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Rusmir BAJRIĆ
Ninoslav ZUBER
Rastislav ŠOSTAKOV

RELATIONS BETWEEN PULVERIZING PROCESS PARAMETERS AND BEATER WHEEL MILL VIBRATION FOR PREDICTIVE MAINTENANCE PROGRAM SETUP

RELACJE MIĘDZY PARAMETRAMI PROCESÓW ROZDRABNIANIA I DRGANIAMI MŁYNA WENTYLATOROWEGO A USTAWIENIA PROGRAMU KONSERWACJI PREDYKCYJNEJ

Beater wheel mills are designed to prepare a coal powder air fuel mixture for combustion in furnace chambers of coal-fired power plants by coal drying, pulverizing, classifying and transport. Their multipurpose function usually results in operation instability accompanied by unacceptable vibration. This usually is a significant problem due to unplanned shutdowns. Beater wheel mill maintenance program requires special attention due to operation under non-stationary conditions. The purpose of this paper was to identify pulverizing process parameter that affect the beater wheel mill vibration level and severity at the same time by using statistical principles under a wide range of operating conditions. This paper intends to establish the foundations to investigate correlation of pulverizing process parameter with beater wheel mill vibration in order to setup a better predictive maintenance program. To achieve this goal, the beater wheel mill vibration under different combinations of selected pulverizing process parameters are analyzed using statistical tools. Experiments were carried out under different conditions for two identical but separated beater wheel mills. The influence of pulverizing process parameter, such as electrical current of the driving motor, mill capacity, boiler production, coal types on mill vibration are investigated to identify the potential malfunction of beater wheel mills and their associated components for predictive maintenance purposes. The results have demonstrated that the selected pulverizing process parameters do not have significant influence on beater wheel mill vibration severity. Unlike most coal mills where pulverizing process parameters must take into account, here with beater wheel impact mills it is not the case and condition monitoring of these mills could be conducted offline or online using standard vibration condition monitoring methods.

Keywords: *predictive maintenance, multiple regression analyses, non-stationary operational conditions, beater wheel mil.*

Młyny wentylatorowe są urządzeniami, które poprzez suszenie, rozdrabnianie, odsiewanie i transport węgla przygotowują mieszankę pyłowo-gazową przeznaczoną do spalania w komorach paleniskowych elektrowni węglowych. Ich uniwersalność zwykle wiąże się z niestabilną pracą połączoną z niepożądanymi drganiami. Jest to zwykle znaczący problem z uwagi na niezaplanowane przerwy w pracy. Program konserwacji młyna wentylatorowego wymaga szczególnej uwagi ze względu na działanie w niestacjonarnych warunkach pracy. Celem artykułu jest wyznaczenie parametrów procesów rozdrabniania wpływających jednocześnie na poziom i natężenie drgań młyna wentylatorowego przy użyciu reguł statystycznych w zróżnicowanych warunkach pracy. Zamierzeniem pracy jest stworzenie podstaw dla badań nad zależnościami między parametrami procesu rozdrabniania a drganiami młyna wentylatorowego w celu ulepszenia programu konserwacji predykcyjnej. Aby osiągnąć założony cel, przeanalizowano przy użyciu narzędzi statystycznych drgania młyna wentylatorowego przy różnych kombinacjach wybranych parametrów procesu rozdrabniania. Badania przeprowadzono w różnych warunkach na dwóch identycznych, lecz odrębnych młynach wentylatorowych. Wpływ parametrów procesu rozdrabniania, takich jak prąd elektryczny silnika napędowego, pojemność młyna, kotły, czy typ węgla, na drgania młyna zbadano w celu określenia potencjalnych awarii młyna i jego części składowych na potrzeby jego konserwacji predykcyjnej. Wyniki badań pokazały, iż wybrane parametry procesu rozdrabniania nie mają znaczącego wpływu na natężenie drgań młyna wentylatorowego. W przeciwieństwie do większości młynów węglowych, w przypadku których należy brać pod uwagę parametry procesu rozdrabniania, kontrola stanu młynów wentylatorowych może być prowadzona w trybie offline lub online za pomocą standardowych metod monitorowania warunków drgania.

