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Simulation of Energy Consumption in Jaw Crusher Using artificial intelligence models

Khaled Ali. Abuhasel [1]
[1] Mechanical Engineering Department, College of Engineering,
University of Bisha,
Bisha, (Kingdom of Saudi Arabia)
Phone/Fax number: +966554040092, e-mail: **kabuhasel@ub.edu.sa**

Abstract. Crushing is an important operation in a variety of industrial applications since it requires a significant amount of energy to blast materials into certain sizes of shattered boulders. Because accurate predictions of the energy required to manage this process are rare in the literature, there have been few efforts to reduce power consumption at the crushing stage by using a jaw crusher, which is the most common type of crusher. The availability of precise power predictions, as well as the optimization of initial crushing processes, would provide useful tools for selecting the best crusher for a given application.
The Adaptive Neuro-Fuzzy Interference System is used to predict the particular power consumption of a jaw crusher in this study (ANFIS). Apart from the power required for rock comminution, the analysis includes an optimization of the crushing process to lower the projected power. In comparison to real data, the results show that the model is successful in correctly estimating comminution power with an accuracy of more than 96%. The findings provide valuable information that can be applied to future studies.

Key words. Neuro-Fuzzy, Energy consumption, ANFIS, Rock strength.

1. Introduction

The size reduction of feed rocks is an important mechanical operation in the processing of raw materials in several industries such as mining and the cement industry. The rock blasting process is the most basic and first important stage in various industrial sectors, in which enormous rocks are broken and divided into tiny pieces before being sent to the processing plant. This procedure can be carried out using mechanical equipment, which are generally referred to as crushers. The primary crushers are capable of handling huge rocks of large size (typically around 1.5 m) to provide blasted rocks with size reduction ratio varying from 3 to 10 [1]. The maximum rock size fed to the crusher compared to the maximum rock size provided by the crusher is known as the rock size reduction ratio. The crushing process is a multi-stage dry process where each stage has small size reduction ratio within range from 3 to 6. Rock breakage is accomplished by crushing, impact, and abrasion corresponding to known modes of rock fracture; including compressive, tensile, and shear. The applied mode can be defined according to the rock mechanics and the load type. Rocks meet crushing (or compressive failure) where rocks of two distinct size ranges are obtained. In this mode, the coarse rocks are produced due to tensile failure, while the small size rocks result from compressive failure occurring at loading points or due to shear stress between projected rocks. In tensile failure mode (impact crushing), the rock possessing higher stress over stress needed to achieve fracture has great tendency to break rapidly producing smaller rock sizes and shapes. In the final mode; shear failure (attrition mode), the rocks are broken due to particle-particle interaction producing great part of fine size rocks. The later mode can occur when too fast feeding of a crusher is applied which is usually undesirable. Crushing in closed circuit operations produce more undesirable fine material than do open circuit operations. The crushing action comes from stresses applied to rock particles by moving parts of the machine.

One of the most famous and old crushers is the jaw crusher. Jaw crushers are in practical usage for about 175 years. There are different jaw crushers that can be distinguished by the presence of two plates where crushed materials are fed between them. One of these plates is fixed while the other swings. Jaw crushers are classified according to the location of this pivoted swinging plate into Blake, Dodge, and Universal crushers. The Blake crusher is considered the most common one, in which the swinging plate is pivoted at the top [2]. This crusher can be realized in two forms as double toggle and single toggle. Due to its simplicity, lower cost, and its higher efficiency, the single toggle jaw crusher is the most realized form in new applications.

Jaw crushers achieve size reduction mainly by compressing particles between relatively slow moving, inclined surfaces. The material being fed into the machine enters from above, where the crushing surfaces are furthest apart, and is crushed into smaller fragments as it descends into the narrowest zone of crushing and is finally discharged by gravity.

