FACTA UNIVERSITATIS
Series: **Automatic Control and Robotics** Vol. 11, N° 2, 2012, pp. 141 - 151

ANALYSIS OF THE CONDITION OF COAL GRINDING MILLS IN THERMAL POWER PLANTS BASED ON THE T² MULTIVARIATE CONTROL CHART APPLIED ON ACOUSTIC MEASUREMENTS

UDC 621.311.22:621.317.36

Emilija Kisić[1], Vera Petrović[1], Sanja Vujnović[2], Željko Đurović[2], Milan Ivezić[1]

[1]School of Electrical Engineering and Computer Science of Applied Studies, Belgrade, Serbia
[2]School of Electrical Engineering, University of Belgrade, Belgrade, Serbia

Abstract. *In modern thermal power plants coal grinding mills are an important and very frequent subsystem. As time passes the grinders in the mills become depleted and the functionality of these mills decreases. Because of that the mills need to be stopped periodically, every 1500 hours, so they can be checked and, if necessary, repaired. During this maintenance check the production of electricity decreases, which often results in a significant financial loss in case when this maintenance was unnecessary. In this paper we propose a new approach based on a measurement of acoustic signals in order to determine the time when it is necessary to stop the mills for repair. The goal is to increase the energy efficiency of the process by eliminating the need to unnecessarily stop the entire subsystem. The proposed procedure is based on an application of T2 multivariate control chart on extracted parameters of acoustic signals in frequency domain.*

Key words: *T^2 control chart, spectrogram, coal grinding mills*

1. INTRODUCTION

Fault detection and predictive maintenance are one of the main issues addressed in industry today. Most methods that are currently used to avoid malfunction of any given component in industry are actually some form of time-based preventive maintenance, i.e. the component is regularly changed after a fixed time schedule and therefore the failures and the reductions of efficiency due to common wear out of materials are reduced. This is a significantly better method than simply waiting for a failure to happen before it can be

---

Received December 14, 2012
Corresponding author: Emilija Kisić
School of Electrical Engineering and Computer Science of Applied Studies, Vojvode Stepe 283, Belgrade, Serbia
E-mail: emilija.kisic@viser.edu.rs

repaired. However, this is not an optimal solution because the working life of the component is shorter than it needs to be and therefore the replacement cost is higher and the maintenance checks are more frequent. A good solution to this problem is presented in this paper and is a form of condition-based maintenance, i.e. the proposed algorithm uses the data about the process gathered while the process is in operation to detect how likely it is for the failure to occur. That data can therefore be used to schedule maintenance and repairs of the system before the break down occurs [1].

In this paper we propose a new method for applying multivariate T^2 control chart on spectral components of acoustic signal. The process on which the algorithm is implemented and tested is a coal grinding mill, a subsystem in thermal power plant Kostolac that is used to pulverize the coal before it gets into the furnace. This algorithm will estimate the health of the plates within the mill based on acoustic measurements taken on the outside of the mill while the mill is in function. We analyzed acoustic signals using a spectrogram for representation of the signal in the frequency domain. After the extraction of 14 amplitudes of spectrogram at frequencies which are higher harmonics of fundamental frequency of the mill rotation, we applied Hotelling's T^2 multivariate control chart on them. As we expected, as time passes and mills are more depleted, more points are outside the control limit on T^2 control chart. For the totally depleted mill all points are outside the control limit on T^2 control chart, and we have information when the timing for mill replacement is. In this way we could increase the energy efficiency of the process by eliminating the need to unnecessarily stop the entire subsystem.

This paper is structured as follows: in the next section we present the general theory of control charts. In section 3 the coal grinding mill, a subsystem in thermal power plant is introduced, in details with its most important features. In section 4 we present the parameter extraction of acoustic signals recorded near the surface of the mill, while the mill is in operation. In section 5 the experimental results are presented. In section 6 the conclusion and a short discussion about the proposed method are given.

2. MULTIVARIATE CONTROL CHARTS

In any production process, regardless of how well it is designed and maintained, a certain amount of natural variability will always exist. Control charts make a clear difference between changes that are the result of numerous, always present immeasurable disturbances in the process and changes that are the result of system fault. The control chart is a statistical tool for fault detection in the system.

The control chart is a graphical display of a quality characteristic that has been measured or computed from a sample versus the sample number or time. A typical control chart contains a center line (CL) that represents the average value of the quality characteristic corresponding to the in-control state, e.g. only common causes are present. Two other horizontal lines, called the upper control limit (UCL) and the lower control limit (LCL), are also shown on the chart. These control limits are chosen so that if the process is in control, nearly all of the sample points will fall between them.

