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ESTIMATING THE POWER DRAW OF GRIZZLY FEEDERS USED IN CRUSHING–SCREENING PLANTS THROUGH SOFT COMPUTING ALGORITHMS

***Ekin KÖKEN**

Abdullah Gül University, Engineering Faculty, Nanotechnology Engineering Department, Kayseri, TÜRKİYE
ekin.koken@agu.edu.tr

Highlights

- The power draw (P) of grizzly feeders is investigated based on their common working conditions.
- Soft computing analyses are performed to build predictive models by considering the collected data.
- The most reliable predictive model is found to be based on the adaptive neuro-fuzzy inference system methodology.

***Corresponding Author:** Ekin KÖKEN, ekin.koken@agu.edu.tr

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ABSTRACT: In this study, the power draw (P) of several grizzly feeders used in the Turkish Mining Industry (TMI) is investigated by considering the classification and regression tree (CART), random forest (RF) and adaptive neuro-fuzzy inference system (ANFIS) algorithms. For this purpose, a comprehensive field survey is performed to collect quantitative data, including power draw (P) of some grizzly feeders and their working conditions such as feeder width (W), feeder length (L), feeder capacity (Q), and characteristic feed size (F_{80}). Before applying the soft computing methodologies, correlation analyses are performed between the input parameters and the output (P). According to these analyses, it is found that W and L are highly associated with P. On the other hand, Q is moderately correlated with P. Consequently, numerous soft computing models were run to estimate the P of the grizzly feeders. Soft computing analysis results demonstrate no superiority between the performances of RF and CART models. The RF analysis results indicate that the W is necessary for evaluating P for grizzly feeders. On the other hand, the ANFIS-based predictive model is found to be the best tool to estimate varying P values, and it satisfies promising results with a correlation of determination value (R2) of 0.97. It is believed that the findings obtained from the present study can guide relevant engineers in selecting the proper motors propelling grizzly feeders.

Keywords: *Adaptive neuro-fuzzy inference system, Classification and regression tree, Grizzly feeder, Power draw, Random forest*

1. INTRODUCTION

Conveyor belts and feeders are among the most critical components in handling a wide range of bulk materials from meter to millimeter scale. In this context, they should ensure accurate and uniform discharge from storage to the upcoming system. Regarding mining engineering applications such as crushing-screening and ore-dressing plants, feeders are of prime importance to maintaining plant sustainability [1]. In crushing–screening plants, grizzly and apron-type feeders are commonly used to increase the capacity and efficiency of primary crushing equipment [2–6].

Primary considerations in deciding which type of feeder to use are the properties of the bulk material being handled (e.g., cohesiveness, maximum particle size, particle friability, propensity for dust generation) [7]. Based on this approach, grizzly feeders may be an alternative to apron feeders when handling bulk materials with high amounts of dust.

Grizzly feeders are typically located before primary crushing equipment in most crushing-screening plants [5, 8, 9]. The main advantage of using grizzly feeders in crushing–screening plants is that grizzly feeders can feed the crushing equipment and remove the undesired particles from the feeding material by sieving simultaneously. In addition, when considering engineering economics, grizzly feeders are cheaper than apron feeders.

In most cases, the selection of proper grizzly feeders is based on the capacity of the primary crushing equipment [10]. For jaw crushers, the geometric properties (i.e., width and length) and the fill factor of grizzly feeders are also important parameters for the suitability and adaptation of these feeders [11]. It is worth reminding that to diminish the undesired effects of vibration arising from primary crushing equipment, Lyashenko et al. [12] proposed a novel design for the bars of grizzly feeders that improved

*Corresponding Author: Ekin Köken, ekin.koken@agu.edu.tr

their efficiency. On the other hand, the power draw (P) of grizzly feeders is highly affected by the vibration of rock-crushing equipment. Since the vibration is associated with the geometric properties and engine power of grizzly feeders, a true determination of power draw propelling grizzly feeders is necessary. However, there is a lack of literature directly focusing on some predictive models that estimate varying P values based on different working conditions.