The crushing surface in a jaw crusher consists of two rectangular plates, one fixed crushing face and an inclined mobile face, which moves a small distance back and forth from the fixed face. The major variables in jaw crushing are the angle of the jaws, rate of jaw movement, displacement of the mobile plate, and the distance between the jaws at the discharge end, which controls the product size as shown in Fig.1 where CSS is the closed Side Setting and OSS is the open side setting [3].

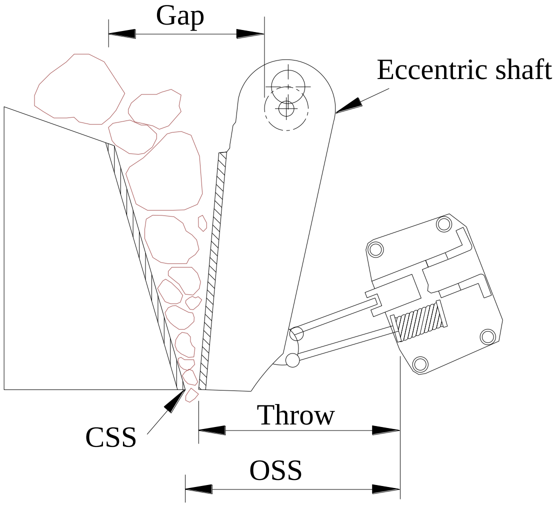

Fig. 1 Kinematic of single jaw crusher [3]

Several studies have dealt with the size reduction focusing on developing a theory, or criterion, that would be useful during the selection and evaluation of crushing equipment. However, none of these studies has satisfactory neither successfully predicted the power consumption; major source of running cost in crushing equipment. Donovan [3] provided deep historical review on the most proposed physical basis regarding criteria of crusher selection, prediction of crusher performance, laws of comminution, mechanisms of rock fracturing, and the corresponding application. As stated by Donovan [3], among common laws of comminution, theories proposed by Von Rittinger in 1867, Kick in 1883, and Bond in 1952 were found to demonstrate properly the relation between product size reduction and the corresponding required input energy throughout the main three laws of comminution. The essential problem within these theories is their limited range of applicability as they were based on empirical equations fitted from experimental data applied in certain cases. Eloranta [4] used Bond's theory to estimate the crusher power consumption and recorded 240% higher predicted power than the actual value. Thus, it is important to consider data provided by the crusher manufacturers and designers who may rely on other methods to size and select crushing equipment for specific blasting operation. Bearman et.al. [5] stated that, these methods are subjected to individual judgment of an individual which leads to conservative over-design of crushers, so additional improvement efforts shall be paid to include rock fracture toughness in addition to all factors in the real crushing plant to be able to predict the corrected input power.

During the last decades, most of cited work regarding rock blasting focused on the physics of particle fracture in addition to the material properties relevant to fragmentation during the crushing process. Single particle breakage was used with the objective of relating breakage pattern and nature of broken material to the resultant fragmented size distribution. Studies using single particle breakage lead to the development of mathematical models describing the size reduction of different breakage materials. These efforts can be extended to relate the fracture consumption energy and produced broken size distribution to the physical property of the broken material.

In attempt to link the energy consumption and performance to the major rock properties of crushing system, Bearman et al. [6] performed massive tests. The work provided an empirical relationship between number of rock strength properties and the crusher power consumption as well as the produced broken size for a cone crusher. In this work, the fracture properties of the rock material were characterized in terms of rock particle strength, breakage energy, and the broken particles fragment size distribution. Any inefficiency in crusher power consumption within these energy intensive equipment leads to the loss of billions of kilowatt-hours of electricity per year [7]. So the most valuable step to reduce this power consumption is to properly improve comminution no matter the applied technology to realize the crushing process [8]. The improvements in feed size operation leads to beneficial optimization in the performance due to lowering of the system capital costs, reducing unit operating costs, and increasing of plant productivity [8]. The use of inefficient crushers may lead to many troubles as the process quality may depend mainly on the quality of crushers to feed the downstream process with product in acceptable reduced size [9]. Thus the necessity to optimize performance and power consumption of primary crusher to reduce the operating costs of quarrying tools is urgent [10].

