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A Comparative Study of Regression Model and the Adaptive Neuro-Fuzzy Conjecture Systems for Predicting Energy Consumption for Jaw Crusher

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Abstract: Crushing is a vital process for different industrial applications where a significant portion of power is consumed to properly blast rocks into a predefined size of fragmented rock. An accurate prediction of the energy needed to control this process rarely exists in the literature, hence there have been limited efforts to optimize the power consumption at the crushing stage by a jaw crusher; which is the most widely used type of crusher. The existence of accurate power prediction as well as optimizing the steps for primary crushing will offer vital tools in selecting a suitable crusher for a specific application. In this work, the specific power consumption of a jaw crusher is predicted with the help of the adaptive neuro-fuzzy interference system (ANFIS). The investigation included, aside from the power required for rock comminution, an optimization of the crushing process to reduce this estimated power. Results revealed the success of the model to accurately predict comminution power with an accuracy of more than 96% in comparison with the corresponding real data. The obtained results introduce good knowledge that may be used in future academic and industrial research.

Keywords: neuro-fuzzy; energy consumption; ANFIS; regression; rock strength

1. Introduction

During the processing of raw materials in different industries such as the mining and cement sectors, the size reduction of fed rocks is primarily a mechanical process [1]. The rock blasting process is the most primary, and the first significant stage in these industrial sectors through which massive rocks are broken and fragmented into suitable smaller sizes before feeding to the processing plant. This process can be realized in mechanical systems commonly known as crushers. Primary crushers are capable of handling huge rocks of considerable size (typically around 1.5 m) to provide blasted rocks with a size reduction ratio varying from 3 to 10 [2]. The reduction ratio is the feed size to the product size.

The crushing process is a multi-stage dry process where each stage has a small size reduction ratio within a range of 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 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 [3]. In tensile failure mode (impact crushing), the rock possessing a higher stress over the stress needed to achieve fracture has a 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 the particle–particle interaction producing a significant 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 unwanted fine material than 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 oldest crushers is the jaw crusher [4,5]. Jaw crushers have been in practical usage for about 175 years. There are different types of jaw crushers; these 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, where the swinging plate is pivoted at the top [6]. This crusher can be a double toggle or 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 [7]. The significant variables in jaw crushing are the angle of the jaws, rate of jaw movement, displacement of the movable plate, and the distance between the jaws at the discharge end, which controls the product size as shown in Figure 1 [8].

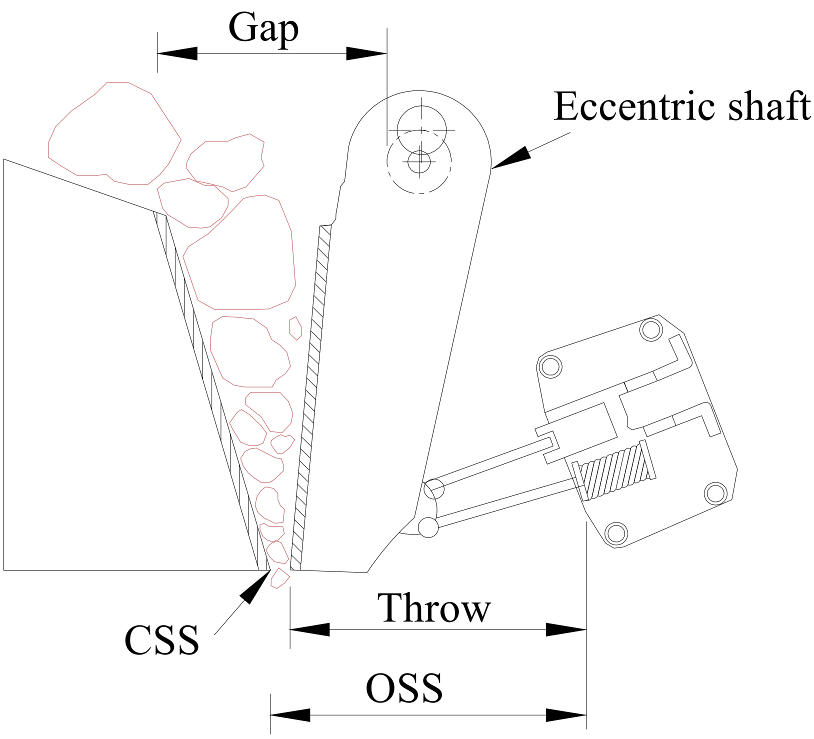


Figure 1. Kinematic of a single jaw crusher [3].