The first step in constructing the control chart requires the analysis of preliminary data set which is assumed to be in statistical control. This phase is called phase I. In this phase it is very important to establish reliable control limits for phase II. In phase II, we use the control chart to monitor the process by comparing the sample statistic for each successive sample as it is drawn from the process to the control limits.

When we monitor only one qualitative characteristic of interest, we use *univariate control charts* [7]. There are many types of control charts which can be chosen depending on the nature of the process [1]. When we monitor more qualitative characteristics which are correlated, we use *multivariate control charts* which take this correlation into account. We can find in literature T^2 [8], MEWMA [9] and MCUSUM [10] control charts. In this paper we performed multivariate analysis with T^2 control chart.

The most familiar multivariate process-monitoring and control procedure is the Hotelling T^2 control chart for monitoring the mean vector of the process. Hotelling was first to propose a multivariate control chart based on a statistical distance [8].

Suppose that m samples are available and that p is the number of quality characteristics that we observe. Let $\overline{x}$ and S be the sample mean vector and covariance matrix, respectively. The Hotteling T^2 statistic is

$$T^2 = (x-\overline{x})^T S^{-1}(x-\overline{x}) \tag{1}$$

where x is the observation vector of size $1 \times p$, $\overline{x}$ is the mean vector of size $1 \times p$, S is the covariance matrix of size $p \times p$ and the symbol ^{T} represents the transpose of a vector or a matrix.

The phase II control limits for this statistics are:

$$\begin{aligned} UCL &= \frac{p(m+1)(m-1)}{m^2mp} F_{\alpha,p,m-p} \\ LCL &= 0 \end{aligned} \tag{2}$$

When the number of preliminary samples m is large ($m > 100$) many practitioners use an approximate control limit, either

$$UCL = \frac{p(m-1)}{m-p} F_{\alpha,p,m-p} \tag{3}$$

or

$$UCL = \chi^2_{\alpha,p} \tag{4}$$

For $m > 100$, equation (4) is a reasonable approximation. The chi-square limit in equation (5) is only appropriate if the covariance matrix is known, but it is widely used as an approximation. Lowry and Montgomery [12] show that the chi-square limit should be used with caution. If p is large ($p > 9$), then at least 250 samples must be taken before the chi-squared upper control limit is a reasonable approximation to the correct value.

Tracy, Mason and Young [13] point out that the phase I limits should be based on a beta distribution. This would lead to phase I limits defined as

$$\begin{aligned} UCL &= \frac{(m-1)^2}{m} \beta_{\alpha,p/2,(m-p-1)/2} \\ LCL &= 0 \end{aligned} \tag{5}$$

where $\beta_{\alpha,\ p/2,\ (m-p-1)/2}$ is the upper percentage point of a beta distribution with parameters $p/2$ and $(m - p - 1)/2$. Approximations to the phase I limit based on the F and chi-square distributions are likely to be inaccurate. A detailed explanation about computing these parameters can be found in [1].

As we can see in the equation (1), the T^2 statistic is a scalar. So, we can plot the value of the T^2 statistic for different time instants, and with an appropriate control limit, the T^2 control chart is obtained. On this chart, each point represents the information extracted from all the p variables. A fault is detected when a point is beyond control limit [11].

3. Case-study: Coal Grinding Mills in Thermal Power Plants

Coal fueled thermal power plants are the biggest energy provider in Serbia and they play a vital role in electricity generation worldwide. It has been estimated that the energy acquired with the use of coal fuels currently constitutes around 40% of global electricity production, as estimated by the International Energy Agency, IEA 2012 [3]. For that reason the improvement of productivity and efficiency of coal fueled thermal power plants is of great importance.

One of the key subsystems in thermal power plants is the coal mill used to pulverize the coal before it gets into the plant furnace. The interior of the mill rotates and the plates located on the inside grind the coal into a small size powder. During that process the plates within the mill slowly get depleted and the productivity of the mill gradually decreases until it becomes completely dysfunctional (Figure 1). In order to prevent this from happening, the plates need to be changed as soon as the productivity of the mill decreases.