In this study, the P of grizzly feeders is investigated in a detailed manner. For this purpose, a comprehensive field survey is conducted to collect quantitative data from several crushing–screening plants in Turkey. Soft computing analyses are performed using the collected data to obtain feasible predictive models for estimating the P for different grizzly feeders.

2. MATERIAL AND METHODS

A comprehensive field survey was conducted to collect quantitative data on grizzly feeders operating in several crushing–screening plants in Turkey. Based on the field survey including 44 mining companies, quantitative data were collected on the working conditions (e.g., conveyor speed (V), the height of the material being conveyed (H), capacity (Q), and characteristic feed size (F_{80})) geometric features (feeder width, (W) and feeder length (L)) and power draw (P) of some grizzly feeders. A working grizzly feeder is shown in Fig 1.

Figure 1. Illustration of a working grizzly feeder.

The Q of grizzly feeders was calculated using Eq 1 [11].

$$Q = 3600 \otimes V \otimes W \otimes H \otimes t_1 \otimes t_2 \quad (1)$$

Where V is conveyor speed (m/s), W is feeder width (m), H is the average material height on feeder (m), t_1 is the size factor ($t_1 = 1$, for sands, $t_1 = 0.80$ to 0.90 for crushed stones up to 152 mm and $t_1 = 0.60$ for crushed stoned over 152 mm) and t_2 is the moisture factor ($t_2 = 1$ for dry material, $t_2 = 0.8$ wet material and $t_2 = 0.6$ for adhesive material like clays).

Furthermore, it should be mentioned that F_{80} was calculated based on detailed sieve analyses using the particles directly flowing on grizzly feeders. The H was determined by measuring the average height of materials transported on grizzly feeders. The quantitative information on the geometric (W, L) and working conditions (e.g., V and P) of grizzly feeders was obtained by considering the catalogues of installed grizzly feeders.

2.1. Soft Computing Methods

In this study, three well-established soft computing methods are adopted. These are based on adaptive neuro-fuzzy inference system (ANFIS), classification and regression tree (CART) and random forest (RF) methodologies. The CART is a machine-learning method for establishing classification and predictive models. Decision trees are represented by a set of questions which splits the learning sample into smaller and smaller parts [13]. A regression tree is similar to a classification tree, except that the dependent variable takes ordered values, and a regression model is fitted to each node, giving some outputs [14].

For the last decades, the CART methodology has been used in different mining engineering disciplines. For example, Hasanipanah et al. [15] employed the CART method to estimate blast-induced ground vibration. Their findings demonstrated that the performance of the CART method is better than that of conventional regression models. By adopting the CART method, Salimi et al. [16] proposed a robust predictive model to evaluate the performance of tunnel boring machines (TBM). Last but not least, Bharti et al. [17] performed detailed slope stability analyses using the CART methodology.

Random Forest (RF) is also a machine-learning method developed by Breiman [18]. Compared with conventional decision trees, RF is more accurate and runs efficiently on large datasets [19]. Based on modern mining engineering approaches, RF has been successfully employed to solve many problems. For example, Matin et al. [20] adopted RF to select exact variables for evaluating rock strength properties. Zhao and Wu [21] proposed a predictive model to estimate the height of the fractured water-conduction zone of coal strata. Gu et al. [22] also used RF to monitor the deformations of a concrete dam in China.

Considering many advantages, researchers have also used an adaptive neuro-fuzzy inference system (ANFIS) to build predictive models used in many engineering problems [23–26]. The main advantage of ANFIS is that it practices a hybrid learning process to estimate the premise and consequent parameters [27].

2.2. Data Documentation

In this study, CART, RF and ANFIS methodologies were adopted to establish some predictive models to estimate the P of grizzly feeders. The CART and RF analyses were performed using Salford Predictive Modeler software. On the other hand, ANFIS analyses were performed in the MATLAB environment. Table 1 shows descriptive statistics of the variables considered in this study.

Table 1. Descriptive statistics of the variables.