Several studies have dealt with 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 satisfactorily successfully predicted the power consumption, a major source of running costs in crushing equipment. Donovan [9] provided an in-depth historical review on the most proposed physical basis regarding the criteria of crusher selection, prediction of crusher performance, laws of comminution, mechanisms of rock fracturing, and the corresponding application. As stated by Donovan [9], among the common laws of comminution, the theories proposed by Von Rittinger in

1867, Kick in 1883, and Bond in 1952 were found to correctly demonstrate the relationship between the 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 are based on empirical equations fitted from experimental data applied in some instances. Eloranta [10] used Bond's theory to estimate the crusher power consumption and recorded a 240% higher predicted power than the actual value. Thus, it is vital to consider data provided by the crusher manufacturers and designers who may rely on alternative methods of sizing and select crushing equipment for specific blasting operations. Bearman et al. [11] stated that these methods were subjective and relied on individual judgment, which led to the conservation over-design of crushers, so additional improvement efforts should be made to include rock fracture toughness in addition to all of the factors in a real crushing plant to be able to predict the corrected input power.

During the last decades, most of the cited work regarding rock blasting was focused on the quantity of matter and the related energy of particle fracture in addition to material properties relevant to fragmentation during the crushing process [12]. Single-particle breakage was used, which has the objective of relating the breakage pattern and nature of broken material to the resultant fragmented size distribution. Studies using single-particle breakage induce mathematical models that describe the size reduction of different breakage materials. These efforts can be extended to relate to the fracture consumption of energy and the produced broken size distribution to the physical property of the broken material.

While attempting to link the energy consumption and performance to major rock properties of the crushing system, Bearman et al. [13] performed extensive tests. The work provided an empirical relationship between the rock strength properties and crusher power intake as well as the produced broken size for a cone crusher. In this work, the fracture properties of the rock material were categorized in terms of rock particle strength, breakage energy, and the fragment size distribution of broken particles. Any inefficiency in crusher power consumption within the energy-intensive equipment leads to the loss of gigawatt-hours of electricity per year [14] (. Therefore, the most valuable step to reduce this power consumption is to properly improve comminution regardless of the applied technology to realize the crushing process [15]. The improvements in feed size operation lead to beneficial optimization in the performance due to the lowering of the system capital costs, reducing unit operating costs, and increasing of plant productivity [15]. The use of inefficient crushers may lead to many difficulties as the process quality may mainly depend on the quality of the crushers to feed the downstream process with product in an acceptable reduced size [16]. Thus, the necessity of optimizing the performance and power consumption of the primary crusher to reduce the operating costs of quarrying tools is urgent [17].

To optimize crushing energy efficiency, proper modeling relating to the stone strength and jaw crusher parameters is required to successfully estimate the power consumption [18]. Modeling based on energy consumption data can be accomplished by soft computing techniques [13,19–21]. The soft computing techniques are useful in providing accurate mathematical relations rather than computing techniques when exact relations are not available [22,23]. Two famous forms of artificial intelligence including neural networks and belief networks have been used to enhance the developed models of onsite aggregation system. The adaptive neuro-fuzzy interference system, ANFIS, is an example of soft computing techniques playing a great role in modeling an accurate input–output matrix relationship [24]. As such, ANFIS is a suitable model to predict specific energy consumption based on the input independent variables in the process of jaw crushing.

As the reducing size process depends on different performance characteristics of the crusher as well as various properties of the feeding rocks, the objective of the current work was to properly combine these parameters to achieve a low power consumption while maintaining a high product quality for a sustainable production process. In this work, the power consumption of the jaw crusher was predicted to provide a specific reduced rock size with the help of ANFIS modeling as one of the computing techniques playing a great importance in modeling the relationship of the input–output parameters. In the next subsection, details of the AFNFIS model are introduced, then the results of the calculations are presented, discussed, and compared with real data from an applied crusher to determine the level of accuracy to predict the required power consumed by the crusher. It is known that the issue of the prediction of the power consumption of a jaw crusher using the ANFIS model has not been addressed until now. Hopefully, the given approach and the findings from this study will be used for further research in the area of crushing performance.

2. Materials and Methods

2.1. ANFIS Modeling

ANFIS is a neural-fuzzy predictive computing system based on an adaptive neural network [24] (. With the help of a 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 the ANFIS technique to follow already given empirical input–output data.

