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Araştırma Makalesi / Research Article

Modeling the Throughput of Horizontal Shaft Impact Crushers Using Regression Analyses, Artificial Neural Networks and Multivariate Adaptive Regression Spline

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Abstract

In this study, the throughput (Q) of horizontal shaft impact (HSI) crushers was investigated using regression analyses, artificial neural networks (ANN) and multivariate adaptive regression spline (MARS). For this purpose, 32 different HSI-type crushers, which operated in the secondary crushing processes of various rock quarries in Turkey, were considered. Various quantitative data (i.e., rotor width (R_w), rotor diameter (R_d), rotor speed (V_r), characterized feed size (d_{80}), operating energy (O_e), and Los Angeles abrasion value (LAAV) of the crushed stone) were collected from each crushing-screening plant. Linear and nonlinear regression analyses were first conducted using the above-mentioned collected data. Then, different ANN and MARS analyses were carried out to estimate the Q of these crushers. As a result, strong predictive models were developed to estimate the Q of HSI-type crushers. The correlation of determination (R^2) of the proposed models (M6–M10) ranged from 0.91 to 0.98, indicating the relative success of the established models. Therefore, the proposed models can reliably be used to estimate the Q of investigated HSI-type crushers. Nevertheless, the number of case studies should be increased to investigate other factors affecting the Q of HSI-type crushers.

Yatay Milli Kırıcılarda Kırma Kapasitesinin Regresyon, Yapay Sinir Ağları ve Çok Değişkenli Uyarlamalı Regresyon Analizi Kullanılarak Modellenmesi

Anahtar kelimeler
Yatay milli kırıcı;
Kırmataş;
Taş ocağı;
Regresyon analizi;
Yapay sinir ağları

Öz

Bu çalışmada, yatay milli darbeli kırıcıların (HSI) kırma kapasitesinin (Q), regresyon analizleri, yapay sinir ağları (ANN) ve çok değişkenli uyarlamalı regresyon analizi (MARS) kullanılarak araştırılmıştır. Bu amaçla, Türkiye'deki çeşitli taş ocaklarında ikincil kırma işlemlerinde kullanılan 32 farklı HSI tipi kırıcı ele alınmıştır. Çeşitli sayısal veriler (rotor genişliği (R_w), rotor çapı (R_d), rotor hızı (V_r), karakterize edilen besleme boyutu (d_{80}), çalışma enerjisi (O_e) ve kırmataşın Los Angeles aşınma değeri (LAAV)) her bir kırma–eleme tesisinden elde edilmiştir. Öncelikle, toplanan veriler kullanılarak doğrusal ve doğrusal olmayan regresyon analizleri gerçekleştirilmiştir. Daha sonra ise, bu kırıcıların Q değerini tahmin etmek için farklı ANN ve MARS analizleri yapılmıştır. Sonuç olarak, kırıcıların Q değerini tahmin etmek için güçlü tahmin modelleri geliştirilmiştir. Önerilen modellerin (M6–M10) belirleme katsayısı (R^2) 0.91 ile 0.98 arasında değişmekte olup, söz konusu yüksek R^2 değerleri geliştirilen modellerin göreceli başarısını göstermektedir. Bu nedenle, önerilen modeller, araştırılan HSI tipi kırıcıların Q değerini tahmin etmek için güvenilir bir şekilde kullanılabilir. Bununla birlikte, HSI tipi kırıcıların Q değerini etkileyen diğer faktörleri araştırmak için örnek çalışmalarının sayısı arttırılmalıdır.

1. Introduction

In crushing–screening plants, rock comminution starts with breaking down huge rock blocks, where jaw crushers and gyratories are mainly used in primary crushing processes. For secondary and tertiary crushing operations, cone, vertical shaft impact (VSI), and horizontal shaft impact (HSI) crushers are mostly preferred with several combinations. In this way, sustainable rock aggregate manufacturing can be achieved based on modern rock aggregate science and technology. Compared with jaw and gyratory crushers, VSI and HSI type crushers can achieve a higher production yield. It should be herein mentioned that since HSI and VSI type crushers wear out more quickly, they can only be used on medium or weak rocks (Duthoit, 2000).