Słowa kluczowe: *konserwacja predykcyjna, analizy regresji wielorakich, niestacjonarne warunki pracy, młyn wentylatorowy.*

1. Introduction

Typically the lignite fuelled power station is consisted of a number of tangentially fired furnaces with beater wheel arranged mill-duct systems. These mill-ducts systems are responsible for grinding the raw coal and distributing the pulverized fuel to the furnace at appropriate concentrations to provide ideal combustion characteristics within the furnace. Because the power station production is in direct relation with beater wheel mill availability, maintenance of beater wheel mill is very important task. Maintenance is a function that operates in parallel to production and can have a great impact on the capacity of the production and quality of the products produced, and therefore, it deserves continuous improvement [16]. According to the study conducted by Mobley [15], between 15% and 40% of total production cost is attributed to maintenance activities in the factory. Furthermore, with the energy costs, maintenance costs can be the largest part of any operational budget [14]. Predictive maintenance is a maintenance policy in which selected physical parameters associated with an operating machine are sensored, measured and recorded intermittently or continuously for the purpose of reducing, analyzing, comparing and displaying the data and information obtained for support decisions related to the operation and maintenance of the machine [6]. Predictive maintenance can be disaggregated into two specific sub-categories: statistical-based predictive maintenance - the information generated from all stoppages facilitates development of statistical models for predicting failure and thus enables the developing of a preventive maintenance policy and condition-based predictive maintenance-condition-based monitoring is related to the examination of wear processes in mechanical components [7]. Condition based monitoring (CBM) is one of the maintenance policies that require an intense use of modern technologies. CBM attempts to avoid unnecessary maintenance tasks by taking maintenance actions only when there is an evidence of abnormal behaviors of a physical asset. A CBM program, if properly established and effectively implemented, can significantly reduce maintenance cost by reducing the number of unnecessary scheduled preventive maintenance operations [2]. It is based on the periodical acquisition of data in order to verify the condition of the critical machinery, diagnosis of the faults and evaluation of the remaining life time of the machine [15]. The predictive maintenance through vibration analysis is the best tool for rotating machinery maintenance purpose. The vibration analysis is a technique, which is being used to track machine operating conditions and trend deteriorations in order to reduce maintenance costs and downtime simultaneously [1, 20]. Machine vibration signals often demonstrate a highly non-stationary and transient nature and carry small yet informative components embedded in larger repetitive signals due to external varying operating conditions and internal natural deterioration characteristics of machinery [21]. The traditional vibration-based diagnostic approaches for rotational machines are largely designed for stationary and known operating conditions. The problem of fault detection under fluctuating load and speed has received commendable attention so far. Usually, the information regarding operating conditions is directly used in the process of calculating feature values. On the other hand, there are approaches that exploit the non-stationary character of the vibration signals generated by mechanical drives operating under variable conditions [22]. Additionally, variable operational conditions may cause significant variation of the energy of investigated component. Vibration signals are particularly dependent on variable load and speed fluctuation [13]. However, these parameters cannot be used to precisely detect faults of machinery in unsteady operating conditions; as in the case here, where the rotating speed and load of the machine are always changing [19, 22]. To minimize the cost of power generation in thermal power stations based on CBM philosophy and vibration based diagnostic signature analysis techniques study for bowl-roller coal pulverizes where used [17]. The influence of operating parameters, such as coal flow, primary air flow, and operating temperature, on roller mill vibration are investigated. The experimental results for industrial tubular ball mil show that the operating modes of the mill, such as mill over-load, stable case, etc., can be diagnosed by proper interpretation of vibration characteristics; and also the unmeasured parameters, i.e., level of coal powder filling the mill, can be monitored on line [12]. Most of the researcher focused on ball and bowl mills but interaction of pulverizing process parameters with beater wheel mill overall vibration have not been reported. The objectives of the present study ware (1) to instigate correlation between pulverizing process parameter, such as electrical current of the driving motor, mill capacity, boiler production, coal types on beater wheel mill overall vibration, (2) to use multiple regression analysis to assess the quality of the beater wheel mill overall vibration prediction in regard of selected pulverizing process parameters with intent to gather appropriate information for beater wheel mill predictive maintenance program setup.