Fig. 1. Condition of the coal grinding plates within the mill immediately after replacement, when they are new (left) and immediately before replacement, when they are depleted (right)

In order to increase the productivity of the mill and prevent coarse pieces of coal to enter the furnace, the state of the plates needs to be correctly estimated. The most common procedure practiced in many power plants across Serbia is one form of time-based preventive maintenance, i.e. plates are changed periodically every couple of weeks (in thermal power plant Kostolac from which the acoustic measurements are taken, that period is around 1500 working hours). This strategy is not particularly efficient and this specified time is not always optimal. The plates deplete in various speed depending on the quality of the plates themselves as well as the quality of the coal which they grind. The maximum working time of the plates is therefore not used.

There is no unique way to detect the optimal time after which the plates should be replaced. The only infallible method is visual inspection of the inside of the mill, and in order to enable that, the entire subsystem of the power plant needs to be stopped and the mill opened. This is both dangerous and costly, especially if during that inspection it is concluded that the replacement of the plates is not necessary.

The advantage of the proposed method of detecting the health of the plates is that it is based on acoustic measurements that are taken outside of the mill, while the mill is in function. This expands the working life of the plates and reduces cost of maintenance by reducing unnecessary disturbances of the entire subsystem.

4. Parameter Extraction of the Acoustic Signals

The recording of the acoustic signal is made with directed microphone at a distance of a few millimeters from the mill while the subsystem for coal grinding is in function. The acoustic signal is recorded with sampling frequency 48 kHz, and the recording was done on average every other week for a period of several minutes. Dates of signal recording and the mills replacement, and also the duration of each acoustic signal are presented in table 1. All signals are recorded at the thermal power plant Kostolac.

Table 1. Recorded acoustic signals

Date of the recording	Signal length
Replacement of the mill is done 19.01.2012.	
02.02.2012.	10min 51s
24.02.2012.	8min 8s
01.03.2012.	8min 8s
15.03.2012.	7min 3s
Replacement of the mill is done 24.03.2012.	
30.03.2012.	6min
05.04.2012.	5min
19.04.2012	6min

Sampling frequency is decreased with decimation from 48 kHz to 4.8 kHz and the analysis is performed on signal duration of one minute for faster implementation of the algorithm.

We analyzed acoustic signals in the frequency domain using a spectrogram. Actually, we wanted to analyze spectral components of acoustic signals and a spectrogram is a very good representation of signal's spectral components. The spectrogram is a representation of a signal in three dimensions: on horizontal axis we have information about time, on vertical axis information about frequency, and amplitude is represented with color scale, or different levels of gray. Strength of spectral components is represented with the intensity of color. In figure 1 there is shown the spectrogram of acoustic signal which was recorded on 30.03.2012. We can clearly see dominant frequencies and conclude that dominant frequencies are higher harmonics of fundamental frequency of mill rotation which is 12.5 Hz. The extracted parameters in the frequency domain are amplitudes of spectrogram on frequencies around higher harmonics or precisely higher harmonics. We chose 14 spectrogram frequencies for extraction and they are presented in vector f:

$$f=[\ 14\ \ 18.7\ \ 23.4\ \ 28.1\ \ 32.8\ \ 60.93\ \ 126.5\ \ 178.1\ \ 187.5\ \ 262.5\ \ 346.8\ \ 754.6\ \ 1200\ 2025]$$

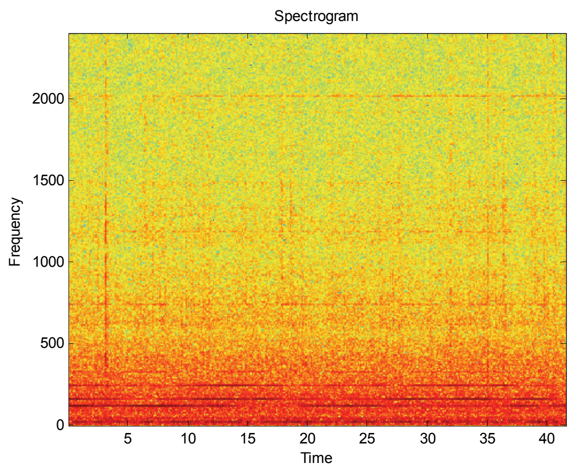

Fig. 2. Spectrogram of acoustic signal recorded 30.03.2012.