When it comes to the operating mechanism of impact crushers, they use impact forces to break down materials in the crushing chamber. For HSI type crushers, feeding materials enter down an inclined chute on one side of the crusher. The rotor throws feeding material to the anvils endowed with wear liners. In this way, they are broken down and discharged from the crushing medium by gravity (Sinnott and Cleary 2015, Köken and Jili 2020). A typical cross-section of an HSI type crusher is illustrated in Fig 1.

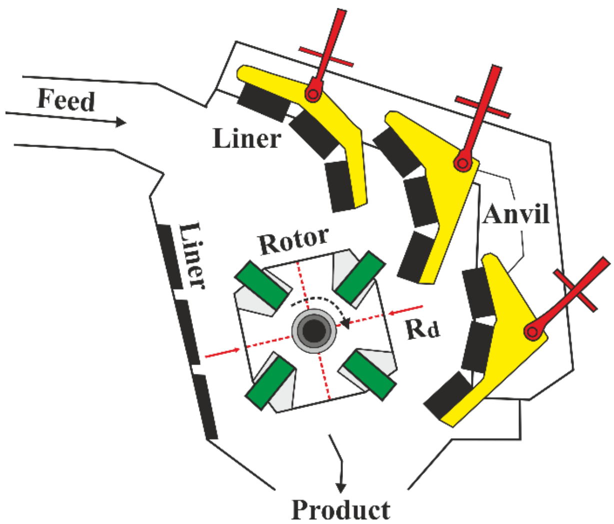

Figure 1. Typical cross-section of an HSI type crusher (Rd: Rotor diameter)

The rock-crusher interactions also play an essential role in assessing the rock comminution relative success. Therefore, each crushing-screening plant has its own specifications regarding the crushers and belt conveyors used in the system. In addition to this, the physical and mechanical rock properties such as dry density (ρ_d), uniaxial compressive strength (UCS), and Brazilian tensile strength (BTS) influence the size reduction ratio (SRR) and specific energy consumption of the compressive crushers.

More profoundly, the UCS of rocks is an essential parameter to quantify the degree of rock crushability (DRC) in jaw crushing (Korman *et al*. 2015, Kahraman *et al*. 2018, Köken and Özarslan 2018). On the other hand, the BTS of rocks can also be a correlative parameter to evaluate the crushing energy consumption in cone crushing (Köken 2020). However, quite limited information has been documented on the performance of VSI and HSI type crushers as a function of different rock properties. Instead, the performance of these crushers has been mainly investigated using the discrete element method (DEM). Notably, the results of DEM methods can be used to estimate the particle size distribution (PSD) of the product and the specific energy consumption of these crushers (Djordjevic *et al*. 2003, Li *et al*. 2014, Sinnott and Cleary 2015, Grunditz 2015, Quist and Evertsson 2016, Barrios *et al*. 2020, Chen *et al*. 2020).

On the other hand, the throughput (Q) of crushers is another quantity that should be considered in terms of sustainability and engineering economics. In this manner, rock aggregate manufacturers want to know the Q at the end of each crushing–screening shift. For this purpose, the whole crushing–screening plant or a significant part of it can be modeled to observe the variations in Q as a function of different working conditions. This is the description of the problem on which the present study is focused. In this study, a total of 32 HSI-type crushers are used to observe how Q changes as a result of different working conditions. This is done to fill a gap in the relevant litature.

Regression analyses, artificial neural networks (ANN) and multivariate adaptive regression spline (MARS) are adopted as data analysis methods to evaluate the Q based on the collected data from several crushing – screening plants in Turkey. As a result of these analyses, several predictive models are developed to estimate the Q of HSI type crushers. The details and summary of the proposed predictive models are introduced in this study.

