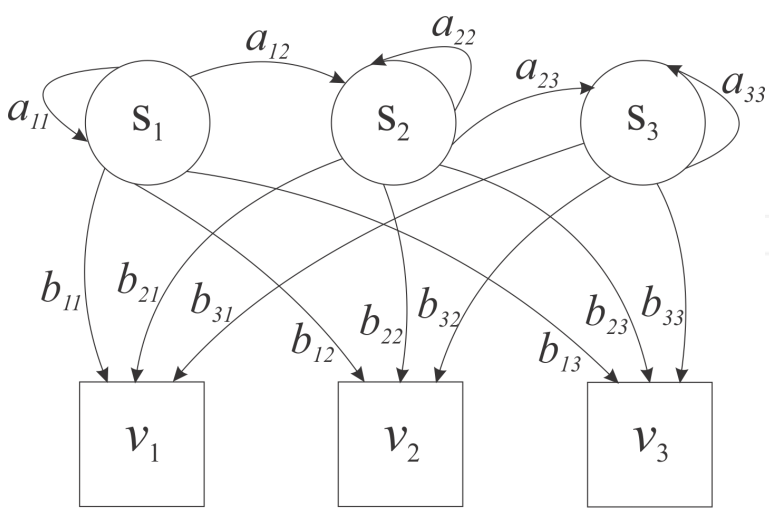


**Figure 4.** *HMM* with three states.

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 non-negative 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 **A** needs to be equal to 1. The observation matrix (also called the emission matrix) $\mathbf{B} = \{b_j(k)\}$ shows the probability that observation *k* was produced by the *j*th state.

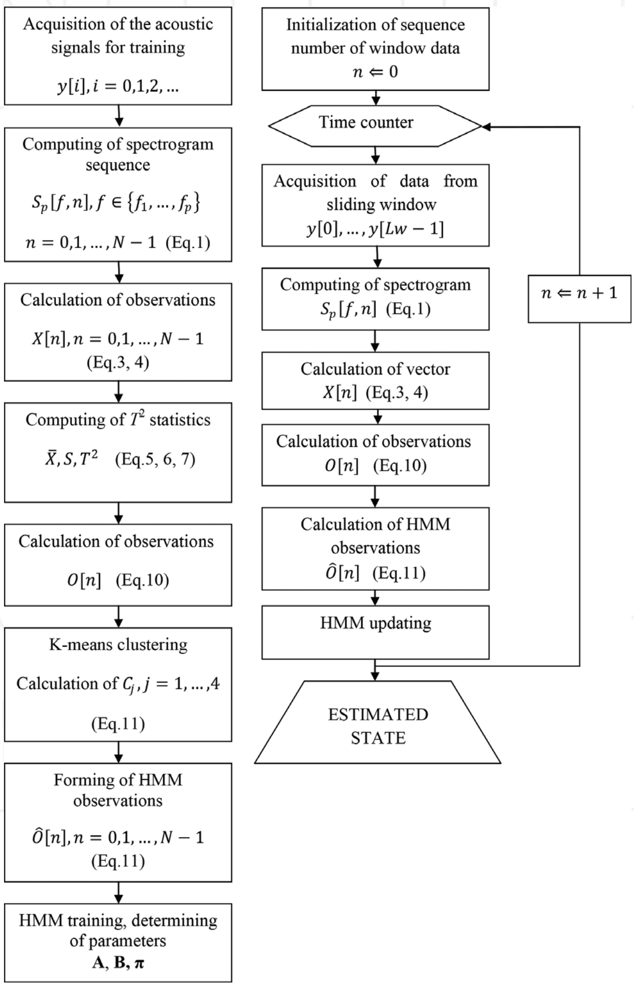


**Figure 5.** Flow diagram of the proposed algorithm: *offline* procedure (left) and *online* procedure (right).

The sequence of initial states $\boldsymbol{\pi} = \{\pi_i\}$ carries information about initial probabilities, indicating the likelihood that a new input sequence will move from a given state. Finally, the *HMM* can be defined by the triplet:

$$\lambda = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi}) \tag{12}$$

There are three fundamental problems that can be solved by means of *HMM*. A detailed description of *HMM*s and the solutions to these three problems is available in Ref. [32].