ANFIS uses five network layers to achieve the fuzzy interpretation steps shown below (Figure 2), where layer one is the parameters entering the system, layer two is the set database layer of the fuzzy, layer three is the fuzzy rule base structure layer, layer four is the decision making layer, and layer five is the output defuzzification layer; more information is available in the literature [25–27].

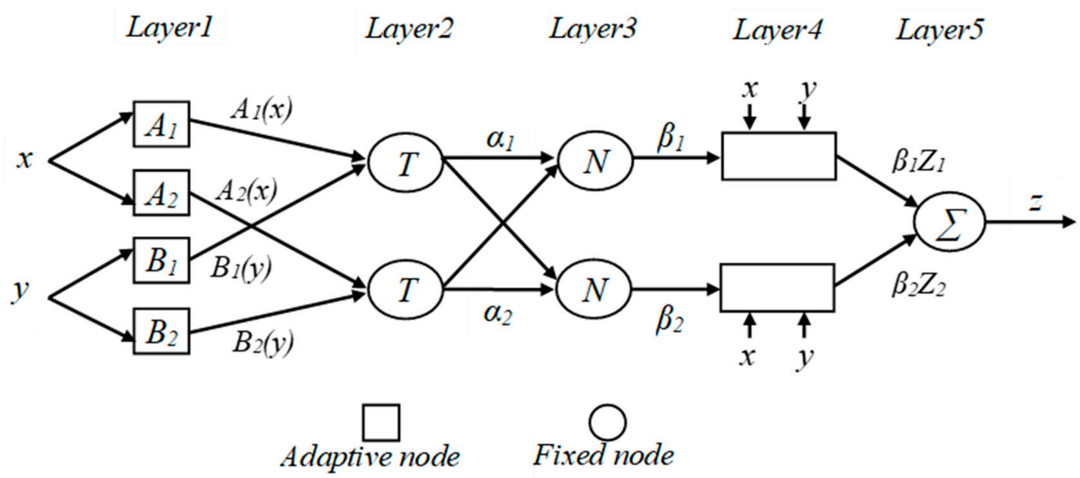


Figure 2. Adaptive Neuro-Fuzzy Interference System(ANFIS) network for a two-input 'Sugeno' fuzzy model.

This system can be explained in terms of two suggested laws and literal values in each input, considering the following five layers:

Layer 1: where the output is the step to make a specified input satisfy the verbal label corresponding to the current node. In this layer, Gaussian membership functions are used to represent verbal values as a connection of aggregate production limits (see Figure 3).