For spectrogram computing we used MATLAB function *spectrogram*. The division of signal on windows is already implemented within the function *spectrogram*. It was necessary to define the length of window, step of analysis (size of overlapping of windows) and the number of points for calculating the fast Fourier transform. In other words, the function *spectrogram* divides the acoustic signal on overlapping windows (we define window length and size of overlapping), and then for every frame it counts the fast Fourier transform in number of points that we define and we can read from spectrogram information about time, frequency and amplitude of signal.

In this paper for the type of window we have chosen Hamming's window. For the length of window we have chosen N=1024 according to the formula

$$N = \frac{(1 \div 3)F_s}{F_f} = \frac{(1 \div 3)4800}{12.5} = (384 \div 1152) \tag{6}$$

where F_s is sampling frequency and F_f is fundamental frequency of the mill rotation. For the step of analysis we took N/2. For the number of points for calculating the fast Fourier transform we chose M=1024 in order to have big resolution, e.g. for sampling of 4800/1024 = 4.68 Hz.

After the extraction of parameters in frequency domain we have 14 qualitative characteristics (14 spectrogram amplitudes on different frequencies that are computed for 389 overlapping windows) for multivariate analysis with T^2 control chart.

5. Experimental Results

In order to determine the timing when it is necessary to stop the mill for replacement we took extracted parameters of acoustic signal recorded on 30.03.2012 for the estimation of mean values and covariance matrix when we know that the new mill is in function. We can say that this is phase I in frame of the statistical process control when the whole subsystem in thermal power plant is under statistical control. These mean values and covariance matrix will be used in phase II of multivariate analysis. We expected change in the dominant frequencies of acoustic signal as time passes, e.g. we expected that T^2 multivariate control chart will show that depleted mills are out of statistical control. We also expected that as the time passes and mills get more depleted, more points will be outside of the control limits until the mill becomes totally depleted and all the points move outside the control limits. In this way according to the recorded acoustic signal it is possible to determine timing for stopping the mill for replacement.

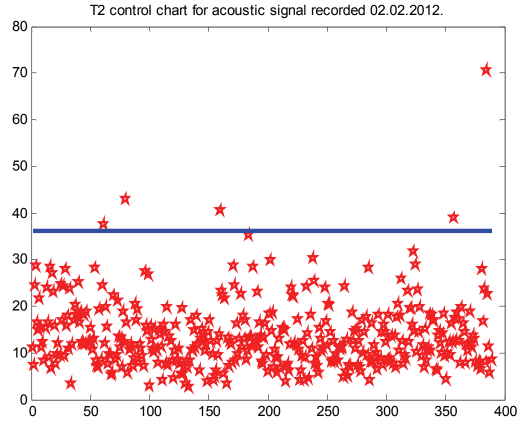

Fig. 3. T^2 control chart for acoustic signal recorded two weeks after the mill replacement

For the computation of T^2 statistics we used formula (1). For upper control limit we used chi-square control limit as in formula (4). We applied T^2 control chart on 14 amplitudes of spectrogram at frequencies *f*. For 14 qualitative characteristics upper control limit is UCL=36.12. Lower control limit is LCL=0.

In Fig. 3, T^2 multivariate control chart is shown for acoustic signal recorded 02.02.2012, two weeks after the mill replacement. On Fig. 4, T^2 multivariate control chart is shown for acoustic signal recorded 24.02.2012, five weeks after the mill replacement. In Fig. 5, T^2 multivariate control chart is shown for acoustic signal recorded 15.03.2012, eight weeks after the mill replacement.

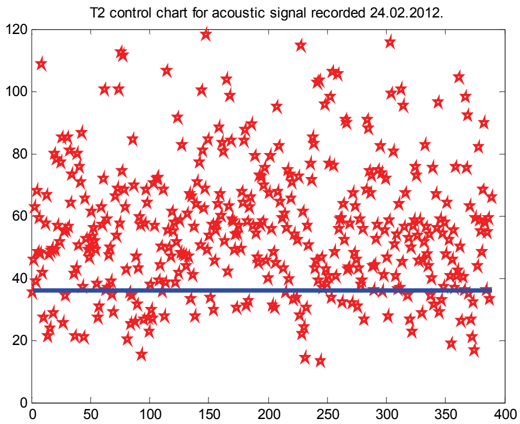

Fig. 4. T^2 control chart for acoustic signal recorded five weeks after the mill replacement