To optimize crushing energy efficiency, proper modeling relating the stone strength and jaw crusher parameters to successfully estimate the power consumption is required. Modeling based on energy consumption data is accomplished by soft computing tools ([11] - [13]). These soft computing techniques are useful to provide accurate mathematical relations rather than computing techniques when exact relations are not available ([14], [15]). Two famous forms of artificial intelligence; including Neural networks and belief networks, were used to enhance the developed models of onsite aggregation system [11]. ANFIS is one of these soft computing techniques playing great role in modeling accurate input–output matrix relationship. ANFIS is ideal to predict specific energy consumption based on input predictor variables in the process of jaw crushing.

As the reducing size process depends on different performance characteristics of crusher as well as different properties of the feeding rocks, the objective of the current work is to properly combine these parameters to achieve low required power consumption while the product quality is high for sustainable production process. In this work, power consumption of jaw crusher is predicted to provide specific reduced rock size with the help of ANFIS modelling; as one of the computing techniques playing great importance in modelling the input-output parameters relationship. In the next subsection details of AFNFIS model is introduced, then results of calculations are presented, discussed, and compared with real data of applied crusher to determine the level of accuracy to predict the required power to be consumed by the crusher.

2. ANFIS modeling

ANFIS is a neural-fuzzy inference computing system based on adaptive neural network. With the help of hybrid learning sequence, ANFIS is used to generate input – output relations considering fuzzy if-then rules to provide different membership functions. The parameters of each function are determined by ANFIS modelling to follow known experimental input-output data.

ANFIS uses five network layers to achieve the following fuzzy interpretation steps as shown in Fig. 2. Where layer (1) is the input parameters, (2) is the fuzzy set database layer, (3) is the fuzzy rule base structure layer, (4) is the decision making layer, and (5) is the output defuzzification layer; more information are available in literature [16 - 19].

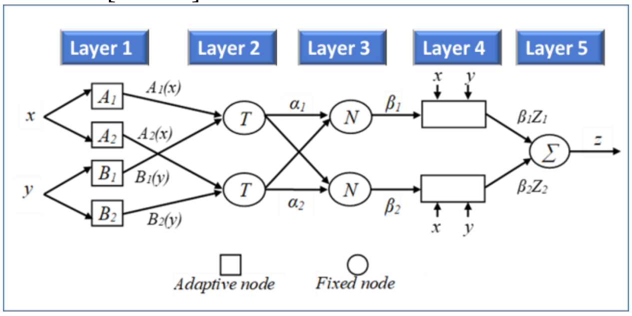

Fig. 2 ANFIS architecture for a two input Sugeno fuzzy model.

The system can be explained in terms of two suggested rules and two verbal values for each input considering the following five layers:

Layer 1: where the output is the step to make given input satisfies the linguistic label corresponding to current node. in this layer, Gaussian membership functions are used to represent verbal terms as connection of the aggregate production limits, see in Fig. 3.

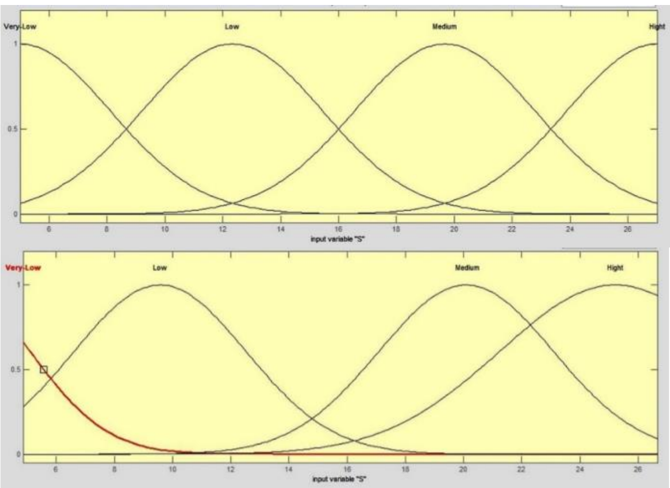

Fig. 3 Initial and final membership functions of stone strength (s); a) initial, b) final

