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RESEARCH PAPER

OPTIMIZING THE WEIGHT CLOGGED OF A VIBRATING SCREEN DURING MINING OPERATIONS

P. Y. Andoh[1], **E. O. A. Acheampong**[2], **A. Agyei-Agyemang**[3], **P. O. Tawiah**[4] and **N. N Andoh**[5]

[1, 3, 4, 5]*Department of Mechanical Engineering, KNUST, Kumasi.*
[2]*Metso Ghana Limited, Dr K. Addo Kuffour Avenue, Plot 1, Block 7, Fox Towers, Patasi, Kumasi*

ABSTRACT
Mining companies usually face challenges of chronic clogging of screening media which causes frequent downtime, low efficiency and wear. Investigation of weight clogged (the amount of material retained on the sieve after screening) in the vibrating screen was carried out on sulphide ore samples during mining operations to study the effects of amplitude of vibration, aperture size and quantity of feed on weight clogged in the vibrating screen and to optimize the weight clogged during mining operations. Sieving analysis experiment was performed on the samples with a vibrator using the 2^3 design of experiments (DOE) method. The results showed that the aperture size was the most influencing factor of weight clogged, followed by the quantity of feed. Amplitude posed the least influence on weight clogged. The effects can be optimized at high amplitude (3 cm), at high aperture size (150 mm) and at low quantity of feed (600 g).

Keywords: *Weight clogged, screening process, factorial design, optimization, mining operation*

INTRODUCTION

A mine essentially consists of a series of operations, including drilling and blasting, crushing, screening, milling, flotation, and leaching. These are interconnected and therefore interrelated, with the performance of one operation affecting the performance of another. It is imperative to optimize each stage thoroughly. Generally, the process of producing a mineral (e.g. gold) can be divided into six (6) main phases, namely finding, the orebody that is creating access to the orebody which consist of two (2) types (Underground – a vertical or declined shaft, and Open-Pit – where the top layers of topsoil or rock are removed); removing the ore by mining or breaking the orebody; transporting the broken material from the mining face to the plants for treatment; processing and refining (Ali, 2003, Wills, 2006).

The journey from the run of mine ore to concentrate and finally obtain the mineral travels through many operations of ore liberation, separation, concentration, and extraction before it reaches the end users (Swapan, 2018). Throughout these operations screenings play a vital role in segregation either separating minerals from waste materials or grouping minerals according to sizes, concentration, and quality.

Consequently, these screens are employed in almost every mineral processing. The vibrating screens are the most utilised in mineral processing mainly due to its higher efficiency in separation, these screens break down the surface tension between particles that speeds up the separation process. Also, their ability to increase stratification of material so they separate at a much higher rate is another reason for its dominance in the mineral processing industry. The main limitation of these vibrating screens is that fine screens are very fragile and prone to becoming blocked very easily.

Vibrating screens can be grouped into three, based on the motion of the vibrating unit: Circular, linear and elliptical. The type of motion depends on the location on the mechanism related to the screen Centre of Gravity and the number of unbalanced shaft lines (Moody, 2007). Screens with a circular motion are the most common type. The vibration is circular because of a single eccentric shaft mechanism and this type of screen may be used for almost any application **(**Cambell, 2008).

Separation probability of a grain is obtained from the ratio between its size to that of the screen opening. The higher the variation in size, the easier it is for them to go through or to be hindered. particles of $0.5a < d < 1.5a$ are known as 'critical class' (where *a* is the mesh opening and *d* is the size of the grain). The rate of material flow through the screen-opening surface varies according to the degree of stratification and probability. particles with $d < 5a$ are of little relevance, since they easily pass through the mesh (Moody, 2007).

A vibrating screen is a machine with surface(s) utilized to differentiate sizes of a material. Screening is the mechanical process, which allows a separation of particles based on size and their acceptance or rejection by a screening media. Materials to be sorted out, when fed on the feed-box or directly on the screening media, lose their vertical velocity component and are opened to vary in direction of travel. Through vibration, the bed of the materials tends to develop into a fluid state which is subjected to processes which make classification possible (Cambell, 2008).

Sieving or screening has been the oldest yet most important unit operation for industrial separation of solid particles or as a laboratory method in size analysis Whitby (1958) studied a batch sieving process, using a standard Tyler Rotap sieve shaker. Several factors including, the size and shape of particles relative to the aperture of the sieve, the mesh size of the sieve, the amount of material on the sieve surface, the direction of movement of the sieve, and the rate of movement of the material relative to the sieve surface, have all been identified to affect operation and the efficiency of sieving in process industry (Allen, 2003).