Variable	Mean	Std. dev.	Min	Max
F_{80} (mm)	426.6	128.7	135	731
H (m)	0.295	0.087	0.09	0.48
V (m/s)	0.294	0.076	0.12	0.47
W (m)	1.21	0.33	0.6	2.1
L (m)	4.40	1.33	1.8	6.0
Q (t/h)	784.5	470.2	116.6	1827.4
P (kW)	21.26	12.36	3.00	55.00

**Note: the number of samples (n) is 44 for each parameter.*

Correlation analyses were also conducted before soft computing analyses to reveal the factors affecting the P of grizzly feeders. Accordingly, the W and L are highly associated with the P. The Q and F_{80} have moderate and minor effects on the P, respectively (Table 2). Although H has a more significant impact than F_{80} on the P, H was not considered an input parameter due to a close relationship between H and Q.

Table 2. Correlation analysis results.

Parameter	W	L	F_{80}	Q	H	V	P
W	1						
L	0.710	1					
F80	−0.277	0.126	1				
Q	0.469	0.691	0.175	1			
H	0.242	0.353	0.066	0.858	1		
V	−0.101	0.008	0.296	0.419	0.010	1	
P	**0.822**	**0.819**	**−0.124**	**0.558**	0.322	0.027	1

Note: Bolded values (e.g., **0.822**) indicate the parameters used in soft computing analyses.

3. RESULTS AND DISCUSSION

As a result of soft computing analyses, three robust predictive models were obtained. When considering the CART model, L, W, and F_{80} were input parameters. Average values in red boxes in Figure 2 were assumed to be estimated P values. The estimated P values were obtained based on the if-then rules summarized in Figure 2. In the RF analyses, mean squared error (MSE) was assumed to be the fitness function. The number of trees in the RF analyses was 200. The database (n=44) was divided into training (70/100) (Figure 3a) and testing (30/100) parts (Figure 3b). As a result of the RF analyses, another robust predictive model was obtained. The W was found to have the most significant influence on the P (Figure 3c).

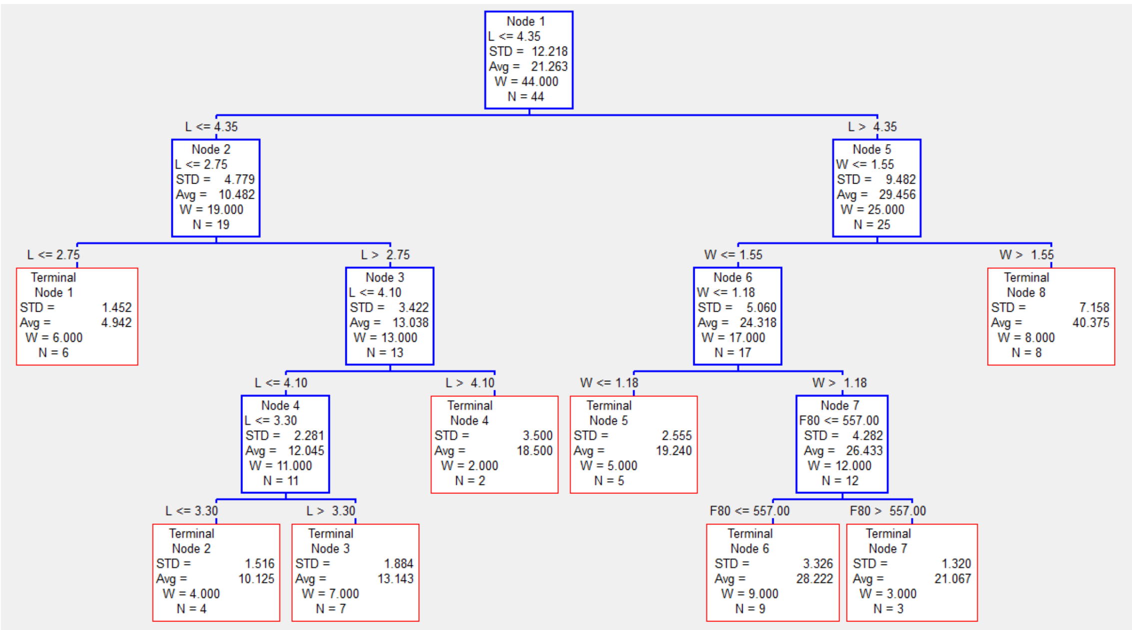

Figure 2. CART decision tree.