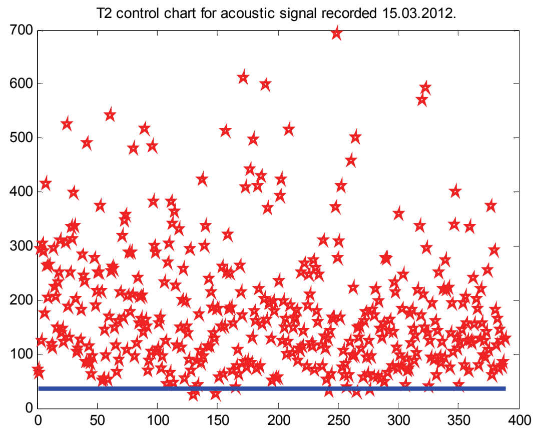

Fig. 5. T² control chart for acoustic signal recorded eight weeks after the mill replacement

After the analyses of Figs. 3, 4 and 5 we can see that number of points which are beyond upper control limit on T² multivariate control chart is bigger as mill is getting more depleted. Eight weeks after the last mill replacement almost all points are outside the control limit and we can say that the whole subsystem in thermal power plant is out of statistical control and it is time for the mill replacement. In order to confirm these results we repeated our analysis on acoustic signals which are recorded two weeks and four weeks after the new mill replacement.

In Fig. 6, T² multivariate control chart is shown for acoustic signal recorded 05.04.2012, two weeks after the mill replacement.

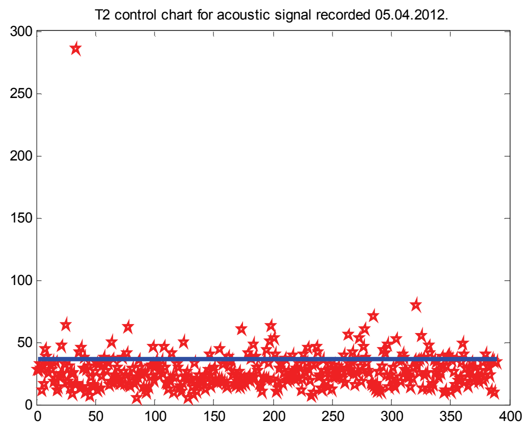

Fig. 6. T² control chart for acoustic signal recorded two weeks after the mill replacement

In Fig. 7, T^2 multivariate control chart is shown for acoustic signal recorded 19.04.2012, four weeks after the mill replacement.

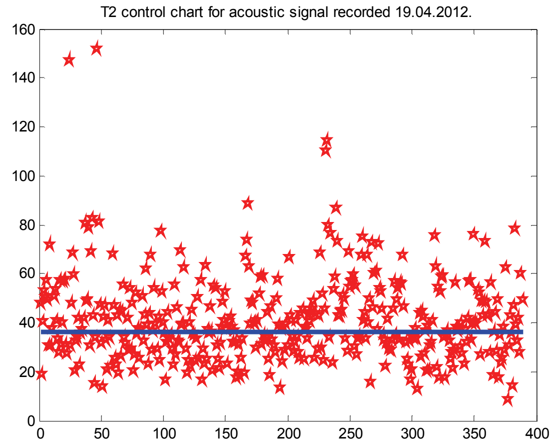

Fig. 7. T^2 control chart for acoustic signal recorded four weeks after the mill replacement

Again, our expectations are confirmed. For all acoustic measurements that we have T^2 multivariate control chart shows bigger number of points outside the control limit as time passes and the mill becomes more depleted.

In Table 2 the exact number of points which are beyond upper control limit for all recorded acoustic signals is given.

Table 2.

Date when acoustic signal was recorded	Number of weeks after the mill replacement	Number of points beyond upper control limit	Number of points beyond upper control limit [%]
02.02.2012.	two weeks	5	1.28%
24.02.2012.	five weeks	317	81.49%
15.03.2012.	eight weeks	383	98.45%
05.04.2012.	two weeks	65	16.7%
19.04.2012	four weeks	218	56%

We can explain the difference between number of points which are beyond the upper control limit for signals recorded 02.02.2012 and 19.04.2012. Both of the signals are recorded two weeks after the mill replacement, but results are different from two reasons. The first possible reason is that during the recording we did not have perfect conditions in the sense of noise presence. We can notice presence of noise in all recorded signals and also some other disturbances like when a rock hits the mill. We did not apply filtration on the signals because of the possible information loss. That can affect the accuracy of the results.