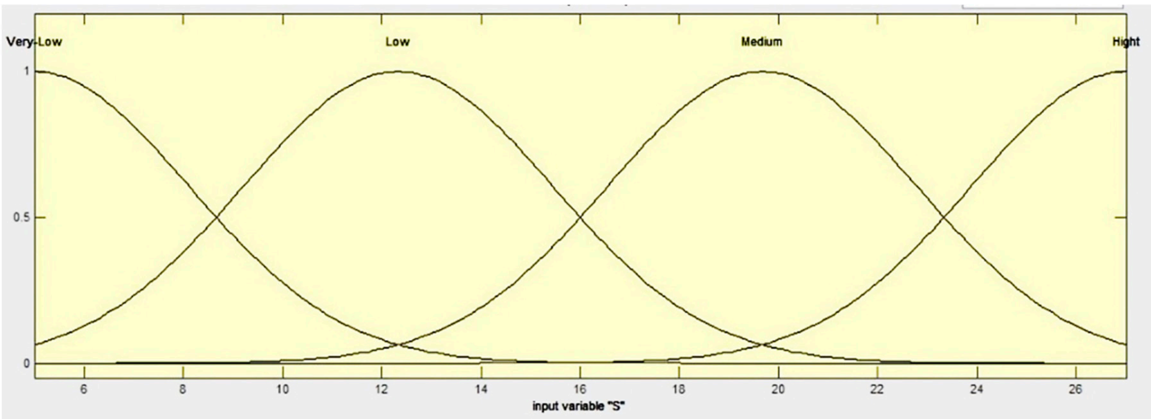
First parameter function

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

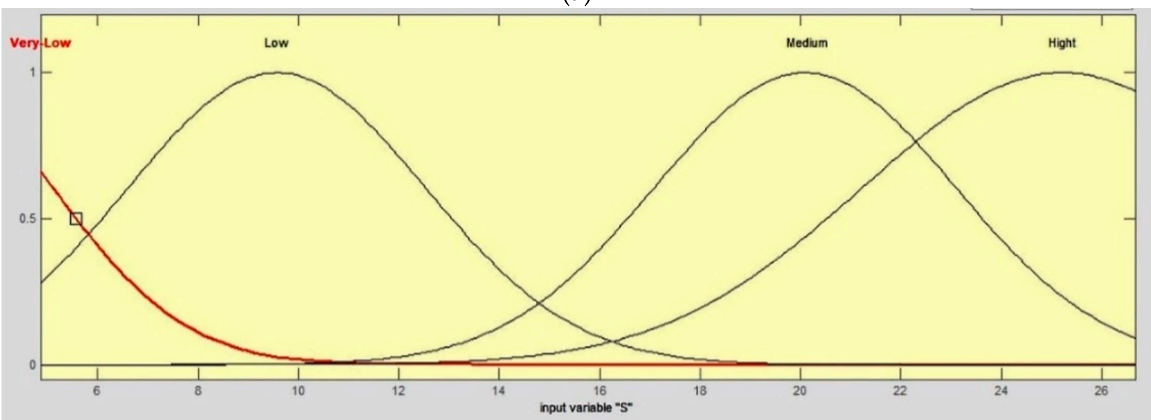
Second parameter function:

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

where $\{a_i, \ldots, b_{i2}\}4$ denote set of parameters.



(a)



(b)

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

As the limit values of modification, the shapes of the model vary considerably as seen below, displaying several forms of the functions on linguistic tags A_i, B_i. The parameters in this layer are described as attitude limits.

In **Layer 2**, each node calculates the firing strength of the related law. Here, the nodes are called the 'rule nodes'. The outputs of the top and the bottommost neurons are as follow:

$$\text{Upper neuron} \qquad \alpha_1 = \mathrm{A}_1(\mathrm{x}) \times \mathrm{B}_1(\mathrm{y}) \tag{3}$$

$$\text{Bottom neuron} \qquad \alpha_2 = \mathrm{A}_2(\mathrm{x}) \times \mathrm{B}_2(\mathrm{y}) \tag{4}$$

In **Layer 3**, every node in this layer is considered by N, which indicates the regulation of the firing powers. The output of the upper and bottom neuron is made normal as follow:

$$\text{Top neuron} \qquad \beta_1 = \frac{\alpha_1}{\alpha_1 + \alpha_2} \tag{5}$$

$$\text{Bottom neuron} \qquad \beta_2 = \frac{\alpha_2}{\alpha_1 + \alpha_2} \tag{6}$$

Layer 4 provides the upper and lower neuron outputs as the result of normal firing intensity and inbuilt particle energy for the process.

$$\text{Upper neuron} \qquad \beta_1 z_1 = \beta_1\ (a_1 x + b_1 y) \tag{7}$$

$$\text{Bottom neuron} \qquad \beta_2 z_2 = \beta_2\ (a_2 x + b_2 y) \tag{8}$$

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

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

Here, the combination set of neutral parameters are learned after providing the system training set $\{(x_k,\ y_k),\ k = 1, \ldots, K\}$. The corresponding sensed function for iterated k is determined by

$$E_k = (y_k - o_k)^2 \quad (10)$$

where y_k is the expected output and o_k is the calculated output by the improved neural net.

The ANFIS model was built in MATLAB using a set of 32 readings (provided in Table 1). Various related functions were used to learn ANFIS; among them, two were closed side sets ((CSS), Gape G), and the reduction ratio (RR) and four functions of the rock strength (S) were selected to generate the ANFIS model.

Table 1. Measured power consumption at different crushing conditions.

No.	Reduction Ratios	Gape (mm)	CSS (mm)	Strength	Power Consumption 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

This study presents a jaw crusher, which is a key tool in the dry process of making a cement plant. The procedure involves inputting the raw material for producing the cement into the jaw crusher. The size of the used rocks for the procedure on average amounted to a similar quantity for all of the experimentations conducted. The settings of the jaw crusher were set as shown in Table 1 so that all values in the experiment could be based purely on strength. Two different sets of experiments were conducted, and the results are recorded in Table 1. In each set of tests, all of the input data were fixed apart from the strength.