First parameter membership function

$$A_i(u) = exp\left[-\frac{1}{2}\left(\frac{u-a_{i1}}{b_{i1}}\right)^2\right] \quad (1)$$

Second parameter membership function:

$$B_i(v) = exp\left[-\frac{1}{2}\left(\frac{v-a_{i2}}{b_{i2}}\right)^2\right] \quad (2)$$

Where {ai1, ai2, bi1, bi2} are the parameter set.

As the values of these limits modification, the functions shapes vary consequently as shown in Fig. 3b, displaying several shapes of membership functions on linguistic tags Ai and Bi. Parameters in this layer are denoted as attitude parameters.

Layer 2 each node calculates the firing forte of the related rule. Here, nodes are named the rule nodes. The outputs of top and bottommost neurons are as follow:

Top neuron $\alpha_1 = A_1(x) \times B_1(y)$ (3)

Bottom neuron $\alpha_2 = A_2(x) \times B_2(y)$ (4)

Layer 3 every node in this layer is considered by N to indicate the regulation of the firing levels. The output of top and bottom neuron is normalized as follow:

Top neuron $\beta_1 = \frac{\alpha_1}{\alpha_1 + \alpha_2}$ (5)

Bottom neuron $\beta_2 = \frac{\alpha_2}{\alpha_1 + \alpha_2}$ (6)

Layer 4 provides the top and bottom neuron outputs as the product of normalized firing level and individual rule output of first and second rule respectively.

Top neuron $\beta_1 z_1 = \beta_1 (a_1 x + b_1 y)$ (7)

Bottom neuron $\beta_2 z_2 = \beta_2 (a_2 x + b_2 y)$ (8)

Layer 5 where the system overall output is determined by each node as the sum of all incoming signals, i.e.

$$z = \beta_1 z_1 + \beta_2 z_2 \quad (9)$$

here the hybrid neural net of parameters (that determine the shape of membership functions) are learned after providing the crisp training set {(xk, yk), k = 1, . . . ,K}. The corresponding error function for pattern k is determined by

$$E_k = (y^k - o^k)^2 \quad (10)$$

Where yk is the desired output and ok is the computed output by the hybrid neural net.

ANFIS model was built in MATLAB using set of 32 readings (provided in Table 1). Different membership functions were used to learn ANFIS; among of them two functions of closed side set, gape, and reduction ratio and four functions of the rock strength were selected to generate ANFIS model.

From Gaussian membership function, the lowermost error of power consumption is determined to be implemented for ANFIS training. The fuzzy rule construction of ANFIS when Gaussian membership function is adopted consists of 32 fuzzy rules produced from the input-output data set based on the Sugeno fuzzy model as shown in Fig. 4.