2. Beater wheel mill pulverized coal firing supplying system

The circulated flue gas of coal furnace is used to transport the fuel. Flue gas is discharged from the furnace, and then the pre-crushed coal transported by a belt conveyor is fed into the flue gas pipe through a feeder. Afterwards, a heat exchanger considerably decreases the flue gas temperature and the flue gas with the fed and crushed coal gets into the beater wheel mill. The beater wheel mill has two basic roles; it is a ventilator and a mill at the same time. Those two functions cannot be controlled separately which is considerable disadvantage of this technology. The mill is a beating–impacting type of mill. Combination mainly takes place by impacting and by beating in smaller extent. Beater wheel mill concept is shown on Fig. 1.

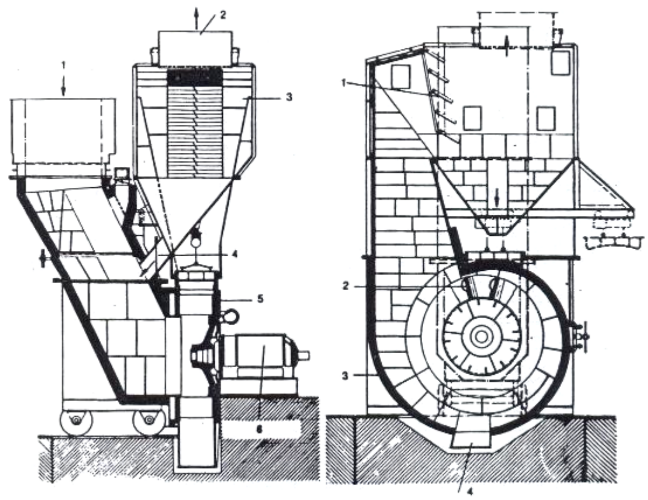

Fig. 1. Beater wheel mill concept; 1-coal and recalculation gasses; 2-mixture; 3-seperation; 4-return of larger coal particles; 5-beater wheel; 6-double bearing; (1)-regulation flap; (2)-beater wheel; (3)-housing armor; (4)-metal bins canal.

The product of the mill–classifier cycle is transported by the flue gas, through a heat isolated pipe into the burner in the furnace [3]. The total power requirement for grinding is dependent on the mill size, the grinding fineness specified and the type and layout of the suction and pressure ducting. The inlet ducting of the mill is mounted on a carriage assembly to facilitate access to the beater wheel. Since the wheel is the principal grinding element it suffers most of the wear. Mill availability is largely determined by the service life of the wheel and the ease with which it can be replaced [8]. It is usual to replace the worn beater wheel with a refurbished wheel and resume the operation. The worn wheel may then be refurbished and rebalanced at leisure [8]. Pulverized coal fuel availability is critical element in achieving an efficient combustion in power plants. To have high availability, maintenance of beater wheel mill is crucial. Failure or high vibration of beater wheel mill require mill shutdown and other fuel usage-like crude oil to maintain furnace production which increase an electricity production costs.