In laboratory work, standard American Society of Agricultural Engineers (ASAE) procedure for particle size analysis of particulate materials requires the use of a stack of sieves (ASAE, 2003). Rhee *et al.* (2014), recommends nested sampling and analysis methods to be more efficient and economical for testing the soil and aggregate material with large-sized particles such as forest road aggregate.

Particle size distribution (PSD) is used to characterize soil (Zhao *et al*. 2010), road surface, and eroded sediment (MacDonald *et al*., 2001). Particle size distribution, which has a crucial influence on physical and chemical properties, is generally determined by sieving with a sieve stack (RETSCH, 2015). Its parameters are calculated from the sieve analysis with the general assumption that the distributions within the sieve fractions are linear, normally distributed and produce a mean particle size that is equal to the average of the sieve intervals (Carstensen and Dali, 1999). But it is not easy to quantify particle size and shape since there are no descriptive single parameter measurements of particle morphology (Meloy, 1984).

The size distribution of particles in granules is the basic feature that determines the rate of undersize passage through a screen hole that is wider than the smallest grain and smaller than the widest grain in a given sample of the material. Size distribution is a measure by sieve investigations, utilizing several acceptable wire mesh sieves with square holes that advance, in the mostly used Tyler standard scale7, (at constant rate of 26.67 mm to 73.66 mm). The size distribution is defined as the weight percentage of each fraction between different sieves in a series. An important useful graphic form is the logarithmic probability grid, utilizing a two-or three-cycle log scale as the y-coordinate and the probability scale as the x-coordinate. The extension of the probability scales outward from the average focuses on the extremes of the grain size distribution (Ali, 2009).

The tendency of any of the particles to go through a square hole in a woven screen media is determined by the variation between its mean geometries including the thickness (d) and the hole (L), and the wire width (t).

Mining companies are faced with a challenge of chronic clogging of screening media that causes frequent downtime, low efficiency and wear. Clogging problems arise when the near-mesh rocks block the screening media openings, preventing the passage of the undersize material. This produces enough re-circulation load as part of the material that should go through the screen comes back to the circuit, decreasing real crusher work output and overloading belt conveyors and other associated equipment. Mine operators usually have to stop the line to knock the trapped material out of the screening media. Moreover, the tertiary bins become over-filled due to the bottleneck downstream. Some of the media shaped to prevent clogging end up wearing out and breaking rapidly during operation, allowing rocks to pass through and increase unwanted sizes downstream.

Sieve blinding or clogging, which reduces the effective transfer area on the surface, resulting in reduction of sieving rates, is considered as the most important and direct controlling factor of sieving performance (Barbosa-Canovas *et al.*, 2005). The phenomenon of screen blocking, during sieving, involves particles of varying sizes and geometries being clogged in sieve holes which significantly decreases the screening efficiency (Lawinska and Modrzewski, 2017).

This study selected certain factors to determine their effect and combined effect on weight clogging and also the square geometry was selected for the aperture shape to address all the various particles geometries.

Hence the aim of this research is to investigate the effects of amplitude, aperture size and quantity of feed and their combined effects on weight clogged in the vibrating screen to minimize the weight clogged during mining operations. This was done by developing and validating a model to predict the weight clogged in the vibrating screen.

MATERIAL AND METHODS

Preparation of sample

The sample used for this research is the gold ores at the Obuasi mine which are of two kinds; these are the quartz and sulphide bodies, which are made of varied sulphide minerals such as arsenopyrite (FeAsS), pyrite (FeS), pyrrhotite [$Fe_{(1-x)}$ S(x=0-0.02)], chalcopyrite (CuFeS) and galena (PbS) (Oberthur *et al.,* 1994). The dominant component which is arsenopyrite, contains iron (Fe-45%), arsenic (As-33%), sulphur (S-20%), with lead (Pb), copper (Cu), zinc (Zn) etc., making up for 2% of dry weight of ores (Oberthur *et al.,* 1994; Foli *et al.,* 2011; Foli 2017). Quartz to sulphide ratio is about 30% to 70%. Carbonates, mostly calcite, occur as a gangue mineral in shear zones (Leube *et al.,* 1990), and together with carbon contents in carbonaceous schist, contain up to 5.02% of dry weight. The carbonates occur in the form of calcite ($CaCO_3$), dolomite ($CaMgCO_3$) and ankerite [Ca (Fe, Mg, Mn) $(CO_3)_2$] averaged 2.93% of dry weight and sulphur with an average value of 0.77% of dry weight (Foli *et al.,* 2011; Foli 2017), occur in country rocks.