2. Materials and Methods

A total of 32 HSI-type crushers operating in various crushing–screening plants in Turkey were considered in this study. Different HSI type crushers have been used in these plants as secondary crushing equipment. Some of the HSI type crushers considered in this study are given in Fig 2.

A similar methodology was followed when obtaining the quantitative data from each crushing–screening plant.More profoundly, quantitative data such as the rotor width (R_w), rotor diameter (R_d), rotor speed (V_r), characterized feed size (d_{80}), crusher's operating energy (O_e), and Los Angeles abrasion value (LAAV) of the crushed stone and the corresponding Q were collected from each crushing–screening plant. The determination of Q depends upon the calculation of crushed particles below 50 mm in this study. As a result, a comprehensive database was generated for regression, ANN and MARS analyses. Table 1 and Table 2 list the collected database and the statistics that describe it.

Figure 2. Several HSI type crushers considered in this study.

3. Data Analysis Methods

3.1. Regression Analyses

In this study, the Q of HSI-type crushers was first investigated through regression analyses. Single, multiple, and nonlinear regression analyses were performed in this context. Before performing these analyses, the correlations between theindependent variables (R_w, R_d, V_r, d_{80}, O_e, and LAAV) and the Q were revealed through Pearson's correlation and Spearman rho analyses. The correlation analysis results are listed in Table 3. Accordingly, the R_w and R_d are moderately correlated with the Q. On the other hand, the O_e can be declared a highly correlative parameter to assess the Q.

The general form of single and multiple linear regression analyses is given in Eq 1. Nevertheless, a typical nonlinear regression model adopted in this study is described in Eq 2.

$$y = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 ......a_n x_n \qquad (1)$$

where y is the dependent variable, x_0 to x_n are the independent variables used in the model, and a_0 to a_n are the numerical constants to be calculated from the analyses.

$$y = a_0 x_0^{t0} x_1^{t1} x_2^{t2} ....x_n^{tn} \qquad (2)$$

where y is the dependent variable, x_0 to x_n are the independent variables used in the model, and t_0 to t_n are the numerical exponential constants to be calculated from the analyses.

Table 1. Case studies considered in this study.

Case	R_w (mm)	R_d (mm)	V_r (rpm)	d_{80} (mm)	O_e (kW)	LAAV (%)	Q (t/h)
1	670	1030	640	64	80	15	88
2	2000	1400	750	90	315	24	271
3	1340	1030	640	64	175	12	116
4	1340	1340	544	64	275	13	194
5	2000	1340	544	64	400	24	275
6	1330	1150	600	121	150	23	223
7	950	1005	695	63	145	35	202
8	1000	1100	650	79	175	25	163
9	1300	1200	550	86	225	18	189
10	1500	1300	550	86	300	21	233
11	860	1015	575	57	100	17	88
12	1370	1015	575	57	125	12	81
13	1400	1400	680	100	200	18	180
14	2135	1525	400	107	450	13	251
15	1500	1500	500	86	400	20	297
16	2000	1500	550	60	120	34	196
17	1600	1400	680	105	315	20	280
18	1000	1050	375	51	65	28	95
19	2000	1400	750	90	315	24	271
20	1000	1350	304	57	93	26	140
21	1200	1350	304	56	110	25	157
22	2120	1057	336	71	500	29	287
23	2000	1600	336	50	265	15	200

Table 1. (continued).

Case	Rw (mm)	Rd (mm)	Vr (rpm)	d80 (mm)	Oe (kW)	LAAV (%)	Q (t/h)
24	1500	1300	720	100	250	18	173
25	1330	1150	555	50	220	26	218
26	1900	1390	420	50	330	26	245
27	1000	1030	640	64	125	15	106
28	1525	1295	550	86	300	18	201
29	1340	1030	580	76	225	20	160
30	1340	1340	610	81	325	18	233
31	950	1005	610	63	130	26	148
32	1600	1400	680	120	315	20	285

Explanations: R_w: Rotor width, R_d: Rotor diameter, V_r: Rotor speed, d_{80}: Characterized feed size, O_e: Operating energy, LAAV: Los Angeles abrasion value of the crushed stone, Q: Cumulative throughput below 50 mm.