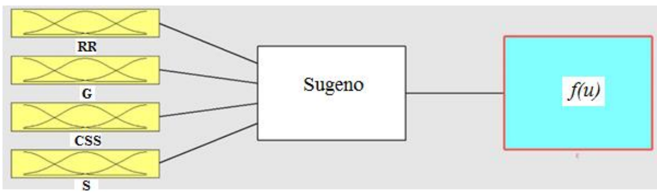

Fig. 4 Fuzzy role architecture of the gaussian membership function

Table 1 Measured power consumption at different crushing conditions

NO.	REDUCTION RATIOS	GAPE (mm)	CSS (mm)	STRE-NGTH	POWER CONSU-MPTION kwh/t
1	1.5	284	31.75	5.697	0.103
2				7.798	0.161
3				18.576	0.02
4				9.899	0.094
5				22.493	0.018
6				12.931	0.001
7				9.994	0.008
8				26.662	0.16
9				9.211	0.139
10				7.067	0.045
11				8.893	0.141
12				12.96	0.198
13				11.293	0.208
14				11.461	0.149
15				10.008	0.11
16				8.71	0.079
17	2.97	224	16	6.097	0.106
18				7.205	0.213
19				9.098	0.23
20				11.99	0.359
21				12.598	0.307
22				6.567	0.321
23				6.696	0.138
24				12.129	0.091
25				10.558	0.178
26				18.164	0.169
27				13.233	0.169
28				13.902	0.313
29				12.874	0.454
30				12.269	0.212
31				9.72	0.282
32				4.863	0.148

During training, the 32 performance measure values (training data set) were used to conduct 500 cycles of learning with an average error of 0.0755 as shown in Fig. 5.

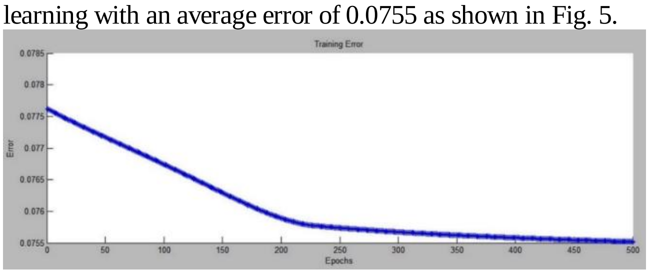

Fig. 5 Relative error in the estimation of power consumption

3. Discussion

Figure 3a, b illustrates the original and the last membership functions of the stone strength. It is noticed that, tuning the final membership function leads to remarkable changes in low and high areas, but in low and medium areas there is minor changes. The major changes in the very low and high areas indicate that all ranges of stone strength have different effect on energy consumption (E). Also, Fig. 3 shows that stone strength had the greatest impact on energy consumption.

Figures 6 and 7 show the effects of the crushing parameters and stone material properties on energy consumption. According to Fig. 6 and 7 reduction ratio (RR), gap (G), and stone strength (S) have considerable effect on energy consumption, while closed side set (CSS) have a minor effect on energy consumption.

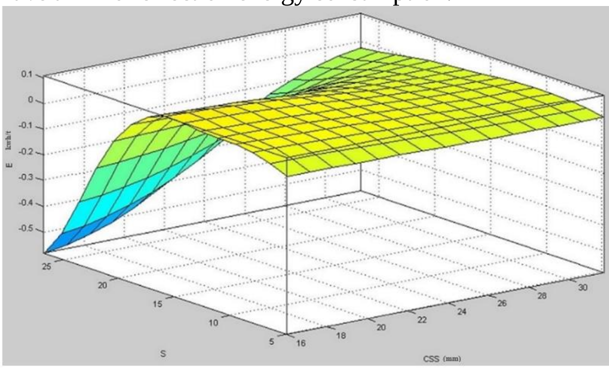

Fig. 6 Energy (E) in relation to change of closed side set (CSS) and Strength (S)

In Fig. 6 at low strength level, it can be seen that the closed side set does not have a considerable effect such as at high level of strength, the consumption energy increases with increasing the closed side set. Moreover, it’s clear that the energy consumption increases with the decrease of stone strength.

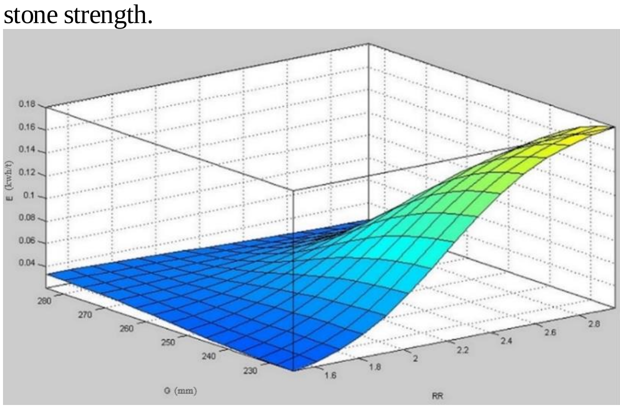

Fig. 7 Energy (E) in relation to change of Gape (G) and Reduction ratio (RR)

Figure 7 shows that the resultant energy consumption decreases with increasing gape width for all ranges of reduction ratio. But at gap ranging from 230 to 250 mm, the energy consumption increases with increasing the reduction ratio for all range of reduction ratio.