**Figure 5** [26] shows how the proposed algorithm for predictive 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 *offline* procedure) in order to determine the necessary statistics and *HMM* training. On the other hand, once the *offline* procedure is over, the algorithm can be implemented in real time and thus providing *online* monitoring of the mill-grinding plates states.

## 5. Results

In this chapter, gained results after applying the proposed technique for predictive maintenance on described problem at thermoelectric power plant will be presented. As it is previously explained, after data acquisition and feature extraction from recorded acoustic signals, $T^2$ control charts are formed.

The acoustic signal recorded on 30 March 2012 was used for $\overline{X}$ and $S$ estimation in Eqs. (6) and (7), 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 coal-grinding 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 chi-squared control limit was taken as the *UCL*, as in Eq. (8). For the 14 quality characteristics, $UCL = 36.12$ (for the value $\alpha = {}_{0.001}$) and $LCL = 0$. In order to justify the using of chi-squared control limit, in **Figure 6**, *Q-Q* plot [29] with $T^2$ quantiles on $y$-axis and chi-squared quantiles on $x$-axis are shown. For illustration, *Q-Q* plot for $T^2$ values for signals recorded on 30 March 2012 is shown, that is, for the signal recorded 6 days after grinding table replacement. During research, this check is done for all the signals in order to confirm that the choice of chi-squared control limit is justified.

From **Figure 6**, we can see that the values follow chi-squared distribution, that is, the figure shows approximately linear trend along the line of 45°, except the last few points which are slightly away from the projected trend line. Before $T^2$ control charts were constructed, we expected that the number of outliers will increase as grinding tables become worn out. **Figure 7** [26] shows the $T^2$ control chart for the acoustic signal recorded on 2 February 2012, 2 weeks after grinding table replacement.

**Figure 8** [26] shows the $T^2$ multivariate control chart for the acoustic signal recorded on 24 February 2012, 5 weeks after grinding table replacement.