To activate the nonlinear models like Eq 2, the whole equation system should be linearized, an example of which is given by Eq 3. Eq 3 was then solved using the Cholesky Decomposition method to achieve the nonlinear model constants.

$$\ln(y) = \ln(a_0) + t_0 \ln(x_0) + t_1 \ln(x_1) + t_2 \ln(x_2) \ldots t_n \ln(x_n) \quad (3)$$

Table 2. Descriptive statistics of the variables considered in this study.

Parameter	R_w (mm)	R_d (mm)	V_r (rpm)	d_{80} (mm)	O_e (kW)	LAAV (%)	Q (t/h)
Min	670	1005	304	50	65	12	81
Mean	1440.6	1249.9	559.2	75.58	234.9	21.27	195.2
Max	2135	1600	750	121.43	500	35	297
Std. dev.	406.6	184.3	128.2	20.63	114.2	5.90	65.2
Q_1	1050	1035	511	57.86	126.3	17.55	150.3
Q_2	1355	1300	575	67.86	225	20.35	198
Q_3	1825	1400	647.5	88.93	315	25.82	249.5
n	32	32	32	32	32	32	32

Explanations: Min: Minimum, Mean: Average, Max: Maximum, Std. dev.: Standard deviation, Q_1: First quartile, Q_2: Second quartile (Median), Q_3: Third quartile.

Table 3. Correlation matrices for the evaluation of Q.

Correlation index	R_w	R_d	V_r	d_{80}	O_e	LAAV
Pearson's correlation coefficient (r)	0.729	0.621	0.054	0.504	0.846	0.258
Spearmen rho value, (ρ)	0.718	0.601	0.013	0.494	0.869	0.269

3.2. Artificial neural networks (ANN)

The artificial neural network (ANN) has been widely adopted to predict several dependent variables based on complex datasets. It is a well-accepted method in most mining engineering problems.

The ability of ANN is that complex datasets can be modeled by using such ANN methodologies (Mayorga and Arriaga, 2007). In practical ANN applications, neural networks have been trained using a feedforward backpropagation algorithm (Saravanan and Sasithra, 2014) to establish empirical formulae based on the weights and biases extracted from neural network analyses. In this study, the neural network toolbox (nntool) was used to develop several neural networks in the MATLAB environment.

For this purpose, the database (Table 1) was randomly divided into training (70/100) and testing/validating (30/100) parts. Various ANN network architectures, hidden layers, and neurons were attempted to determine the most suitable and practical structural combination. After 592 neural network simulations, the ANN architecture adopted in this study is illustrated in Fig 3. In the context of the ANN simulations, input parameters were defined as R_w, R_d, V_r, d_{80}, O_e, and LAAV of the crushed stone. Four hidden layers combined the input parameters to the output (Q).

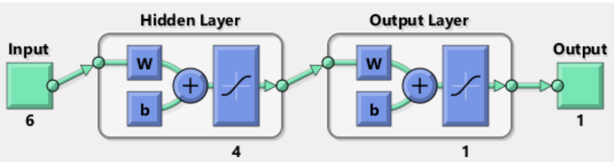

Figure 3. ANN architecture adopted in this study.

Before performing the ANN analyses, the database was normalized between −1 and 1 using Eq 4. Then, the normalized database was loaded into the MATLAB environment to implement such ANN analyses. As a result, a robust predictive model was developed to estimate the Q of HSI-type crushers. The mathematical expressions of the developed model were revealed by adopting the deterministic approach previously described by Das (2013).

$$V_N = 2\left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}\right) - 1 \quad (4)$$

where x_i is the relevant parameter to be normalised, x_{min}, and x_{max} are the minimum and maximum values in the database (Table 2).

3.3 Multivariate Adaptive Regression Sipline (MARS)

The MARS was firstly proposed by Friedman (1991) as a nonparametric regression method, which can be perceived as a hybrid linear model.