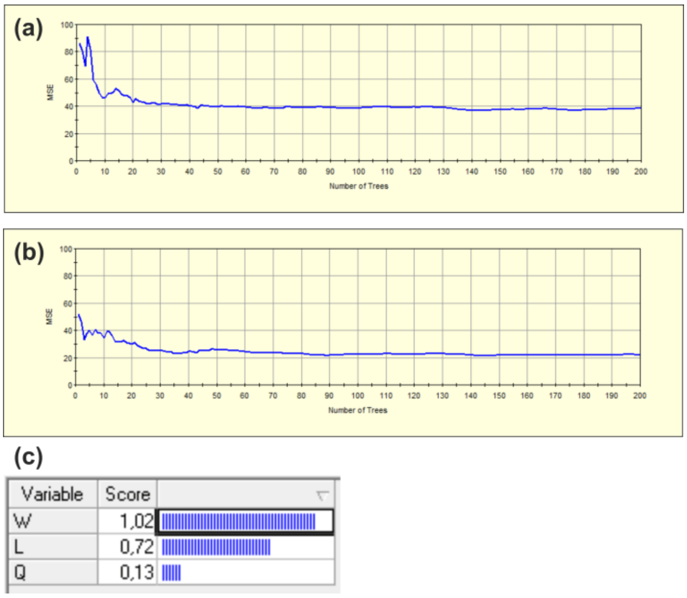

Figure 3. RF outputs a) Training process b) Testing process c) Relative importance of the input parameters.

The input parameters in the developed ANFIS model were W, L, F_{80}, and Q (Figure 4a). During the training process, ANFIS analyses continued until the minimum relative error was achieved (Figure 4b). Similar to what has been done previously, the dataset was divided into training (70/100) and testing (30/100) datasets. The ANFIS model structure is given in Figure 4c. For each input parameter, four Gaussian membership functions were defined (Figure 4d), and based on four if-then rules, P values were estimated.

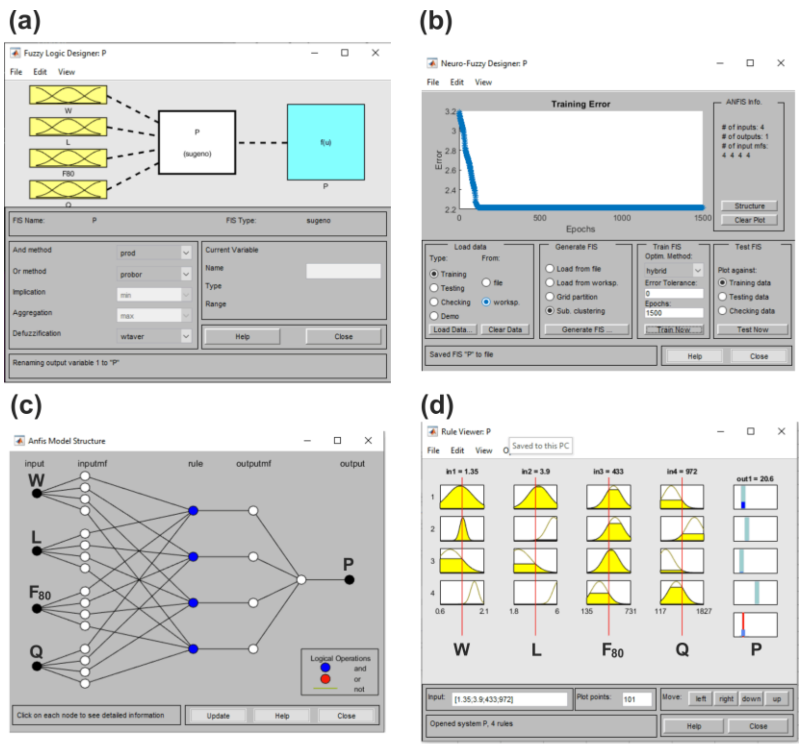

Figure 4. ANFIS outputs a) Input parameters, b) Training process c) ANFIS model structure d) Rule viewer.