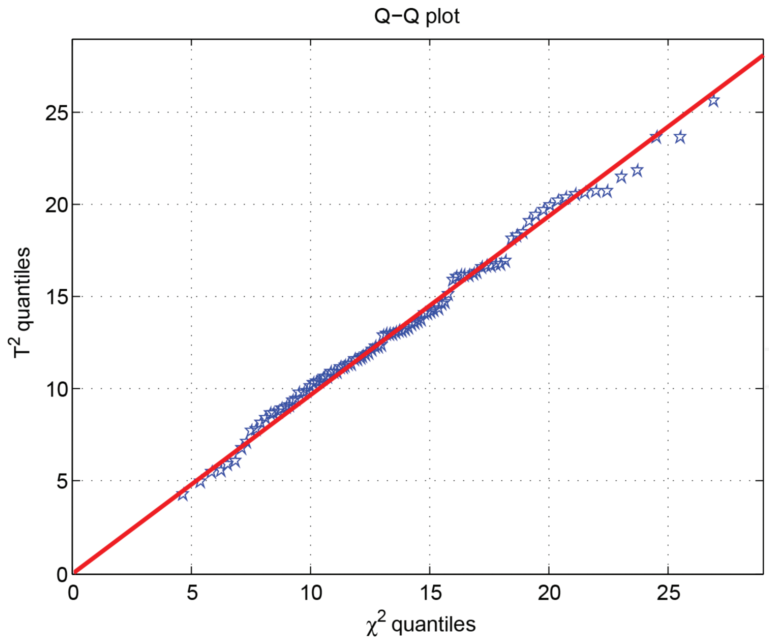


**Figure 6.** *Q-Q* plot for recorded acoustic signal 6 days after grinding table replacement.

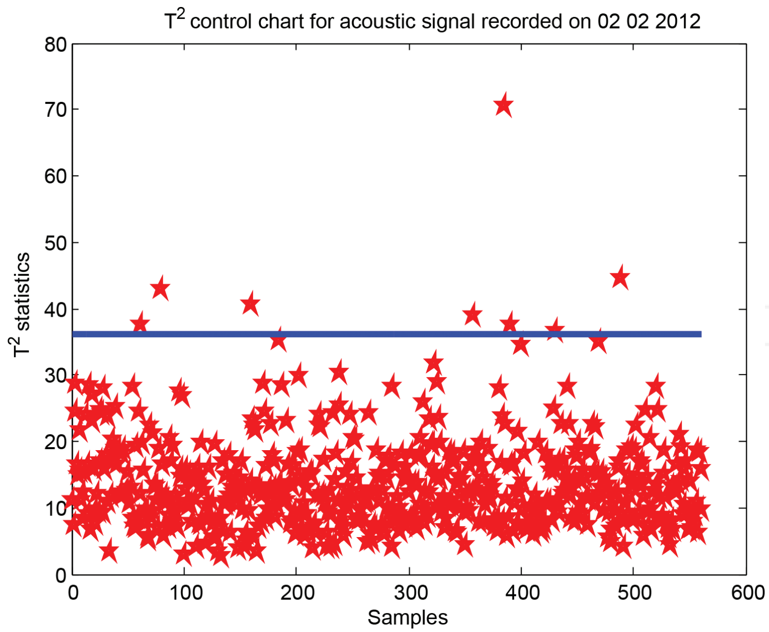


**Figure 7.** $T^2$ control chart for acoustic signal recorded 2 weeks after grinding table replacement.

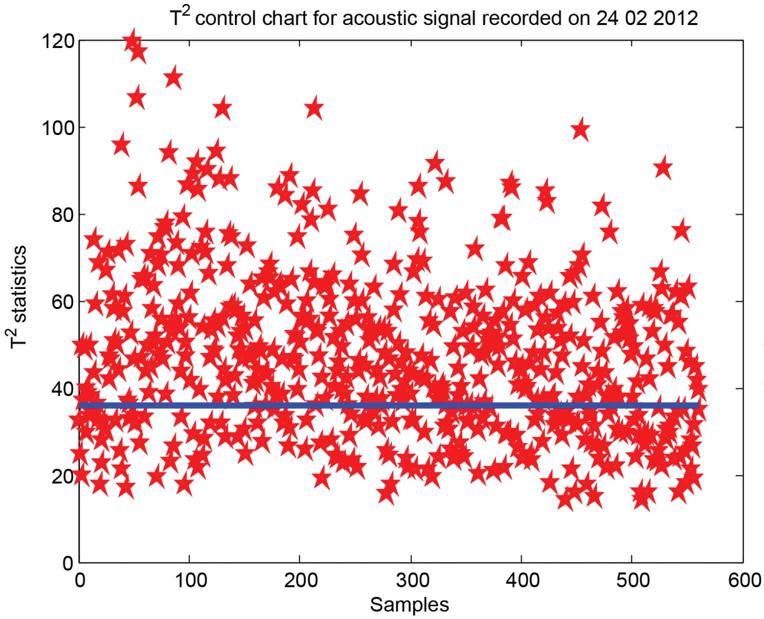


**Figure 8.** $T^2$ control chart for acoustic signal recorded 5 weeks after grinding table replacement.

**Figure 9** [26] shows the $T^2$ control chart for the acoustic signal recorded on 15 March 2012, 8 weeks after grinding table replacement.

It is apparent from **Figures 7–9** 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 confirm the results, the multivariate analysis was repeated using the signals recorded on 5 and 19 April 2012. Table 2 shows the exact number of outliers for all the recorded signals for the different values of *UCL* (i.e. for different values of parameter $\alpha$).