4. Model verification

The predicted power consumption (Ep) versus measured power (Em) consumption from real case study are compared in Table 2 and Figure 8.

The group of real data comprised of eight cases was used to run ANFIS, then ANFIS provides the predicted power consumption. Then attained Ep by ANFIS is compared with the measured Em. It is clear noticed that, the maximum deviation is less than 6.5%, thus ANFIS model provides comparable value of power consumption very close to the actual values.

The error percent Ei for any sample of data i (i varied from 1 to m, here m=8) between the predicted values of energy by ANFIS model (Ep_i) and the measured values (Em_i) is estimated from the following equation:

$$E_i = \frac{\lfloor Em_i - Ep_i \rfloor}{Em_i} \times 100 \qquad (11)$$

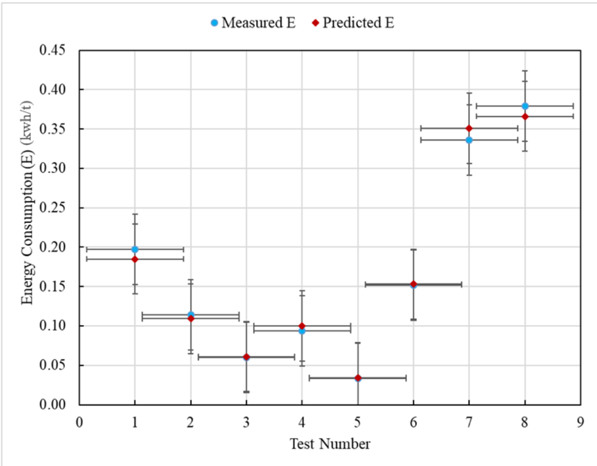

Fig. 8 Error bars for the predicted energy with the help of ANFIS model versus the measured energy values for different test data

while the corresponding average error percent Eav is computed using the following relation:

$$E_{av} = \frac{\sum_{i=1}^{m} E_i}{m} \qquad (12)$$

\Table 2: The ANFIS predicted powers versus the measured power consumed by jaw crusher

Test No.	PARAMETERS				POWER CONSUMPTION kwh/t		ERROR (%)
	RR	Gape (mm)	CSS (mm)	S (MPa)	Measured E	Predicted E	
1	1.5	284	31.75	21.666	0.197	0.185	6.09
2				8.33	0.114	0.109	4.39
3				6.286	0.06	0.061	1.67
4				8.069	0.094	0.1	6.38
5	2.97	224	16	4.897	0.033	0.034	3.03
6				8.071	0.152	0.153	0.66
7				8.635	0.336	0.351	4.46
8				11.021	0.379	0.366	3.43
					Average Error		3.76

Based on the average error percent provided in Table 2, ANFIS model successes to predict the power consumption with 3.67% deviation from the measured data. Thus, ANFIS model with gaussmf has accuracy more than 96% to predict energy consumed by jaw crusher.

5. Conclusion

In this study, the ANFIS model with gaussmf was utilized to obtain an accuracy relation for estimating the power consumption of a jaw crusher. The closed side set, gap, stone strength, and intended reduction ratio are among the predictor input inputs. The ANFIS model was created using a set of 32 particular energy consumption values measured under varied crushing settings.

The adequacy of the proposed model to provide the precise energy usage was next evaluated using another set of 8 collected data. The ANFIS model with gaussmf has a high level of accuracy (more than 96%) for predicting the specific energy consumption of jaw crushers, according to the average error percent.

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