This group of minerals have a cubic or dodecahedral crystal structure with rough or curved faces. It has a granular or compact massive nature. It has one different cleavage and is highly anisotropic. Its crystal nature is monoclinic. Sulphide minerals are the source of various invaluable metals, mostly gold, silver, and platinum. They are the ore minerals of most metals utilized by industry, as for example antimony, bismuth, copper, lead, nickel, and zinc. Other industrially useful metals such as cadmium and selenium occur in small quantities in numerous common sulphides and are recovered in refining methods (Galleries, 2018; Britannica, 2017).

Selection of control factors

In this study, screening processes are planned using statistical two-level full factorial experimental design. The process was conducted considering three processing parameters: Amplitude of the vibration, a (cm), Aperture Size of the topmost sieve, s (mm) and Quantity of Feed placed on the topmost sieve, f (g) and overall, 16 experiments were carried out. Table 1 shows the values of various processing parameters used for experiments.

Experimental method procedure

A sample was taken and thoroughly dried at a temperature of 60°C to reduce its moisture content. The dry weight, known as the initial weight, was measured carefully with the electronic measuring scale in an airtight environment to ensure minimal interference and carefully put on the topmost and covered with a lid of series of sieves. The dried sample was carefully put on the topmost sieve and covered with the lid of the series of sieves (Fig. 1).

Table 1: Experimental matrix

VARIABLES	LOWER LEVEL (-)	UPPER LEVEL (+)
Amplitude (cm)	2	3
Aperture size (µm)	75	150
Quantity of feed (g)	600	800

Note: Aperture is the size of the topmost sieve

Fig. 1: Preparation of samples
(Source: AngloGold Ashanti, Obuasi)

At the first setting condition, the 600g of the dried sample was feed onto the 75 µm aperture size of the topmost sieve with 2cm amplitude of vibration, the weight clogged (the amount of material retained on the series of sieve after screening) was measured and recorded. This process was repeated for the remaining set of conditions and the results were tabulated and presented in the Table 2. The experiment was conducted at respective sets of the amplitude, aperture size and quantity of feed as indicated in Table 1. This implies that there are $2^3 = 8$ experimental conditions. The experiment was replicated yielding a total of 16 experiment runs.

The computed averages were used as the responses for each condition in calculating the main effects and the interaction effects for the response.

ANALYSIS AND DISCUSSION OF RESULTS

Computation of effects and the standard error

The main effect of each of the process variables reflects the changes of the respective responses as the process variables change from a low to a high level. The average of the four measures is the main effect of the factor (variable).

The main effect of the amplitude is

$$E_a = \frac{1}{4}\{(w_2 + w_4 + w_6 + w_8) - (w_1 + w_3 + w_5 + w_7)\} \quad (1)$$

The main effect of the aperture size is

$$E_s = \frac{1}{4}\{(w_3 + w_4 + w_7 + w_8) - (w_1 + w_2 + w_5 + w_6)\} \quad (2)$$

The main effect of the quantity of feed is

$$E_f = \frac{1}{4}\{(w_5 + w_6 + w_7 + w_8) - (w_1 + w_2 + w_3 + w_4)\} \quad (3)$$

Two or more of the variables may jointly affect the responses. These joint influences are referred to as interactions. These interactions are given as follows:

The interaction between the amplitude and the aperture size is defined as:

$$E_a = \frac{1}{4}\{(w_2 + w_4 + w_6 + w_8) - (w_1 + w_3 + w_5 + w_7)\} \quad (4)$$

The interaction between the amplitude and the quantity of feed is defined as:

$$I_{af} = \frac{1}{4}\{(w_1 + w_3 + w_6 + w_8) - (w_2 + w_4 + w_5 + w_7)\} \quad (5)$$

The interaction between the aperture size and the quantity of feed is defined as:

$$I_{sf} = \frac{1}{4}\{(w_1 + w_2 + w_7 + w_8) - (w_3 + w_4 + w_5 + w_6)\} \quad (6)$$

Table 2: Results of experimental runs of process parameters on weight

Points	Code			Run 1	Run 2	Mean
	a	s	f			
1	-	-	-	178.1	184.3	w = 181.20
2	+	-	-	174.9	180.9	w = 177.90
3	-	+	-	74.3	75.2	w = 74.75
4	+	+	-	70.7	71.3	w = 71.00
5	-	-	+	278.9	281	w = 279.95
6	+	-	+	233.5	257.8	w = 245.65
7	-	+	+	97.8	98	w = 97.90
8	+	+	+	92.9	93.8	w = 93.35

Note: (-) represents the lower level of the variables, (+) represents the upper level of the variables

The three-factor interaction is expressed as

$$I_{asf} = \frac{1}{4}\{(w_2 + w_3 + w_5 + w_8) - (w_1 + w_4 + w_6 + w_7)\} \quad (7)$$

The mean of the runs is defined as

$$E_M = \left[\sum_{1}^{8} w_i \big/ 8\right] \quad (8)$$

where w_i are the weights clogged.