From the Gaussian membership function, the lowermost error of power consumption was determined to be implemented for ANFIS training. The input–output system construction of ANFIS when Gaussian membership function is used and entails 32 fuzzy rules produced from the related system of the input–output dataset corresponding to the Sugeno fuzzy model, as shown in Figure 4.

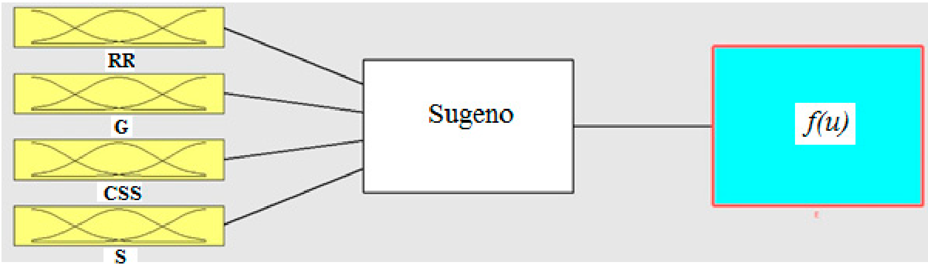


Figure 4. Fuzzy rule architecture of the Gaussian membership function

During the training stage, 32 efficiencies of the performance (training dataset) were used to conduct 500 intervals of learning, accommodating an estimated error of 0.0755, as shown in Figure 5.

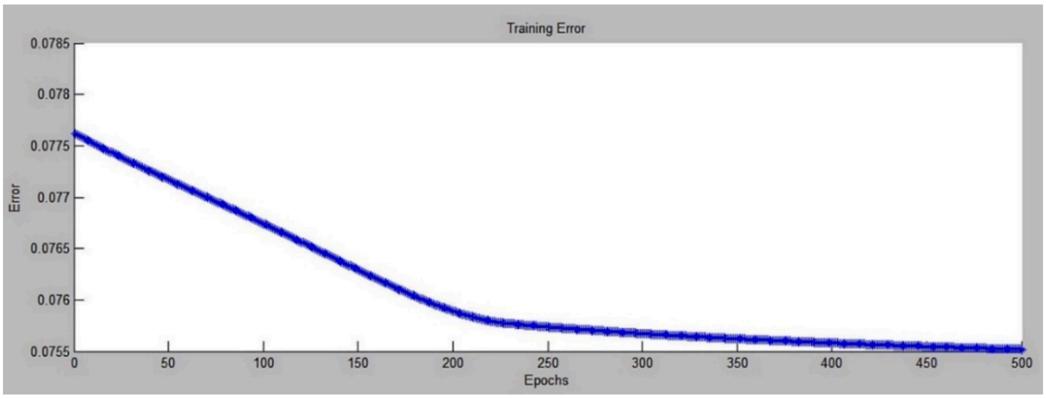


Figure 5. Training error.

2.2. Multiple Regression Model

Several engineering problems include identifying the association between two or more variables, in this case, known as correlation [28]. Finding how the variables are correlated is called regression analysis; these are powerful statistical methods that have been employed by researchers in many areas [29]. Regression modeling is the process by which correlation are fitted to data. In a nonlinear model of regression, considered as a special case, the nonlinear independent functions are used to work on the data, and the output values are compared from the values. In this study, multiple-input variables were used; therefore, we used the "multiple nonlinear regression" function. In this event, the multiple nonlinear regression evaluates the relationship between four variables by finding a nonlinear fit equation to the calculated data. Multiple non-linear regression includes refining the data and examining the correlation between all variables [30]. The generalized nature of a multiple non-linear regression model is shown in Equation (11):

$$Y = b_0 + \sum_{i=1}^{i=n,} b_j \, X_i^{b_{j+1}} \; j = 2i - 1 \tag{11}$$

where Y is the output; X_i is the independent variables of the system; and b_0, b_1, … , b_n are the correlation parameters. The coefficients were then trained to coincide with the model's output and the training output.

3. Results and Discussion

3.1. ANFIS Model

Figure 3a,b illustrate the original and the last membership functions of the stone strength. It was noted that tuning the final membership function led to remarkable changes in the low and high areas, but in the small and medium regions, there were minor changes. The significant changes in the very low and high areas indicated that all ranges of stone strength had a different effect on energy consumption (E). Additionally, Figure 3 shows that stone strength had the most significant impact on energy consumption.