The performance of the proposed models was visualized through scatter plots (Figure 5).

Accordingly, the ANFIS model was found to be the best predictive tool with a correlation of determination value (R^2) of 0.97. When compared to the performance of the CART and RF models, there is no superiority in estimating varying P values. Nevertheless, these models (CART and RF) gave undulating results when considering grizzly feeders with higher capacity (P > 37 kW). This phenomenon was not observed in the ANFIS model.

Moreover, the performance of the proposed predictive models was also revealed by a comprehensive performance evaluation table (Table 3) based on some performance indicators such as R^2 and root means square error (RMSE). Accordingly, for the training data (n=31), the R^2 and RMSE values were found to be between 0.887 – 0.966 and 2.136 – 4.223 kW, respectively. Based on the testing data (n=13), these values were better than the ones found in the training data. Based on this performance evaluation table, different statistical indicators suggest that the best predictive model in this study is based on the ANFIS methodology.

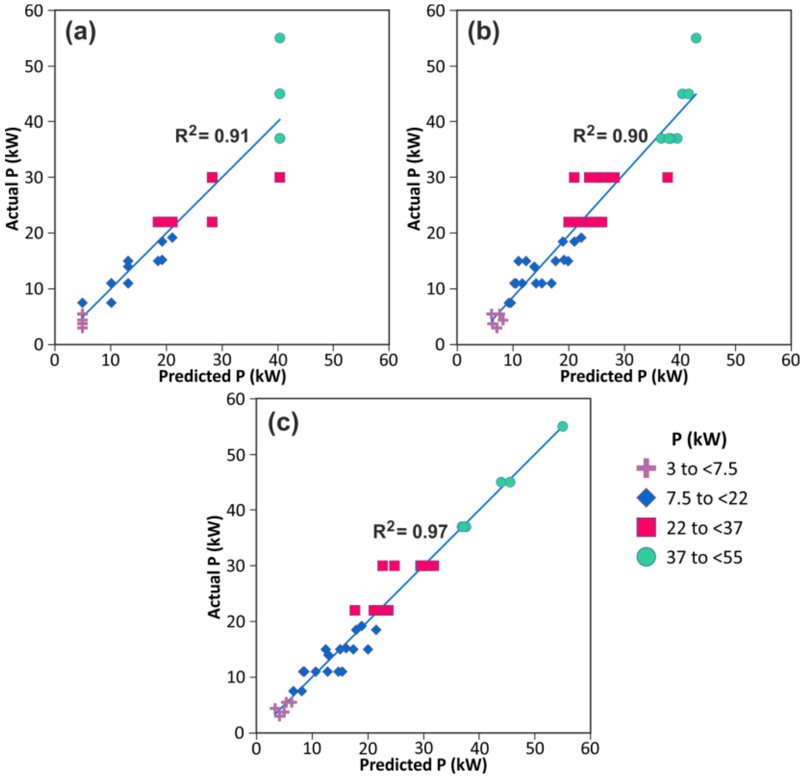

Figure 5. Scatter plots of the proposed models (a) CART (b) RF (c) ANFIS

Table 3. Statistical indicators of the proposed models.

Statistical indicator	Methodology	Training Data (70/100, n = 31)	Testing Data (30/100, n = 13)	All data (n=44)
R^2	CART	0.887	0.960	0.908
	RF	0.897	0.937	0.905
	ANFIS	0.966	0.972	0.968
RMSE (kW)	Methodology	Training Data (70/100, n = 31)	Testing Data (30/100, n = 13)	All data (n=44)
	CART	4.223	2.245	3.749
	RF	4.148	3.429	3.949
	ANFIS	2.316	1.949	2.214

It was also found that the proposed ANFIS method acts differently based on varying P classes. In this study, four different P classes were defined based on a k-means clustering algorithm.