When genuine run replicates are created under a given set of experimental conditions, the variation among their associated observations are used to estimate the standard deviation of a single observation and, hence, the standard deviation of the results. In general, if g sets of experimental conditions are replicated and the n_i replicate runs made at the i^{th} set yield an estimate S_i^2 having $v_i = n_i - 1$ degree (s) of freedom (Hunter, 1978), the estimate of run variance is

$$s^2 = \frac{v_1 s_1^2 + v_2 s_2^2 + v_3 s_3^2 + \ldots + v_g s_g^2}{v_1 + v_2 + v_3 + \ldots + v_g} \quad (9)$$

With only $n_i = 2$ replicates at each of the g sets of conditions, the formula for the i^{th} variance reduces to

$$s_i^2 = d_i^2 \big/ 2 \quad (10)$$

with $v_i = 1$, where d_i is the difference between the duplicate observations for the ith set of conditions.

Thus, Equation 9 will yield

$$s^2 = \sum \left(d_i^2 / 2\right) \big/ g \quad (11)$$

In general, if a total of N runs is made conducting a replicated factorial design, then the variance of an effect is given as

$$V(effect) = \frac{4}{N} s^2 \quad (12)$$

and the standard error of the effect is given as

$$s_e = \sqrt{V(effect)} \quad (13)$$

Hence, the three main effects (amplitude, a, aperture size, s and quantity of feed, f), the two-factor effect is a measure of the interactions of any two variables and the three-factor interaction effect, amplitude, aperture size and quantity of feed were estimated using the mean of the runs. Table 3 summarizes the findings.

Identification of important effects

The objective is to select factors that have large effects on the responses by developing a factorial design and collect the response data to fit a model. From Table 3 it is not clear which of the effects are important and which are unimportant. Hence, the response data collected is used to generate (two graphs, Normal and Pareto) at a confident level of 95% to evaluate the effects. The study was conducted to investigate the effects of varying amplitude, aperture size and quantity of feed on weight clogged during mining operations. The Minitab 17 statistical software was used to generate models and plots for prediction and further analysis. After the experiment, a model was developed and subsequently used to determine how well the model fits the data gathered during the experiment.

Fig. 2 shows the plot of main effects of amplitude, aperture size and quantity of feed on weight clogged. The main effect plot shows the extent of an effect at low and high levels. The weight clogged as shown on the plot is low (146.98 g) when the amplitude is 3 cm, and high (158.45 g) when the amplitude is 2 cm.

This implies that the weight clogged tends to decrease with increasing amplitude. The weight clogged is low (84.25 g) when the aperture size is 150 μm, but high (221.18 g) when the aperture size is 75 μm. This shows that the weight clogged reduces by increasing the aperture size. The weight clogged is low (126.21 g) when the quantity of feed is 600 g and high

Table 3: Coefficient of analysis for weight clogged

Term	Effect	Coef	SE Coef	T-Value	P-Value	VIF	Status
Constant		152.71	1.62	94.3	0		real
a	-11.47	-5.74	1.62	-3.54	0.008	1	real
s	-136.93	-68.46	1.62	-42.28	0	1	real
f	53	26.5	1.62	16.36	0	1	real
as	7.33	3.66	1.62	2.26	0.054	1	chance
af	-7.95	-3.98	1.62	-2.45	0.04	1	real
sf	-30.25	-15.13	1.62	-9.34	0	1	real
asf	7.55	3.78	1.62	2.33	0.048	1	real

