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Understanding the influencing parameter for wear volume loss of roll crusher wear protection material

From the package study of wear from its beginning many systematic plan of action has been devised. The surface damage observed in many field such as crusher operating plants, bulk material handling of equipment's as operated in mining industries. This paper deals with identification of the effect of parameter, used for factorial design, on wear volume loss with the help of ANOVA.

Keywords: *Roll crusher, wear, ANOVA*

I. Introduction

From the past decades, roll crusher has been in use to crush less abrasive feed materials like gypsum, coal, limestone etc. The feed material although having less tensile strength in it has an ability to produce damages on roll surface. When factors responsible for the damages become severe, the wear mode changes shape from abrasive to impact wear. Thus the roll crusher is the very best example of it [1]. Depending on crusher types, wear is classified as abrasive, gouging, pure impaction or impact-abrasion. Impact wear is when the abrasive material strikes with kinetic energy on the surface of the contacting body with its repetitive action. Impact wear is therefore having higher magnitude of energy stored in it [2]. Adhesion, abrasion, erosion, surface fatigue, and wear due to thermal action are the mechanisms involved in impact wear. The roll crusher faces this problem of impact wear when the feed material strikes on the rolls before crushing action of feed observed [3]. When the crushing action of feed material begins then wear in roll crusher is characterised by scratching, surface deformation, gouging and indentation. The damages on the surface of the rolls are almost more severe when high stress is involved during crushing. Therefore to reduce the damages from the roll surface several modifications have been done on the basis to improve production quality of feed in crushing. The primary alternative material to protect surface of the rolls from damage is by providing wear protections [4].

As per the literatures available for knowing the surface modification of wear protection material from damage, statistical modelling by considering parameters responsible for wear was performed by many researchers. Based on this purpose Radhika et al [5] were performed a test on wear and frictional behaviour of reinforced composites of hybrid metal matrix. The experiment was carried on pin-on-disc wear tester. The plans of experiments were done with the help of Taguchi's technique. Further they selected an orthogonal array for analysing the data for wear rate and friction coefficient using ANOVA and regression equations. From their results sliding distance and load had most influencing behaviour on the results for wear rate and friction coefficient. Statistical investigation as performed by Mandal et al [6] on wear behaviour under combined action of rolling and sliding of alloy against hardened and tempered steel (AISI 4340). The factorial design of experiment of 2^3 was then carried-out to understand the effect of the factors on wear. The selected parameters are contact stress, speed and duration with respect to wear.

The review on statistical modelling of abrasive wear is performed to identify the effect of parameters from the one used for statistical analysis. As limited number of literatures are available for modelling of wear of roll crusher's wear protection materials. This paper deals with the purpose to identify the wear factors selected responsible for the damage of wear protection surface of roll crusher using ANOVA.

II. Data for design of experiment (DOE)

In the present paper work has been performed to determine the effect of parameters on wear volume loss from roll crusher plants. The parameters were selected from coke handling plant as shown in Table 1. The rolls surface in coke handling plant is protected against wear with the help of G × 130 Mn-Cr. 17.2. The hardness (H_{Liner}) of this wear protection material ranges from 350 to 400 BHN. The feed material used in for crushing was coke with hardness value of (H_F) of 4.5 to 5.5 mohs. To analyse the DOE, full factorial design was the first task to complete as shown in Table 2. The design was performed using 'P^n' relation where 'n' is the total factors/ parameters and 'P' stands for the number of level selected for the task as shown in Table 2. In Table 2, the three selected parameters are load, sliding distance and hardness with two levels selected i.e., low(-) and high (+). Therefore, total 8

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numbers of tasks was performed as shown in Table 3. The effect of parameters on wear volume loss at 95% confidence level. If the p-value obtained through ANOVA is less than 5% significance level than the particular parameter or their interaction with other parameter has significant contribution in wear volume loss. The result of ANOVA is shown in Table 4.

TABLE 1 DATA COLLECTED FROM THE PLANT

Plant/Feed material	Liner material	H_{Liner} (BHN)	H_{Feed} (mohs)
Coke	Mn-Cr	350 to 400	4.5 to 5.5

TABLE 2 PARAMETERS SELECTED FOR FACTORIAL DESIGN WITH TWO NUMBERS OF LEVEL

Parameters/ factors 'P'	Levels 'n'		
	Unit	–	+
Load (A)	N	6	10
Sliding distance (B)	m	746442	870850
Hardness (C)	MPa	1173	1340

TABLE 3 RESULTS OF 2-LEVEL FACTORIAL FOR WEAR VOLUME LOSS OF PLANT OF PLANT- A

Load (N)	Sliding distance (m)	Hardness (MPa)	Change
–	–	–	334.227
+	–	–	742.412
–	+	–	381.812
+	+	–	636.353
–	–	+	445.448
+	–	+	557.046
–	+	+	389.933
+	+	+	649.888