The difference in the number of points above the *UCL* for the signals recorded on 2 February and 19 April 2012 can be explained. Namely, both signals were acquired 2 weeks after grinding table replacement, but the results are different for two reasons: (1) The signal acquisition conditions were not ideal because of noise. All the recorded signals reflect this noise, as well as other disturbances (e.g. when a large chunk of coal or stone hits the mill). The signals were not filtered, because of the possible information loss. 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.

According to **Table 2**, we can conclude that with the choice of parameter $\alpha$ = 0.001, 'over controlling' control chart is constructed, while with the choice of parameter $\alpha$ = 0.025, false alarm rate is too large. Anyway, no matter which value of *UCL* we have chosen, the number of outliers is larger as grinding tables are getting worn out. Namely, in the proposed method

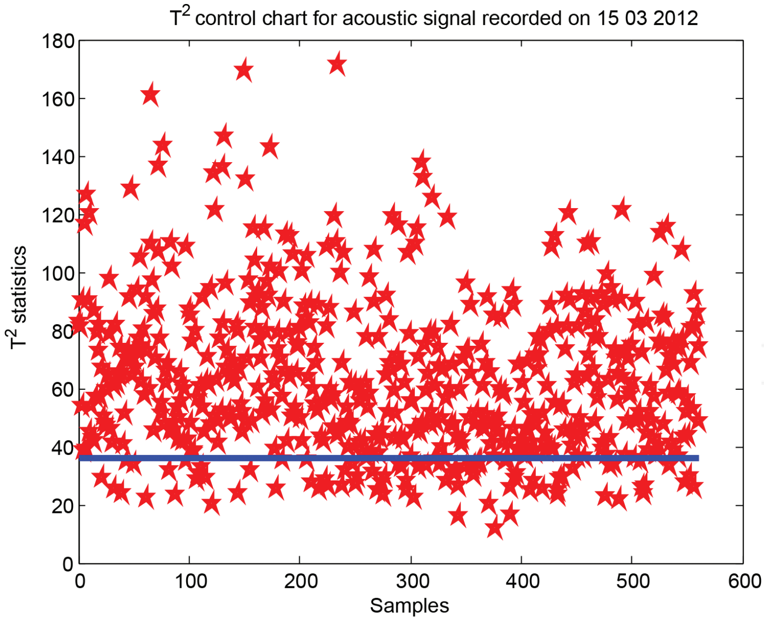


**Figure 9.** $T^2$ control chart for acoustic signal recorded 8 weeks after grinding table replacement.

control charts were not used for classical fault detection, yet for forming of $T^2$ statistics that will be parameterized for making the *HMM* observations. The choice of the *UCL* does not have an influence on $T^2$ statistics value, that is, on forming of observations for *HMM*. Thus, the choice of parameter $\alpha$, that is, making of compromise between the first type error and the second type error, does not have an influence on observation values for *HMM*, which is not usually the case

| Date of recording | Number of weeks after grinding table replacement | Number of points above UCL (%), $\alpha$ = 0.001, UCL = 36.12 | Number of points above UCL (%), $\alpha$ = 0.005, UCL = 31.32 | Number of points above UCL (%), $\alpha$ = 0.01, UCL = 29.14 | Number of points above UCL (%), $\alpha$ = 0.025, UCL = 26.12 |
|---|---|---|---|---|---|
| 2 February 2012 | 2 weeks | 1.43% | 2.14% | 2.46% | 5% |
| 24 February 2012 | 5 weeks | 68.27% | 79.5% | 83.78% | 88.41% |
| 15 March 2012 | 8 weeks | 84.85% | 90.91% | 92.87% | 95.54% |
| 05 April 2012 | 2 weeks | 16.75% | 27.63% | 32.98% | 43.14% |
| 19 April 2012 | 4 weeks | 57.58% | 70.05% | 74.87% | 81.64% |

**Table 2.** Number of points above UCL.

when classical control chart needs to detect the fault and when the choice of parameter $\alpha$ has large influence for the correct determination of *UCL*.

After $T^2$ control charts were constructed, 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 10** [26] shows the estimated probability density functions of the $T^2$ control chart samples for the signals recorded 2, 5 and 8 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).