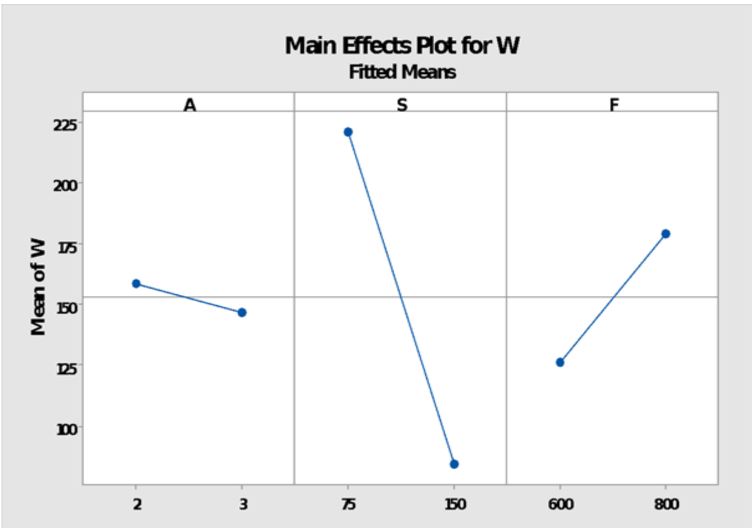

Fig. 2: Main effects plot for weight clogged

(179.21 g) when the quantity of feed is 800 g.

Fig. 3 depicts the plot of interaction effects of amplitude, aperture size and quantity of feed on weight clogged. The plot examines two-way interactions. The plots also evaluate the lines to understand how interactions affect the dependent variable. The dotted lines represent low levels and the solid lines represent high levels of the independent variables. The combined effect of aperture size and quantity of feed on the weight clogged is significant and has the strongest strength of interaction since the lines of interaction greatly depart from being parallel. The combined effect of amplitude and aperture size on the weight clogged is not significant. The combined effect of the amplitude and quantity of feed on weight clogged is significant since its lines of interaction are not parallel.