There are two important parts in typical MARS models. One is the forward pass and the other one is backward pass. In the forward pass, MARS models are initiated with constant terms, which are called basis functions (BFs). On the other hand, in the backward pass, the BFs are connected with linear regression models.In this study, a novel MARS model was introduced to estimate the Q of HSI type crushers as a function of previously mentioned independent variables. The dataset was divided into training and testing datasets like in the ANN analyses. The MARS analyses were performed using the software R and the details of the proposed MARS model was given in the following section.

4. Results and Discussion

Single and multiple linear regression analysis results are listed in Table 4. Accordingly, one can claim that single linear regression-based models (M1-M4) did not yield satisfactory prediction performances to estimate the Q of HSI type crushers. The correlation of determination (R^2) values of these models ranged from 0.25 to 0.72. On the other hand, multiple linear regression analysis results provided more consistent results than the M1–M4 models. The R^2 values of the multiple regression models (M5 and M6) were found to be between 0.88 and 0.92, respectively. Of these models, the M6 model can be declared the most feasible model in the context of multiple linear regression analyses. Herein, it should be mentioned that the independent variables of R_d, d_{80} O_e, and LAAV can be reliably considered for the evaluation of Q.Nonlinear regression analysis results are also given in Table 5. It can be seen that two nonlinear models (M7 and M8) also provided consistent R^2 values, ranging from 0.91 to 0.94. Moreover, in the models of M7 and M8, the above-mentioned independent variables (R_d, d_{80}, O_e, and LAAV) were also used effectively.

The independent variables of R_w, R_d, V_r, and LAAV of the crushed stone were also emphasized by Babele (2016) as some factors which should be considered to assess the performance of the HSI-type crushers. In addition to the regression analyses, the predictive models based on ANN and MARS are also given in

Table 6 and Table 7, respectively. The measured and predicted Q values obtained from the M6 – M10 models are plotted in Fig 4. Accordingly, the performance of these models is satisfactory, and the predicted and measured Q values are in good agreement. Therefore, these models (M6–M10) can be reliably used to estimate the Q of HSI type crushers.Accordingly, the ANN model can be declared by far the most suitable model in this study. The R^2 for this model is 0.98, which indicates its relative success.

Table 4. Single and multiple regression analysis results.

Model No	Empirical formula	Coefficient	Standard error	t value	R^2
M1	$Q = 26.7 + 0.1169R_w$	26.7	30.2	0.89	0.53
		0.1169	0.02	5.845	
M2	$Q = -79.2 + 0.2196R_d$	–79.2	64.01	–1.237	0.39
		0.2196	0.0507	4.331	
M3	$Q = -74.4 + 1.599d_{80}$	–74.4	39.0	–1.907	0.25
		1.599	0.498	3.210	
M4	$Q = 81.7 + 0.4832O_e$	81.7	14.5	5.634	0.72
		0.4832	0.0555	8.706	
M5	$Q = -98.1 + 0.0912R_d + 0.4272O_e + 3.711LAAV$	–98.1	33.9	–2.893	0.88
		0.0912	0.0268	3.402	
		0.4272	0.0433	9.866	
		3.711	0.727	5.104	
M6	$Q = -140.7 + 0.0789R_d + 0.774d_{80} + 0.3831O_e + 4.175LAAV$	–140.7	28.7	–4.902	0.92
		0.0789	0.0214	3.687	
		0.774	0.184	4.206	
		0.3831	0.0358	10.701	
		4.175	0.585	7.136	

Table 5. Nonlinear regression analysis results.

