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Failure rate analysis of jaw crusher using artificial neural network

Crusher is the primary equipment which is employed for comminuting the mineral in processing plants. Hence, any kind of failure of equipment will accordingly hinder the performance of the plant. Therefore, to minimize sudden failures, proper brainstorming needs to be done to improve performance and operational reliability of jaw crushers. This paper considers the methods for analysing failure rates of jaw crusher through 2-parameter Weibull distribution using ANN (Artificial Neural Network). 40 numbers of Weibull distribution parameters are evaluated to examine R^2 *(Regression coefficient) using ANN. ANN multilayer perceptron model constructed with back-propagation algorithm using shape, scale and time parameters as input and failure rate as an output from Weibull distribution.*

Keywords: *Jaw crusher, Weibull distribution, ANNs and failure rate.*

I. Introduction

Reliability of a unit comprising subsystems in series are evaluated by multiplying the reliabilities of individual subsystem [1]. As the number of components increase, reliability of the unit decreases. Operational reliability investigation is desirable for reducing the maintenance cost and improving the performance of the plant [2]. The TBF (time between failure) data of one year duration from the plant maintenance record book have been considered for analysis. The K-S test performs multiple GOF tests to determine the best distribution from the pool of failure data [3]. Failure data are examined by 1-parameter and 2-parameter exponential, normal, lognormal, gamma, generalized gamma, logistic, log-logistic, 1-parameter and 2-parameter Weibull distributions. The 2-parameter Weibull distribution found to be the best-fit distribution. ML estimation method is used to find the shape and scale parameter of 2-parameter Weibull distribution [4]. In this 2-parameter Weibull distribution density function is given in the equation (1) and failure rate h is given in equation (2) [5], where *h (t)* is the failure rate, â is the shape parameter, η is the scale parameter and *t* is the time. The primary advantage of Weibull distribution is the ability to provide reasonably accurate analysis with extremely small data size. ANN models have the capability to detecting complex underlying nonlinear relationships between 40 numbers of input and output data, and can be trained using several effective training algorithms. The input data considered as shape, scale and time parameter, and output as failure rate of 2-parameter Weibull distribution for ANN process. However, in the last few years, ANNs with regression analysis have been used to predict UCS (uniaxial compressive strength) from texture characteristics of rocks [6], air quality forecasting community [7], electricity consumption [8], field of wood science [9] etc. This paper applied ANN method for jaw crusher and its components. ANNs are designed according to their connection architecture, learning algorithm, number of hidden layer, number of nodes in a hidden layer and transfer function. Also, these design criteria affect the performance of ANNs. The ANN model having the best prediction performance is detected by trying various networks. The ANN method is to determine R^2 values which indicates the goodness of fit of jaw crusher and its components.

$$f(t)=\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)\beta_e^{-\left(\frac{t}{\eta}\right)^{\beta}}, \beta>0, \eta>0 \qquad \text{... ... 1}$$

$$h(t)=\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)\beta-1 \qquad \text{... ... 2}$$

II. Jaw crusher

Crushing is the first stage of size reduction of rocks received from mines. They are heavy-duty machines used to reduce the run-of-mine ore down to a predetermined size. The jaws are set at an angle to each other. The moving jaw moves forward towards the fixed jaw causing fragmentation of rocks inside the crushing chamber and then moves backward in the next half of its working cycle. The crushed materials get discharged by gravity from the bottom of the crusher during the return stroke.

III. Artificial neural networks (ANNs)

ANNs have been trained to overcome the restriction of the traditional methods to solve multifaceted problems [10]. ANN

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algorithm simulates human learning processes through establishment and reinforcement of linkages between the input and output data. The linkages then connect input and output data in the absence of training data. Numerous ANN algorithms have been suggested, such as Radial Basis Function [11], Elman recurrent [12], and Hopfield neural networks [13]; however, back-propagation algorithm is most popular. In this study, back propagation algorithm has been used, which is more powerful, accurate and faster methods. The input layer has three neurons corresponding to the shape parameter, scale parameter and time failed parameter and the output is failure rate from Weibull distribution as shown in Fig.1. The input and output data of jaw crusher are mentioned in Tables 1 and 2. The network having 6 hidden neurons and the lowest error is selected. MATLAB neural network tool is used for the configuration, training and optimization of ANN model. 40 data are randomly divided into three groups for training, testing and validation of the model. Among 40 data, 28 (70% of whole data) data were selected for ANN training process, 6 (15% of whole data) data selected for ANN validation process and the remaining 6 (15% of whole data) data are used for ANN testing process.. ANN is to determine R^2 which indicates goodness of fit of the jaw crusher and its components.