Fig. 4 shows a Pareto chart of the standardized

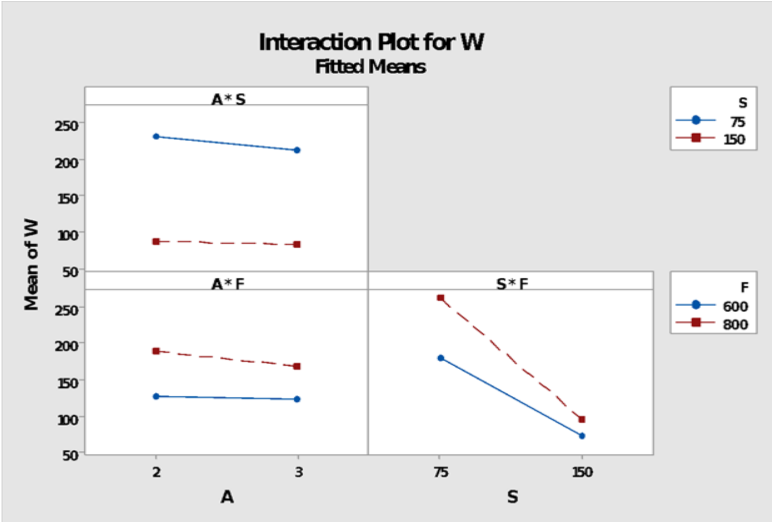

Fig. 3: Interaction plot for weight clogged

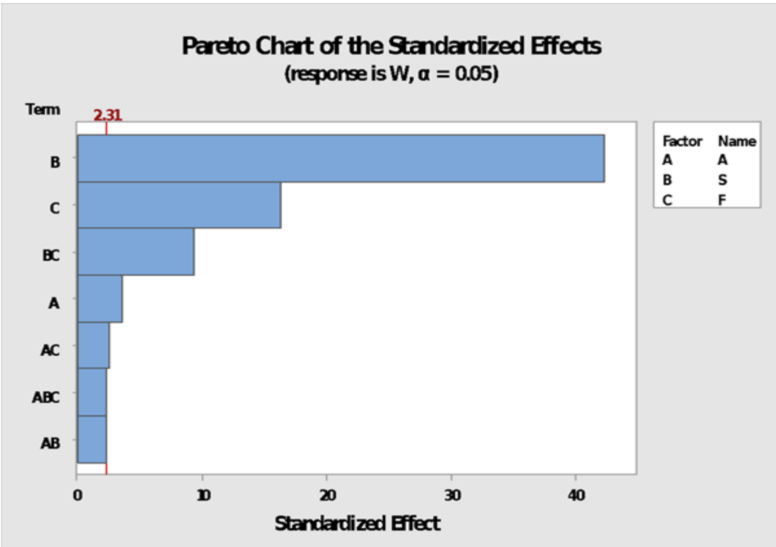

Fig. 4: Pareto chart of standardized effects for weight clogged

effects of amplitude, aperture size, quantity of feed and their interaction effects on weight clogged at 95% confidence level. The Pareto chart is another useful tool to check the significance of the effects. It utilizes the principle of the normal plot of standardized effects. The effect or factor becomes significant if it crosses the reference line whose reference standardized effect is 2.31. The effect is insignificant if it does not cross the reference line. The aperture size is significant with an absolute standardized effect of 42.28, since it crosses the reference line of 2.31. The quantity of feed is also significant with an absolute standardized effect of 16.36, since it crosses the reference line of 2.31. The combined effect of the interaction of aperture size and quantity of feed is significant with an absolute standardized effect of 9.34, since it crosses the reference line of 2.31. The amplitude is significant with an absolute standardized effect of 3.54, since it crosses the reference line of 2.31. The combined effect of the interaction of amplitude and quantity of feed is significant with an absolute standardized effect of 2.45, since it crosses the reference line of 2.31. That of the interaction of all three: amplitude, aperture size and quantity of feed, is also significant with an absolute standardized effect of 2.33, since it crosses the reference line of 2.31.

However, the combined effect of the interaction of amplitude and quantity of feed is insignificant with an absolute standardized effect of 2.26, since it does not cross the reference line of 2.31.

Fig. 5 shows the normal plot of the standardized effects on weight clogged. The norm plot portrays the statistical significance and direction of the main and interaction effects as well as their percentage on the response variable at 95% confidence level and at 5 % significance. The effect of quantity of feed is significant with a percentage of 90.54 and a standardized effect of 16.36. The quantity of feed has a positive value and this implies that as it increases, weight clogged also increases. The effect of aperture size is significant with a percentage of 9.46 and a standardized effect of -42.28. The standardized effect of aperture size is a negative value and this implies, as it increases weight clogged decreases. The effect of amplitude is significant and has a standardized effect of -3.54 with a percentage of 36.49. The standardized effect of amplitude is negative and this shows that as it increases the weight clogged decreases. The combined effect of the interaction of amplitude and aperture size is insignificant with a percentage of 63.51 and a standardized effect of 2.26. The standardized effect of amplitude-aperture size interaction is positive, indicating that as it increases weight clogged also increases.

The effect of the interaction of amplitude and

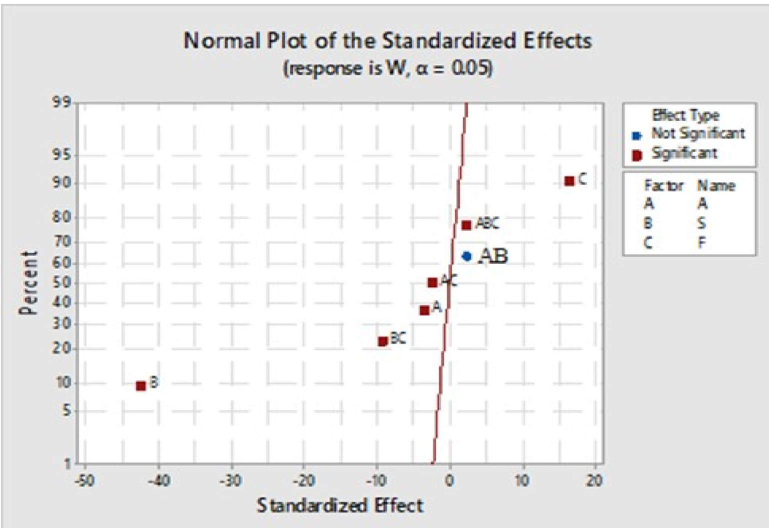

Fig. 5: Norm plot of standardized effects for clogged weight

quantity of feed is significant with a percentage of 50.00 and a standardized effect of -2.45. It has a negative value and this shows that as it increases the weight clogged decreases. The combined influence of the interaction of aperture size and quantity of feed is significant with a percentage of 22.97 and a standardized effect of -9.34. The negative value implies that as it increases the weight clogged decreases. The combined effect of the interaction of all three: amplitude, aperture size and quantity of feed, has a percentage of 77.03 with a standardized effect of 2.33. It is therefore significant, but less significant. The closer the factor is to the reference line (2.31), the less significant its effect becomes and the farther the factor is from the line the more significant its effect becomes. Any factor which lies on the reference line has a completely insignificant effect.

Generation of prediction model for the clogged weight

A full 2^3 model consists of three main effects, three two factor interactions and one three-factor interaction. It is easier to obtain residuals from a 2^k design by fitting a regression model to the data.