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

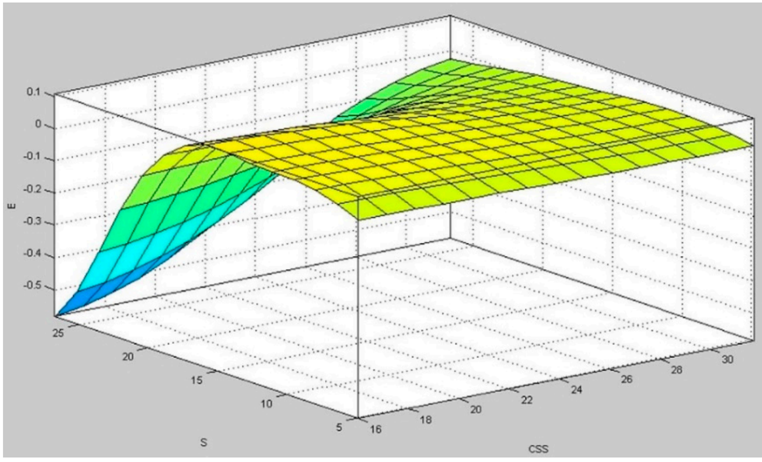


Figure 6. Energy (E) in relation to change of closed side set (CSS) and strength (S).

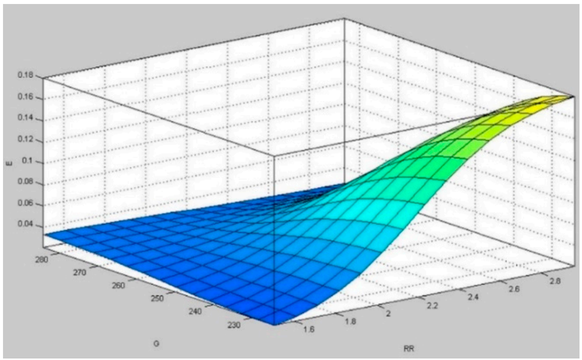


Figure 7. Energy (E) in relation to change of gape (G) and the reduction ratio (RR).

In Figure 6 at a low strength level, it can be seen that the closed side set did not have a considerable effect such as at the high level of strength, and the consumption energy increased with the increase in the closed side set. Moreover, the energy consumption increased with the decrease in stone strength.

Figure 7 shows the variation of energy consumption with the variation in gape width and reduction ratio. Note the gap range of 230–250 mm; the energy consumption was directly proportional to the reduction ratio across the whole range of the reduction ratio.

3.2. ANFIS Model Verification

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

Table 2. The ANFIS predicted powers versus the measured energy consumed by the 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
					R^2		0.9947

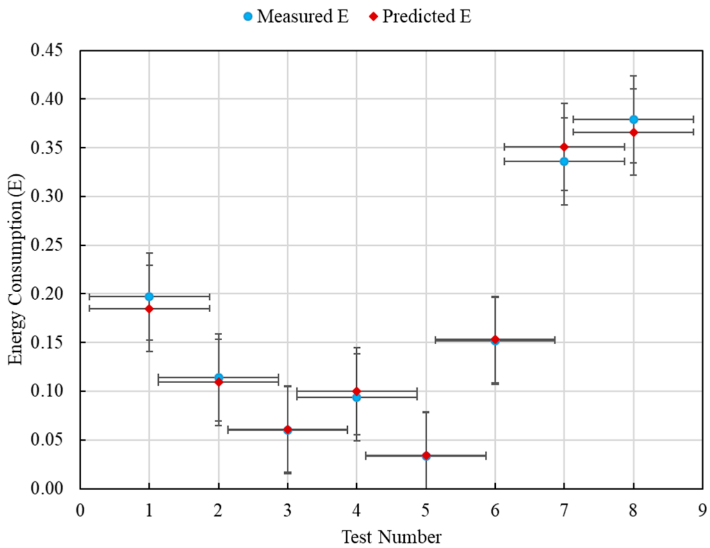


Figure 8. Error bars for the predicted energy with the help of the ANFIS model versus the measured energy values for different test data.