Model No	Empirical formula	Coefficient	Standard error	t value	R^2
M7	$Q = 0.0295R_d^{0.665}O_e^{0.4832}LAAV^{0.474}$	0.0295	0.033	0.894	0.91
		0.665	0.150	4.433	
		0.4832	0.042	11.504	
		0.474	0.076	6.237	
M8	$Q = 0.0118R_d^{0.627}d_{80}^{0.266}O_e^{0.444}LAAV^{0.555}$	0.0118	0.0109	1.082	0.94
		0.627	0.121	5.181	
		0.266	0.062	4.290	
		0.444	0.035	12.685	
		0.555	0.065	8.538	

Table 6. Empirical formulae of the proposed ANN model

Model 9, M9	$Q = 105.84\tanh\left(\sum_{i=1}^{4} A_i - 0.13313\right) + 189.69, R^2 = 0.98$
$A_1 = 0.76546\tanh\left(2.1677\,{}^{n}R_w + 0.73011\,{}^{n}R_d - 1.1217\,{}^{n}V_r + 2.9732\,{}^{n}d_{80} + 1.8984\,{}^{n}O_e + 1.0837\,{}^{n}LAAV - 1.1457\right)$	
$A_2 = 1.1042\tanh\left(-1.2294\,{}^{n}R_w - 2.1824\,{}^{n}R_d + 1.1466\,{}^{n}V_r + 0.56007\,{}^{n}d_{80} + 1.5385\,{}^{n}O_e + 0.47989\,{}^{n}LAAV + 1.6631\right)$	
$A_3 = -1.3492\tanh\left(0.98166\,{}^{n}R_w - 1.9627\,{}^{n}R_d + 0.79974\,{}^{n}V_r + 0.53444\,{}^{n}d_{80} - 0.48799\,{}^{n}O_e - 0.9131\,{}^{n}LAAV + 0.29478\right)$	
$A_4 = -0.9252\tanh\left(-0.95099\,{}^{n}R_w - 0.55787\,{}^{n}R_d - 0.25184\,{}^{n}V_r - 1.6566\,{}^{n}d_{80} - 3.9728\,{}^{n}O_e - 1.3035\,{}^{n}LAAV - 5.1534\right)$	
Normalization functions	
${}^{n}R_w = 0.0014R_w - 1.9147$ ${}^{n}R_d = 0.0034R_d - 4.3782$ ${}^{n}V_r = 0.0045V_r - 2.3632$	
${}^{n}d_{80} = 0.0282d_{80} - 2.4085$ ${}^{n}O_e = 0.0046O_e - 1.2989$ ${}^{n}LAAV = 0.087LAAV - 2.0435$	

Table 7. Empirical formulae of the proposed MARS model

Model 10, M10	$Q = 40.0244 + 0.417655BF1 + 3.82068BF2 + 0.09705BF3 + 0.07311, R^2 = 0.92$					
Basis functions (BFs)	BF1	$Max(0:O_e - 65)$	BF2	$Max(0:LAAV - 12)$	BF3	$Max(0:R_d - 1015)$
	BF4	$Max(0:V_r - 304)$				