For this experiment, the model is defined as:

$$w = \beta_0 + \beta_1 a + \beta_2 s + \beta_3 f + \beta_4 as + \beta_5 af + \beta_6 sf + \beta_7 asf \pm e \tag{14}$$

$$\beta_0 = mean; \quad \beta_1 = \frac{E_a}{2}; \quad \beta_2 = \frac{E_s}{2}; \quad \beta_3 = \frac{E_f}{2};$$

where $\beta_4 = \frac{I_{as}}{2}; \quad \beta_5 = \frac{I_{af}}{2}; \quad \beta_6 = \frac{I_{sf}}{2}; \quad \beta_7 = \frac{I_{asf}}{2}$ (15)

and e is the experimental error

For Real World, substitute a, s and f as follows;

$$a = \frac{A - \frac{1}{2}(A_L + A_H)}{\frac{1}{2}(A_H - A_L)}; \quad s = \frac{S - \frac{1}{2}(S_L + S_H)}{\frac{1}{2}(S_H - S_L)}; \quad f = \frac{F - \frac{1}{2}(F_L + F_H)}{\frac{1}{2}(F_H - F_L)} \tag{16}$$

The significant effects and interactions are used to develop the empirical model for the response with the use of Equations 13 and 14 and Table 3. Thus, using their coefficients in Table 3, the coded model and uncoded for weight clogged are given as equations 16 and 17 respectively;

$$w = 152.71 - 5.74a - 68.46s + 26.50f + 3.66as - 3.98af - 15.13sf + 3.78asf \pm e \tag{17}$$

$$w = -597 + 180.7A - 4.03S + 1.484F - 1.214AS - 0.306AF + 0.002013ASF \pm e \tag{18}$$

Fig. 6 depicts residual plots for weight clogged. Included in the plots are normal probability plot, histogram, versus fits and versus order. Residual plot is made up of graphs that are used to examine the goodness-of-fit in regression and Analysis of variance (ANOVA). Examining residual plots helps one to predict whether the ordinary least squares assumptions are met.

If these assumptions are satisfied, then ordinary least squares regression will produce unbiased coefficient estimates with the minimum variance. From the normal probability plot, it can be deduced that the data is normally distributed which shows that the model is significant and thus fits the data well. The histogram plot gives the outcome of each variable as a check for outliers and normality. The histogram depicts that the first bar is further away from the second bar showing the presence of an outlier which is due to data collection or entry errors as a result of other external factors which influences data collection during the experiment. In Fig. 6, Residuals versus order plot shows whether there are systematic effects in the data as a result of the period or order of information gathering. From the plot the residuals appear to be randomly scattered about the zero mark. There is however, no proof that the error terms are related with each other, and thus, the independence condition of the effects is met. The positioning of most of the residuals were just on 0 with the rest quite farther away.

In testing the model, the R-squared analysis was used. The higher the R-squared value, the better the model fits the data. The predicted R-squared indicates how well a regression model predicts responses for observations. The R-Squared predicted shows that the model as fitted, predicts 98.53% of the variability in weight clogged. The R-squared is 99.63% and thus,

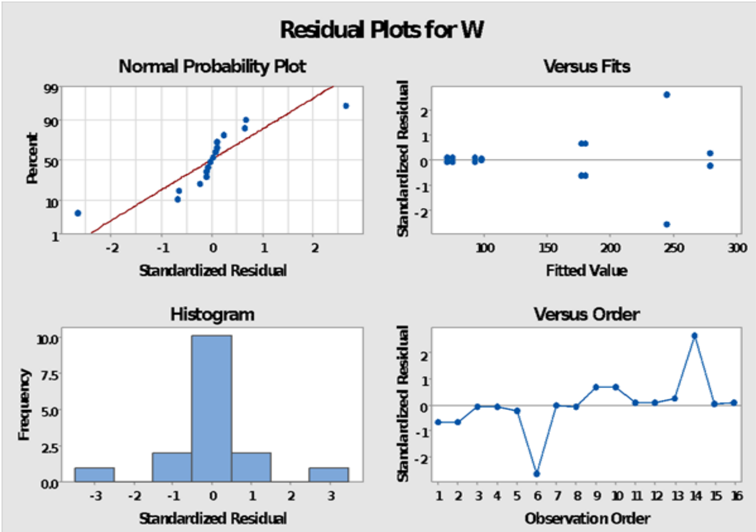

Fig. 6: Residual plots for weight clogged

denotes that the model fits the data well. The predicted model was validated if the experimental results fall within the predicted values of weight clogged. The experimental error was determined using the equation,

$$e = \pm\frac{2S_p}{N} t_{\alpha/2} \tag{19}$$

where N is the number of runs of the experiment, t is the distribution , α is the confidence level, v is the n-1 degree of freedom, and S_p is the pool variance, defined as

$$S_p = \sqrt{1/2 \frac{\sum d_i}{n}} \tag{20}$$

where d_i is the difference between the duplicate observations for the set of conditions and n is the number of experimental sets of condition (8). For 2 replicates at each of the sets of conditions, N is 16 and v is 1. Using equation (20), the pool variance is 6.477. Adopting 95% confidence, $t_{a/2}$; v is 1.96. From equation (19), the experimental error is ±1.59. Table 4 shows the results obtained for experimental and the predicted model results.