The final step of the proposed algorithm was to construct the *HMM*. The states of *HMM* are chosen so to represent the 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 1600 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 the 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. Namely, this research started from the assumption that *HMM* has only three states, but if it is needed that the grinding table

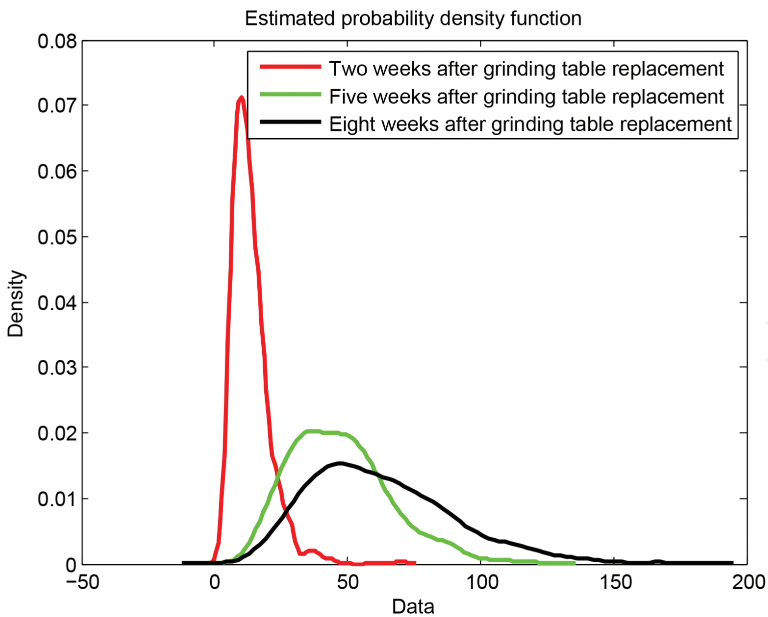


**Figure 10.** Estimated probability density functions for signals recorded 2, 5 and 8 weeks after grinding table replacement.

conditions are characterized with greater precision, the number of states could be increased. **Figure 11** [26] shows the sequence of observations and corresponding HMM states.

It is apparent from **Figure 11** 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 8 weeks after replacement.