TABLE 4 ANALYSIS OF VARIANCE (ANOVA) FOR WEAR VOLUME LOSS OF PLANT-A

Source	P-value
Model	0.009
Linear	0.006
Load (N)	0.003
Sliding distance (m)	0.156
Hardness (MPa)	0.064
2-Way Interactions	0.017
Load (N) *hardness (MPa)	0.012
Sliding distance (m) x hardness (MPa)	0.035
3-Way Interactions	0.011
Load (N) × sliding distance (m) × hardness (MPa)	0.011

A. RESULT STUDY ON P-VALUE

The p-value obtained using ANOVA shows that load, the two-way interaction and three-way interaction is less than 5% level of significance. This suggests that these factors have major influence on wear volume loss as compared to sliding distance and hardness.

B. RESULT STUDY ON MAIN EFFECT PLOTS

From the result obtained under ANOVA for main effect plot as shown in Fig.1, it simplifies that the load increases with the increase of wear volume loss. Whereas, with the increase in sliding distance and hardness there is slight decrease in wear volume loss.

C. RESULT STUDY ON RESPONSE SURFACE PLOTS

From Fig.2 for response surface plots it is considered that load has great influence on wear volume loss than sliding distance and hardness. This term has correlation with self-hardening property of wear protection material. As self-hardening property increases wear decreases. Therefore, hardness has less significant effect on wear volume loss.

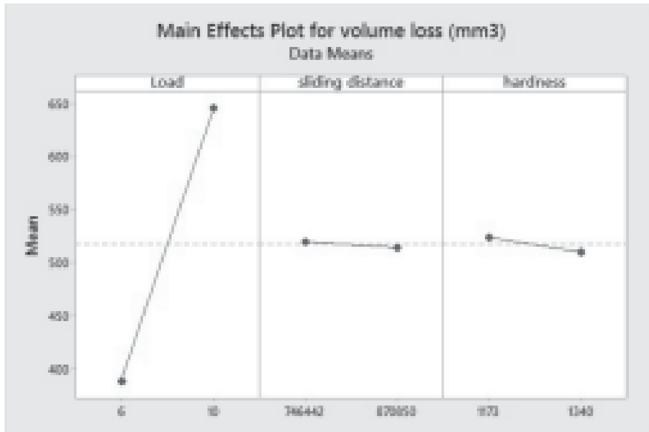

Fig.1 Main effect plots obtained under ANOVA

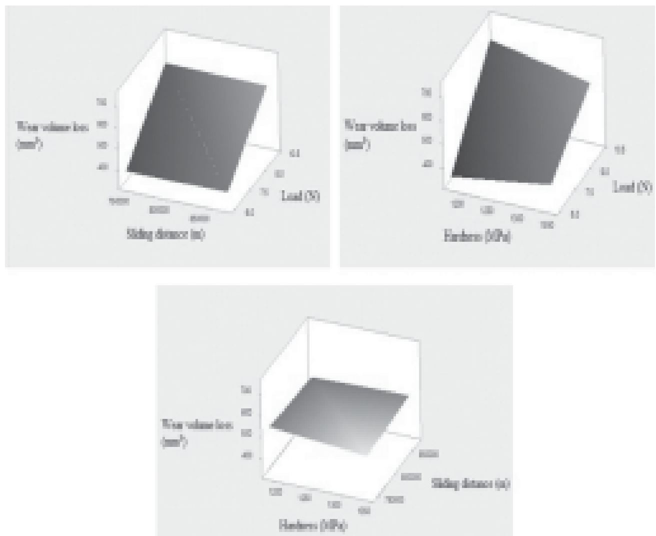

Fig.2 Results of response surface plot

III. Conclusions

The design of experiment found useful to understand the effect of parameters on wear volume loss from the surface of the rolls. With the help of ANOVA it has been found that load is the major influencing parameter on wear volume loss. There

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Table 3 Epoch and Validation result of jaw crusher and its components

System	Best epoch	Best validation
Jaw crusher	23	0.00000012
Back toggle plate	237	0.000000017
Chute liner plate	6	0.00000037
Jaw plate	1	0.000000096
Tie rod	17	0.000000011

Table 4 R^2 of jaw crusher and its components

System/component	ANN
Jaw crusher	98.99%
Back toggle plate	98.95%
Chute liner plate	94.37%
Jaw plate	99.14%
Tie rod	95.19%

Conclusions

Considering the relationship between inputs and output, the results obtained by the prediction models are highly encouraging and satisfactory. The ANN is found to be effective statistical method for failure rate analysis. The ANN has a very high R^2 between predicted and observed values. The R^2 value is high which agrees that the results are strongly correlated. Such analysis is important for better utilization of the equipment. The major goal for the implementation of this investigated technique is to modify the maintenance schedule to eliminate the failure modes.

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is slight change in mechanical properties with the change in hardness. Therefore, new generation of surface has better work hardening property due to increase in hardness.

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