From the results, if the experimental weight falls within the range of predicted values, then it is accurate, which is denoted by 'Y', otherwise it is denoted by 'N'. From the results, it can be concluded that 81.25% falls within the predicted values, hence, the predicted model can be used to estimate the clogged weight if the experimental condition is known (refer to Table 1).

Optimization of weight clogged

The optimization plot was generated and the results are illustrated in Fig. 7.

From Fig. 7, it can be observed that the optimal screen conditions for clogged are indicated in brackets with the values of 3 cm for the amplitude,150 µm for the aperture size and 600 g for quantity of feed producing a minimum value of 71.0 g clogged weight.

Table 4: Comparison of experimental values with predicted values of weight clogged

Run 1			Run 2		
Experimental Weight (g)	**Predicted Weight (g)**	**Accuracy Y/ N**	**Experimental Weight (g)**	**Predicted Weight (g)**	**Accuracy Y/ N**
178.10	181.20 ± 1.59	N	182.30	181.20 ± 1.59	Y
176.90	177.90 ± 1.59	Y	180.90	177.90 ± 1.59	N
74.30	74.75 ± 1.59	Y	75.20	74.75 ± 1.59	Y
70.70	71.00 ± 1.59	Y	71.30	71.00 ± 1.59	Y
278.90	279.95 ± 1.59	Y	281.00	279.95 ± 1.59	Y
244.50	245.65 ± 1.59	Y	257.80	245.65 ± 1.59	N
97.80	97.90 ± 1.59	Y	98.00	97.90 ± 1.59	Y
92.90	93.35 ± 1.59	Y	93.80	93.35 ± 1.59	Y

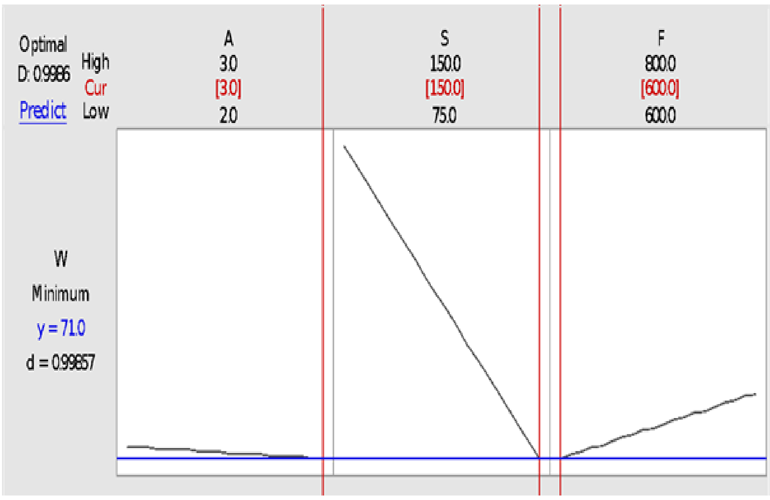

Fig. 7: Optimization plot for weight clogged

CONCLUSION

The effects of amplitude, aperture size and quantity of feed on weight clogged in the vibrating screen during mining operations were investigated. A model was developed and used to predict the weight clogged on the vibrating screen during mining operations. Then the model for predicting weight clogged was validated and the weight clogged was optimized using factorial design techniques to minimize it.

The study reveals that as the amplitude increases, the weight clogged decreases by 11.47 g (7.5%). As the aperture size increases, the weight clogged decreases by 136.93 g (89.67%). Increasing the quantity of feed, increases the weight clogged by 53.00 g (34.71%). A third order linear model in uncoded units to predict weight clogged was obtained:

$$W = -597 + 180.7A - 4.03S + 1.484F - 1.214AS - 0.306AF + 0.002013ASF \pm e$$

The R-Squared predicted shows that the model as fitted predicts 98.53% of the variability in weight clogged. The average percentage error for the model for predicting weight clogged was 0.65, indicating that the model is valid. The optimal conditions for weight clogged are at higher amplitude (3.0 cm), higher aperture size (150 mm) and lower quantity of feed (600 g).

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