2.1. Beater wheel mill maintenance

Beater wheel mill vibrations influence the durability, operating condition and the product quality of many coal power plants. Vibrations can lead to component failures, speed fluctuations, surface defects and strip thickness undulations. The coal pulverizing process consists of sudden unstable condition and usually leading to high vibration resulting pulverizing shutdown and economic losses. Beater wheel mills, an important part of steam production process in most of Balkan countries coal-fired power plants have experienced many vibration problems during operation [4]. Therefore, studies of pulverizing process parameters are important and interesting for the determination of the beater wheel mill vibration origin, influence and distribution. While the construction geometry characteristics of beater wheel mill vibration have been studied [4], there is no available data for pulverizing process parameters and beater wheel mill vibration interaction. During operation, conditions are changing all the time and they are stochastic [10]. However, when rotation of the rotor, multiplied by the number of beater plates, approaches a resonant frequency, the vibration could rises well beyond an acceptable limit and resonances can be excited in the pipe, base, valve, pump or other nearby equipment [5]. Quality balance of rotor at the beginning, need for rotor replacement and its unbalance progression during operation could be clearly identified using vibration frequency spectrums at the beginning and end of lifetime of the beater wheel mill, primarily in axial direction [4]. Continuous and quality monitoring of beater wheel mill increases safety and productivities, reducing failure time and provide continuous operation in close optimum conditions [4].

3. Material and methods

To identify the relationship between the selected pulverizing process parameters and beater wheel mill overall vibration, multiple correlation and multiple regression analysis were used. Correlation measures the strength of inter relationship between the selected pulverizing process parameters and overall mill vibration. Multiple regression analysis is used to assess the quality of the prediction of the dependent variable. It corresponds to the squared correlation between the predicted and the actual values of the dependent variable. It can also be interpreted as the proportion of the variance of the dependent variable explained by the independent variables. When the independent variables (used for predicting the dependent variable) are pair wise orthogonal, the multiple correlation coefficient is equal to the sum of the squared coefficients of correlation between each independent variable and the dependent variable. This relation does not hold when the independent variables are not orthogonal [9]. It can be important to determine whether a multiple regression coefficient is statistically significant, because multiple correlations calculated from observed data will always be positive. The multiple regression procedure capitalizes on chance by assigning greatest weight to those variables which have the strongest relationships with the criterion variables in the sample data [18]. The ability of any single variable to predict the criterion is measured by the simple correlation and the statistical significance of the correlation can be tested with the t-test, or with an f-test. Often it is important to determine if a second variable contributes reliably to prediction of the criterion after any redundancy with the first variable has been removed [9]. Regression analysis is not always needed for prediction or explanatory models; sometimes the intention is only to adjust a regression equation to available data. In fact King [11] argues that the objective of a regression analysis is simply to measure the effects of predictors on the dependent variable. The experiments for the study were implemented under practical working conditions at synthetic soda ash producer FSL-Fabrika Sode Lukavac, Tuzla, Bosnia and Herzegovina, at furnace supplied by two fuel preparing systems, each with a beater wheel mill used for drying, pulverizing and conveying coal to furnace. Both beater wheel mills were used in the study. In this research beater mill produced by RGMK Serbia with 2090 mm rotor diameter driven by a three-phase electrical motor (320 kW and 987 min^{-1}) was used. Vibration measurement was carried out on the mill rotor double bearing housing support. In the vibration measurement, a vibration measurement device (Pruftechnik, Vibscanner) was used. The piezoelectric accelerometer (PruftechnikVIB 6.142 R) was mounted on the double bearing housing in axial direction. The accelerometer was connected to the vibration measurement device and vibration amplitudes Va-Root Mean Square were collected. Electrical motor speed was held constant at 987 min^{-1} in the measurements. Selected pulverizing process parameters in the tests were: electrical current of the driving motor Am, mill capacity Tkp, boiler production Qk, coal types St-Stanari, Ba-Banovići, Mr-Mramor. Measurement of mill overall vibration and selected pulverizing process parameters was simultaneously. Mill capacity setting was adjusted by the operator during the tests. Sampling systems were conducted for two fuel supplying systems, separately, followed the practical production needs only sampling time was constant. Eight tests for first and second fuel supplying systems were conducted. This procedure was applied to all test and 7 days was the time between tests. Duration of experiment was limited to 56 days and after this period unacceptable vibration was generated which required mill rotor replacement. The data recorded were statistically analyzed using multiple correlations and multiple regression analysis to study the effects of selected pulverizing process parameters to mill vibration.