The second and more important reason is that the depletion of the mills depends on the quality of the plates themselves as well as the quality of the coal which they grind. That is the reason why we cannot be sure when it is the real timing for the mill replacement unless we open the mill and stop the whole subsystem. Our results confirmed this and showed that number of points beyond upper control limit is different for the signal which was recorded 24.02.2012, two weeks after the mill replacement and 05.04.2012, also two weeks after the mill replacement. We can say that the proposed method gives good results.

6. CONCLUSION

In this paper is proposed a new method for applying multivariate T^2 control chart on spectral components of acoustic signal. This is not a traditional fault detection method, because the proposed algorithm uses the data about the process gathered while the process is in operation to detect how likely it is for the failure to occur. The advantage of this method is that it is not invasive, i.e. it is not necessary to stop the entire subsystem in a thermal power plant for inspection.

We can conclude that this method gives good results and can be used to increase the energy efficiency of the process in thermal power plants by providing the information when it is necessary to stop the entire subsystem for mill replacement.

In our future work we can apply MEWMA and MCUSUM control charts on acoustic signals in order to confirm these results.

REFERENCES

1. G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess, B. Wu, “Intelligent Fault Diagnosis and Prognosis for Engineering Systems”, John Wiley & Sons, NJ, USA, 2006.
2. D. C. Montgomery,“Introduction to Statistical Quality Control”, Fifth Edition, New York, John Wiley & Sons, 2005.
3. http://www.iea.org/aboutus/faqs/coal/
4. R. L. Mason, J. C. Young,“ Multivariate Statistical Process Control with Industrial Applications”, ASA-SIAM, 2002.
5. E.J. Jackson, “Multivariate Quality Control, Techniques of Statistical Analysis”, pp. 111-184, 1985.
6. T. Kourti, J.F. MacGregor, "Multivariate SPC Methods for Process and Product Monitoring", Journal of Quality Technology, Vol. 28(4), 1996, pp. 409-428.
7. W. A. Shewhart, "Economic control of quality of manufactured product", D. Van Nostrand Co., 1931.
8. H.Hotelling, “Multivariate quality control”, Techniques of Statistical Analysis, pp. 111-184, 1947.
9. C. A. Lowry, W. H. Woodall, C. W. Champ, S. E. Rigdon, “A multivariate exponentially weighted moving average control chart”, Technometrics, Vol. 34(1), pp. 46-53, 1992.
10. J. Pignatiello, G. Runger, “Comparison of multivariate cusum charts”, Journal of Quality Technology, Vol. 22(3), pp. 173-186, 1990.
11. S. Verron, T. Tiplica, A. Kobi, "Multivariate control charts with a Bayesian network", ^{4th} International Conference on Informatics in Control, Automation and Robotics (ICINCO'07), Angers: France, 2007.
12. C. A. Lowry, D. C. Montgomery, “A review of multivariate control charts ”, IIE transactions, Vol. 27(6), pp. 800-810, 1995.
13. N. D. Tracy, J. C. Young, R. L. Mason, “Multivariate control charts for individual observations”, Journal of Quality Technology, Vol. 24(2), pp. 88-95, 1992.

ISPITIVANJE STANJA MLINOVA U TERMOELEKTRANAMA NA OSNOVU T² MULTIVARIJABILNOG KONTROLNOG DIJAGRAMA PRIMENJENOG NA AKUSTIČKA MERENJA

Emilija Kisić, Vera Petrović, Sanja Vujnović, Željko Đurović, Milan Ivezić

U savremenim termoelektranama mlinovi za mlevenje uglja su važan i veoma čest podsistem. Tokom vremena, udarne ploče u mlinovima postaju istrošene i efikasnost ovih mlinova postaje sve manja. Stoga se mlinovi moraju zaustavljati periodično, svakih 1500 sati, kako bi se proverilo njihovo stanje i po potrebi izvršio remont. Tokom ove redovne provere stanja mlinova, proizvodnja električne energije opada, što veoma često dovodi do značajnih finansijskih gubitaka ukoliko remont nije bio neophodan. U ovom radu je predložena nova metoda bazirana na merenju akustičkih signala kako bi se odredio vremenski trenutak kada mlin treba da se zaustavi radi remonta. Cilj je povećanje energetske efikasnosti procesa izbegavanjem nepotrebnog zaustavljanja mlinova. Predložena metoda se zasniva na primeni T^2 multivarijabilnog kontrolnog dijagrama na izdvojene parametre akustičkog signala u frekvencijskom domenu.

Ključne reči: *T^2 kontrolni dijagrami, spektrogram, mlinovi za mlevenje uglja*