Table 1 Shape, scale and time parameter (input data) of jaw crusher

	β	η	t	No.	β	η	t
1	2.7	564	381.5	21	0.4	190.2	127.6
2	0.9	128.4	41.2	22	1.7	490.3	265.6
3	2	398.2	232.8	23	0.8	249.6	62.3
4	0.4	332.9	30	24	0.5	120.5	152.9
5	4.4	248.4	195.5	25	0.7	462.7	95.7
6	1.7	510.7	270.3	26	0.4	224.2	375.8
7	0.7	648.9	141.5	27	0.8	143.4	36.7
8	3.4	670	650	28	1.6	194.9	98.7
9	1.4	127	60.8	29	0.7	385.2	79
10	0.9	139.5	41.6	30	301	228	162.1
11	0.7	214.8	47.2	31	2.7	377.5	256.4
12	3.7	405.2	305.1	32	2.1	300.6	179.8
13	2.5	270.5	178.3	33	1.3	195.7	84.6
14	2.2	289	274.9	34	1.7	236.4	126.5
15	1.8	444.8	250.5	35	0.4	128.8	225.9
16	3.1	142	100.5	36	1	245.6	87.3
17	0.8	242.8	69.1	37	1.3	195	86.7
18	0.4	225.5	116.4	38	0.3	290.9	44.5
19	1.3	330.4	143.6	39	0.5	180.1	225.9
20	0.6	206.7	36.5	40	1.3	280.7	126.5

Table 2 Failure rate (Output data) of jaw crusher

	Failure rate	No.	Failure rate	No.	Failure rate	No.	Failure rate
1	0.0005	11	0.0008	21	0.0002	31	0.0007
2	0.0013	12	0.0008	22	0.0004	32	0.0007
3	0.0006	13	0.0009	23	0.0007	33	0.0009
4	0.0009	14	0.001	24	0.0003	34	0.0008
5	0.0014	15	0.0005	25	0.0004	35	0.0009
6	0.0004	16	0.0018	26	0.0003	36	0.0007
7	0.001	17	0.0007	27	0.0012	37	0.0009
8	2e-17	18	6e-05	28	0.0009	38	0.0003
9	0.0014	19	0.0005	29	0.0005	39	0.0002
10	0.0012	20	0.0009	30	0.0012	40	0.0006

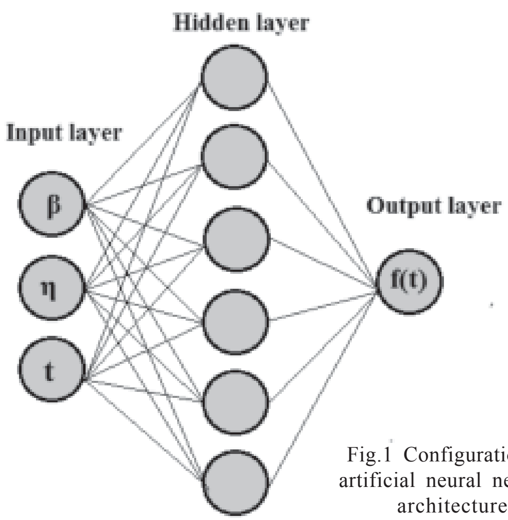

Fig.1 Configuration of artificial neural network architecture

IV. Results and discussion

The present study, feed forward and back propagation multilayer ANN is chosen for solution of the problem. The relationship between observed values and predicted values by the ANN models for all data is illustrated in Table 4. The 1000 epochs have been done in this ANN process. It is decided that the 0.000000096 targeted error values for jaw plate would be sufficient for the training of ANN. The training of the ANN was stopped after 1 epoch because the targeted value 0.000000096 is reached and is shows in Table 3. Among of all components, jaw plate has been minimum epoch and also minimum error. The R^2 value are found as 98.99% for jaw crusher, 98.95% for back toggle plate, 94.37% for chute liner plate, 99.14% for jaw plate and 95.19% for tie rod using the ANN model. As per epoch and R^2 value of jaw plate has low failure rate.

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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UNDERSTANDING THE INFLUENCING PARAMETER FOR WEAR VOLUME LOSS OF ROLL CRUSHER WEAR PROTECTION MATERIAL

(Continued from page 147)

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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