4. Results and discussion

Selected pulverizing process parameters and overall mill vibration for the first and second fuel supplying system is shown on Fig. 2. It displays grouped Scatter Plots of overall mill vibration against other selected pulverizing process parameters over the different mill capacity. Correlation coefficient matrix for selected pulverizing process parameters and mill overall vibration is shown in Fig. 3, for first fuel supplying system as model 1, Fig. 4 for second fuel supplying system as model 2 and Fig. 5 considering both fuel supplying systems as model 3. Histograms of the variables appear along the matrix diagonal and scatter plots of variable pairs appear off-diagonal. Relationships provide interesting interaction information of selected pulverizing process parameters and mill vibration. Observing first fuel supplying system boiler production Qk correlation coefficient was highest while the mill capacity Tkp was lowest, presented in Fig. 3. All correlation coefficient was relatively low. Observing second fuel supplying

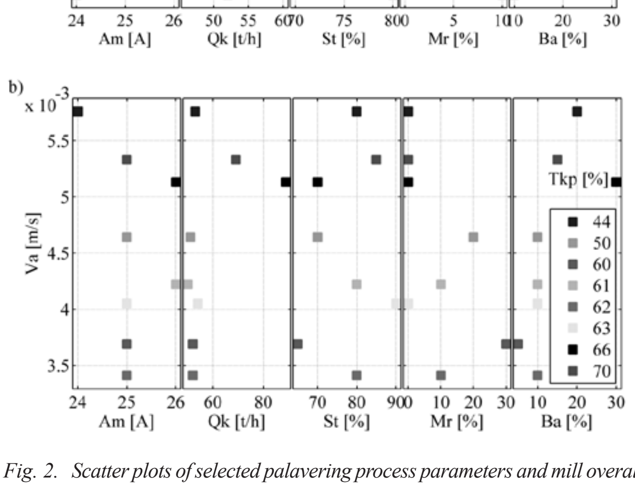

Fig. 2. Scatter plots of selected palavering process parameters and mill overall vibration: (a) First fuel supplying system; (b) Second fuel supplying system