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

The error per cent *Ei* for any sample of data i (i varied from 1 to m, here m = 8) between the predicted values of energy by the ANFIS model (*Epi*) and the measured values (*Emi*) was estimated from the following equation:

$$E_i = \frac{\lfloor Em_i - Ep_i \rfloor}{Em_i} \times 100 \tag{12}$$

While the corresponding average error percent *Eav* was computed using the following relation:

$$E_{av} = \frac{\sum_{i=1}^{m} E_i}{m} \tag{13}$$

Based on the average error per cent provided in Table 2, the ANFIS model successfully predicted the power consumption with a 3.67% deviation from the measured data. Thus, the ANFIS model with gaussmf had an accuracy of more than 96% to predict the energy consumed by the jaw crusher.

3.3. Working with the Regression Model

The regression system was designed, and the regression statistics of the Energy (E) were also calculated using MATLAB and the results are as shown in Figure 9 and Table 3. It can be summarized that the value of the coefficient correlation, R, of the energy prediction was about 0.41. This indicates that the regression system of best fit accounted for 42% of the variability of energy. The inferences and the calculated values of varying energy values are shown below, which further indicate that these values varied with each other as opposed to the ANFIS model. This may be the result of the varying coefficients of correlation between the independent variables. This can well be shown by the ANFIS systems.

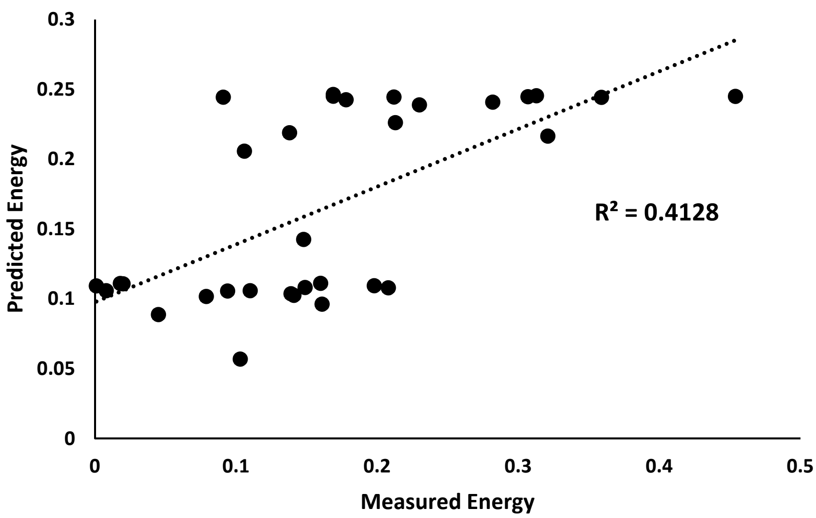


Figure 9. Comparing calculated and inference energy consumption by the regression model.

Table 3. Regression statistics and coefficient values for the regression equation of energy prediction.

Regression Statistics		Coefficient	
Root Mean Squared Error	**0.086**	Intercept	$b_0 = -79.4983$
R^2	0.413	reduction ratios	$b_1 = -14.417$, $b_2 = 0.30816$
Adjusted R^2	0.35	Gape	$b_3 = 0.7962$, $b_4 = 0.9599$
p-value	0.00169	Css	$b_5 = -3.0399$, $b_6 = 0.961$
		Strength	$b_7 = 70.200$, $b_8 = -4.117$

4. Conclusions

In this work, the ANFIS model with gaussmf was used to obtain an accuracy relation to estimate the jaw crusher power consumption. The predictor input data included the closed side set, gap, stone strength, and targeted reduction ratio. A set of 32 specific energy consumption values were measured at various crushing conditions to generate the corresponding ANFIS model. Then, another set of eight measured data were used to evaluate the accuracy of the generated model to provide the specific energy consumption. Based on the average error percent, it was found that the ANFIS model with gaussmf had a high level of accuracy (more than 96%) to predict the specific energy consumption of jaw crusher. It was observed that the ANFIS model was more efficient than the regression model in terms of R^2. Alternatively, the results showed that in some cases, the regression analysis, although a standard method in the modeling of such systems, failed to be reliable (R^2 = 0.41), and hence, high-end models like the ANFIS model are preferred. The current study results proved the effectiveness of ANFIS as an accurate means of predicting the amount of energy applicable in the process of crushing. Therefore, the management team could further use the new model to assess the consumption of power early enough to enable them to take any necessary measures to avoid mistakes. The usefulness of the developed model could be improved further by a support system of decisions to assist the professionals working in the cement production plant.

Conflicts of Interest: The authors declare no conflicts of interest.

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