For example, the average relative error (ARE) decreases with increasing the capacity of the grizzly feeders (e.g., 37kW ≤ P < 55kW). The ARE values for these classes were found to be as follows:

- Class I (3 to < 7.5 kW), ARE = 22.65%
- Class II (7.5 to < 22 kW), ARE = 15.30%
- Class III (22 to < 37 kW), ARE = 6.39%
- Class IV (37 to < 55 kW), ARE = 0.88%

To the best of the corresponding author's knowledge, there is no investigation in the literature on the P of grizzly feeders. In this context, the findings obtained from the present study can guide one willing to design a proper grizzly feeder in a crushing-screening plant. Nonetheless, the number of case studies should be increased to improve the CART and RF models.

For this purpose, additional input parameters, such as the flow characteristics of the materials being conveyed, might also be necessary. In addition, a continuous material flow on grizzly feeders, which means a fixed H value, should also be required to sustain and select proper engines in material transportation.

Finally, in order to implement the ANFIS methodology, a design chart was also developed based on the typical working conditions of grizzly feeders. In this design chart (Figure 6), different P values can be easily estimated by considering the parameters of W, L, and Q. It is worth remembering that this design table is based on some assumptions, such as H ≤ 0.5W and F_{80} = 250 mm. These assumptions are typical for most grizzly feeders operating in crushing–screening plants from the database specified.

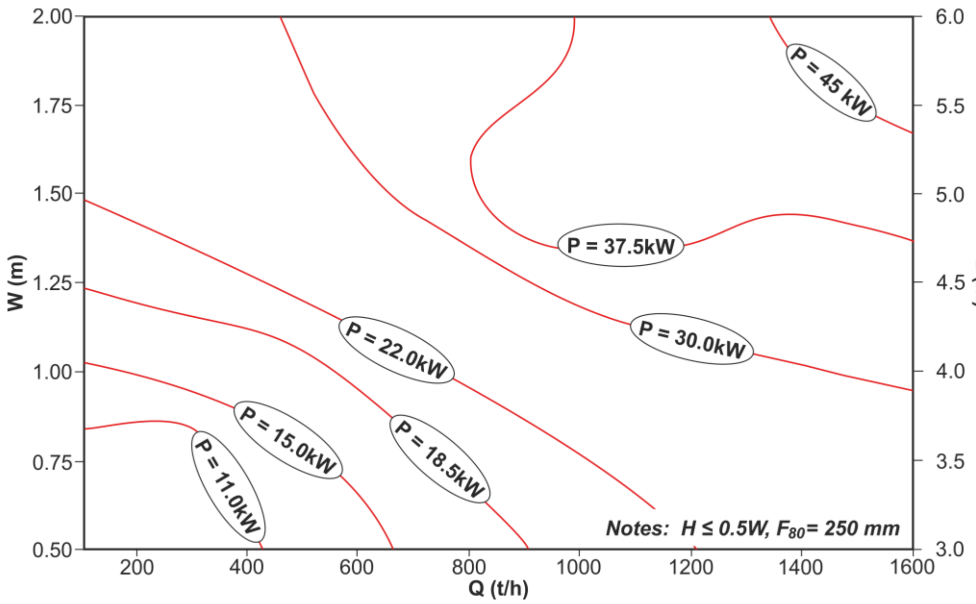

Figure 6. Proposed design chart to estimate the P based on different design parameters.

4. CONCLUSIONS

The present study introduces robust predictive models to estimate the P of different grizzly feeders. For this purpose, a comprehensive field survey is conducted to collect quantitative data on the grizzly feeders used in several crushing–screening plants in Turkey (Table 1).

Several soft computing analyses were performed based on the collected data. As a result of these analyses, three predictive models were obtained to evaluate varying P values. The R^2 values for the models are between 0.90 and 0.97, showing their relative success (Figure 5). The best predictive model to estimate the P values is based on the ANFIS methodology. Nevertheless, there is no significant difference between the performance of the CART and RF models.

In order to implement the proposed ANFIS methodology, a design chart is also provided in this study (Figure 6). Different P values can be easily estimated by using this design chart based on various parameters of W, L and Q. In this manner, the present study is believed to be beneficial to those who want to design proper grizzly feeders applicable for crushing – screening plants.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Data Availability

Enquiries about data availability should be directed to the corresponding author.

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