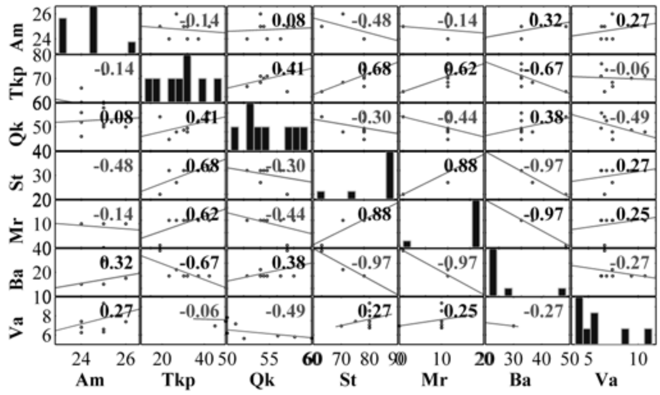

Fig. 3. First beater wheel mill correlation coefficient matrix

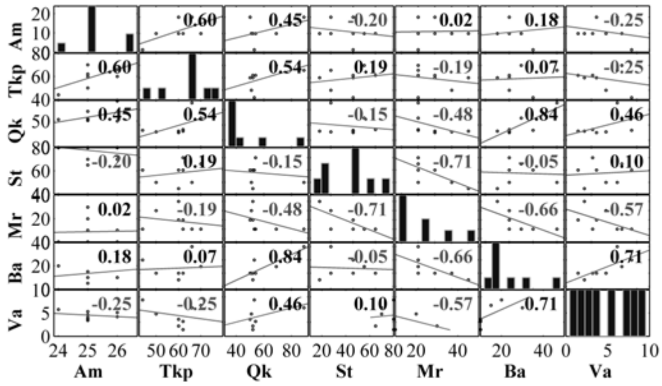

Fig. 4. Second beater wheel mill correlation coefficient matrix

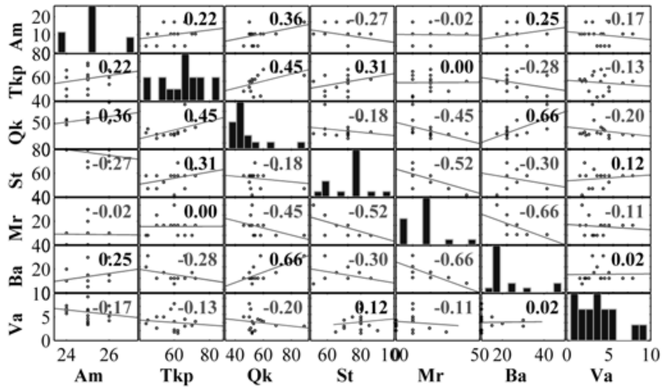

Fig. 5. Combined, first and second beater wheel mill correlation coefficient matrix

system, coal type Ba had highest correlation coefficient and the coal type St lowest, presented in Fig. 4. All other correlation coefficient was relatively low, too. Taking in to consideration both fuel supplying system and correlating vibration amplitude with selected pulverizing process parameters, it is evident low correlation interaction. In this case, with more data taking in consideration, the highest correlation coefficient had boiler production Qk and the lowest coal type Ba presented in Fig. 5.

Results of correlation coefficient analysis indicate that beater wheel mill overall vibration is not significantly correlated with selected pulverizing process parameters. Values of the correlation coefficient coal type Ba for the second beater wheel mill are relatively high and positive which indicates relation with beater wheel mill vibration in a positive linear sense. This could be explained due the relatively hard coal, much harder than other two types used in pulverizing mixture. Increasing the percentage of coal type Ba it results in increase of beater wheel mill vibration, presented in Fig. 4. Tables 1-3 shows results of analysis of variance for first, second and third model, respectfully.

Multiple regression analysis was used to test possibility of mathematical model development and the analysis of variance method was used to test their adequacy. The goal of the multiple regression analysis was to determine the dependency of selected pulverizing process parameters to beater wheel mill vibration. The input variables for model prediction were: electrical current of the driving motor, mill capacity, boiler production, coal types and output variable was mill overall vibration. The analysis of variance as model was used to test model regression significance. This approach uses the variance of the observed data to determine if a regression model can be applied to the observed data. The analysis of variance calculations for multiple regressions are nearly identical to the calculations for simple linear regression, except that the degrees of freedom are adjusted to reflect the number of explanatory variables included in the model. With this organization of the data sets, the modeling study for the beater wheel mill has been carried out. Model 1 estimating the relationships among selected variables for the first fuel supplying system, model 2 for the second fuel supplying system and model 3 for combined data sets of first and second fuel supplying systems. According to multiple regression analyses, 88 % for model 1, 73 % for model 2 and 15 % for model 3; beater wheel mill vibration variability depends on selected pulverizing process parameters. This analysis was out for a 5% significance level, i.e., for a 95%

Table 1. First wheel regression coefficients

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95%	Upper 95%
Intercept	-192,85	71,410	-2,700	0,1141	-500,1	114,39	-500,1	114,39
Am	1,8933	0,9467	1,9999	0,1835	-2,180	5,9665	-2,180	5,9665
Tkp	0,4949	0,3561	1,3896	0,2991	-1,037	2,0272	-1,037	2,0272
Qk	-0,9712	0,5287	-1,837	0,2076	-3,245	1,3035	-3,245	1,3035
St	1,9943	0,6809	2,9288	0,0995	-0,935	4,9240	-0,935	4,9240
Ba	1,5532	0,6080	2,5545	0,1251	-1,062	4,1693	-1,062	4,1693
Mr	0,0000	0,0000	65535	0,0000	0,0000	0,0000	0,0000	0,0000