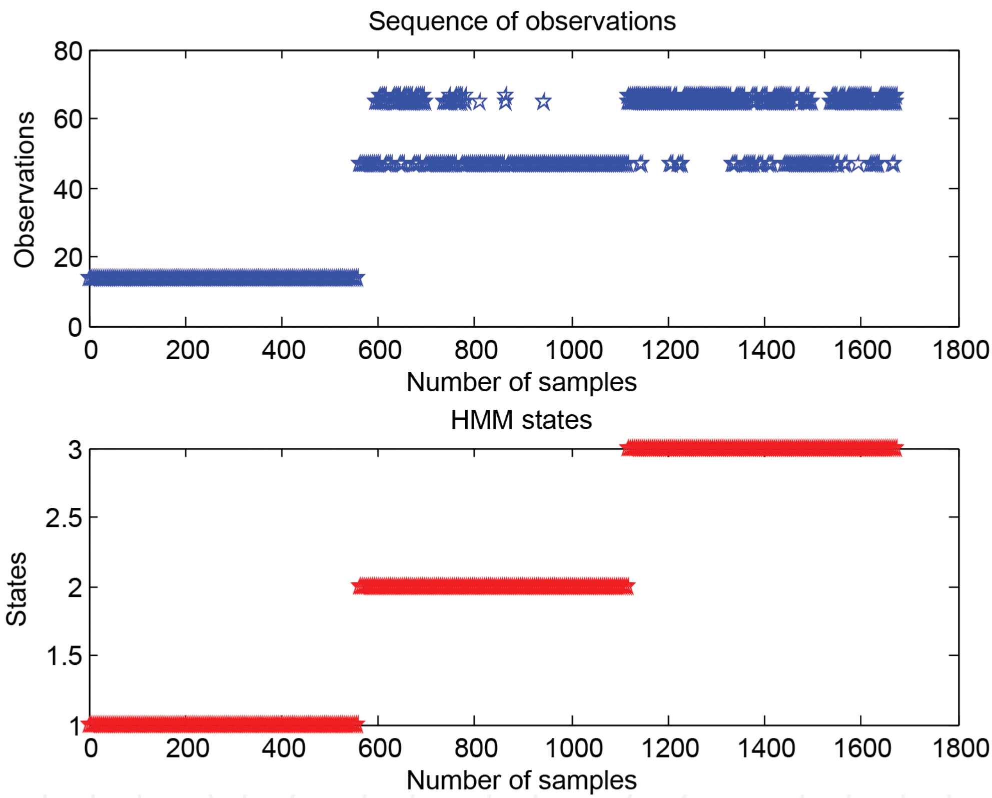


**Figure 11.** *HMM* states.



## 6. Conclusion

Based on the presented results, we can make several conclusions. Firstly, the assumption set at the beginning of this research, that useful information from spectral components of acoustic signals can be extracted is confirmed. Based on this information, the condition of rotating elements of the mill can be recognized. As it is previously explained, in the literature there are mostly preferred vibration signals in regard to the acoustic signals, when we talk about informative content. Given

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that the recording of acoustic signals is much cheaper than the recording of vibration signals, and processing of acoustic signals is much simpler from vibration signals processing, confirmation about informative content of acoustic signals is very important.

The originality of the proposed method is a combination of control charts and *HMM*s in failure prognostic, as well as in the application of control charts on extracted components from spectrogram. Namely, in the literature one can find control charts whose construction is based on spectral analysis of the signal [33]. Here, a different approach is proposed, that is, to apply the $T^2$ control charts on spectral components of the signal. Based on the results, this approach has proven to be very efficient. In the literature, one can also find the application of control charts and *HMM*s for degradation process diagnosis [34], as well as for fault detection [35], but in these papers standard *p*-charts and Hotelling $T^2$ control charts are used. Reports of other research dealing with the detection of certain types of failures at thermoelectric power plants can be found in the literature [36–38]. Also, *HMM*-based diagnostic models founded upon the condition of the system can be found in Refs. [39, 40]. In regard to all mentioned references, the original approach is proposed here.

As it is previously described, in the case of failure prognostic, in literature the most common approach is the first approach, that is, the estimation when the fault will occur (*RUL* estimation). In this research, the accent is on the second approach, that is, on the estimation of probability that the machine will work without failure until some future time (in our case, until the next interval when inspection and grinding table replacement are needed). With the proposed method, *HMM* gives us the information about grinding tables condition, that is, when the grinding tables are worn out, so that their replacement is needed.

The advantage of the proposed method is that it is non-invasive, because for the acquisition of condition-monitoring data it is not necessary to interrupt coal-grinding subsystem operation and shut down the whole subsystem. Another advantage is that it is based on acoustic signals processing which are simpler for processing and acquisition in regard to vibration signals. Software realization of the proposed algorithm is not too much complex and it is not time consuming when *HMM* is once trained.

A shortcoming of this method is the recording of acoustic signals in the presence of the unavoidable noise, which can influence on the accuracy of the results. Presented results are gathered *offline*, that is, *HMM* is trained based on the already recorded signals. For applying this method on *online* data, much larger amount of data are needed for adequate *HMM* training and more accurate determining of time moment when the grinding table replacement is needed. Anyhow, the proposed method can be applied in real time and used for higher stability and reliability of one of the most important subsystems in a thermoelectric power plant.

Further direction in this research would be the making of an adaptive system which would be adjustable to new statistics which are consequences of components ageing, not just the condition of grinding tables plates. Also, significant study could be made when condition-monitoring data would be recorded vibration signals, for comparative analysis with acoustic signals. Additional event data could upgrade the proposed method in combination with condition maintenance data. Some future research could be to make optimal maintenance policy in thermoelectric power plant, according to gain results.

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