Table 2. Second wheel regression coefficients

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95%	Upper 95%
Intercept	-0,2279	32,685	-0,007	0,9951	-140,8	140,40	-140,8	140,40
Am	-0,1393	0,7031	-0,198	0,8612	-3,164	2,8858	-3,164	2,8858
Tkp	-0,1124	0,1403	-0,801	0,5072	-0,716	0,4913	-0,716	0,4913
Qk	0,1014	0,1399	0,7247	0,5439	-0,500	0,7032	-0,500	0,7032
St	0,1090	0,2524	0,4317	0,7080	-0,977	1,1951	-0,977	1,1951
Ba	0,0000	0,0000	65535	0,0000	0,0000	0,0000	0,0000	0,0000
Mr	0,0590	0,1971	0,2992	0,0000	-0,789	0,9071	-0,789	0,9071

Table 3. Both wheels regression coefficients

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95%	Upper 95%
Intercept	17,341	22,2522	0,7793	0,4538	-32,23	66,922	-32,23	66,922
Am	-0,4974	0,9925	-0,501	0,6271	-2,708	1,7140	-2,708	1,7140
Tkp	0,1387	0,1790	0,7745	0,4566	-0,260	0,5376	-0,260	0,5376
Qk	-0,1833	0,1694	-1,082	0,3046	-0,560	0,1941	-0,560	0,1941
St	0,0000	0,0000	65535	0,0000	0,0000	0,0000	0,0000	0,0000
Ba	0,2361	0,2805	0,8417	0,0000	-0,388	0,8612	-0,388	0,8612
Mr	0,0056	0,1162	0,0484	0,9624	-0,253	0,2645	-0,253	0,2645

Table 4. Summary of the multiple linear regression models

Model	RR	R^2	Adjusted R^2	Standard error	Observations	Significance F
1	0.94	0.88	0.11	0.98	8	0,6170
2	0.85	0.73	-0.41	0.79	8	0,4029
3	0.39	0.15	-0.36	2.25	16	0,8825

confidence level. Model summaries in the terms of regression statistics are presented in Table 4.

After the models were obtained, including all variables considered predictors, the statistical significance of the model was tested. In the first place it was necessary to understand whether a mathematical model combining the predictors considered would be able to model the reality found in the field work. The value found for R^2 was 0.88 for model 1, 0.73 for the model 2 and 0.15 for model 3, which shows a poor match between the model and reality. The Significance F was used to evaluate the explanation of the regression model; since the Significance F for all three models is much higher than 0.05 for a confidence level of 95%, then the null hypothesis is accepted, there is no statistically significant association between selected pulverizing process parameters and overall mill vibration, indicate inappropriate multiple regression model build. In all three models, since the t values for all predictor coefficients are lower in absolute value than t-critical, it was considered that the models are not well adjusted. Also, 34% for model 1, 51% for model 2 and 92% for model 3; beater wheel mill vibration cannot be explained by selected pulverizing process parameters. Standard regression error, 0.98 for model 1, 0.79 for model 2 and 2.25 for model 3, indicates poor regression equations for all three models.

5. Conclusions

Linear relationship between the beater wheel mill overall vibration and selected pulverizing process parameters significantly does not exist and creation of mathematical model would not be adequate are major contributions of presented study. Beater wheel mill vibration cannot be fully correlated with the selected pulverizing process parameters and those parameters are not the only parameters that determine the level of mill overall vibration due to low correlation coefficients presented in statistical analysis. To effectively setup predictive maintenance program selected pulverizing process parameters need to be excluded as important factors. Unlike most coal mills where pulverizing process parameters must take into account, here with beater wheel impact mills it is not the case and condition monitoring of these mills could be conducted offline or online using standard vibration condition monitoring methods.

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Rusmir BAJRIĆ
Public enterprise Elektroprivreda BIH
Coal Mine Kreka
Mije Keroševica 1,
Tuzla, Bosnia and Herzegovina
E-mail: rusmir.bajric@kreka.ba

Ninoslav ZUBER
Rastislav ŠOSTAKOV
Faculty of Technical Sciences
University of Novi Sad
Trg Dositeja Obradovica 6, Serbia
E-mails: zuber@uns.ac.rs , sostakov@uns.ac.rs