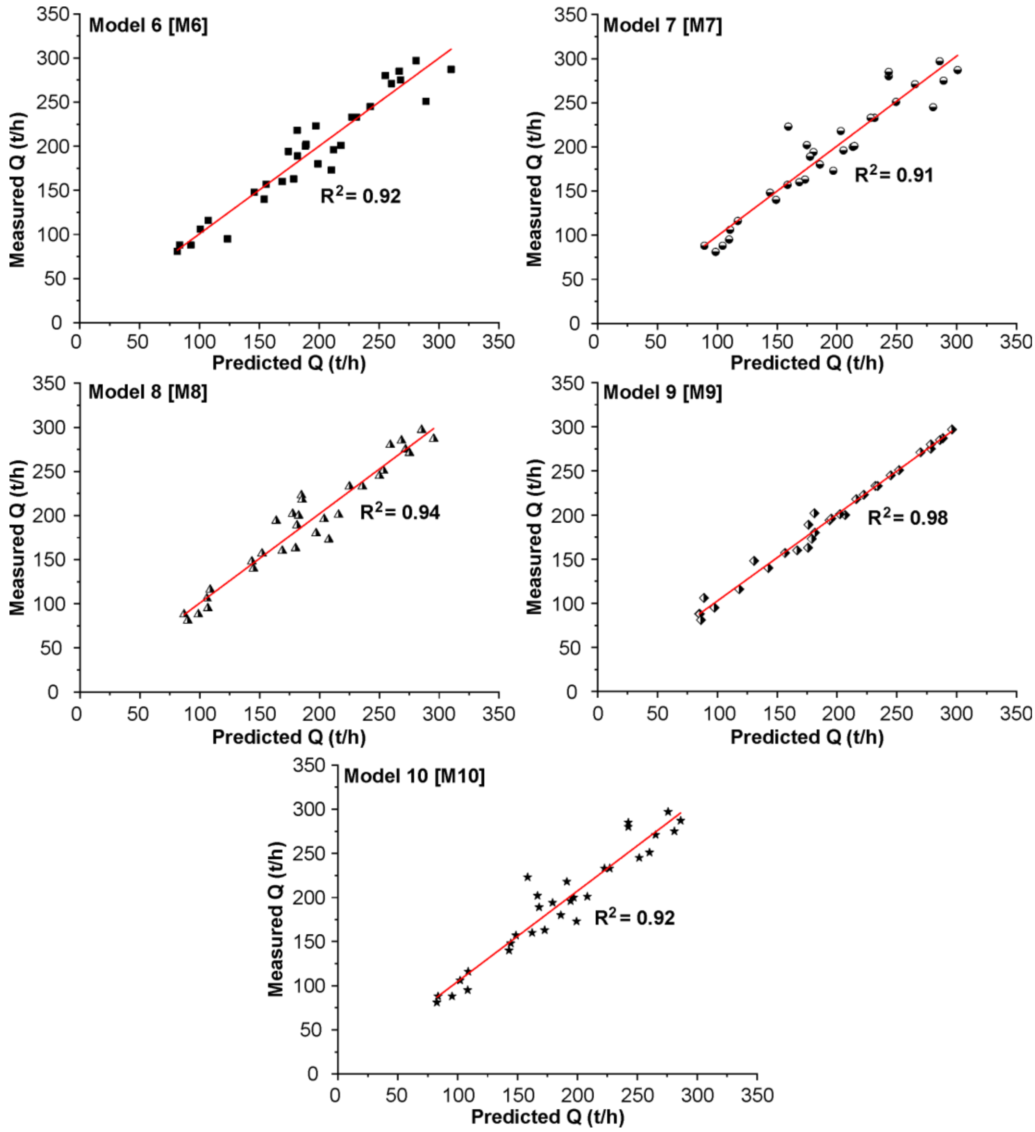

Figure 4. Predicted and measured Q values for the proposed models.

The effectiveness of the parameters used in M6 – M10 models were also investigated through sensitiviy analyses. In this study, the cosine amplitude method (CAM) was used to assess the sensivity degree of each input parameter used in the M6 – M10 models.

Several researchers (Momeni *et al*. 2014,Faradonbeh and Monjezi 2017 and Hosseini*et al*. 2019) also adopted the CAM method to evaluate the sensivity degree of each input parameter. The correlation degree (r_{ij}) for the sensivity analyses were calculated using Eq 5.

$$r_{ij} = \frac{\sum_{i=1}^{n}\left(x_i y_i\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i\right)^2 \sum_{i=1}^{n}\left(y_i\right)^2}} \tag{5}$$

where x_i is the input parameter, y_i is the outputparameter, and n is the number of datasetsused in the analysis.

It is worth reminding that higher the value of r_{ij}, the greater is the effect ofthe relevant input parameter.Based on the sensivity analysis results (Fig 5), it is clear to see that the r_{ij} of all parameters considered in this study was found to be greater than 0.90, showing their relative importance. However, it should be mentioned that the sensitivity analyses demonstrated that, when input parameters arechanged, their effects are also changed for the models introduced in this study. For example, in the M6 model, the r_{ij} of R_d and O_e is 0.96, which shows their relative importance. On the other hand, in the model of M9, the r_{ij} of R_w is 0.98, showing the most important parameter of this model. To sum up, the the R_d, d_{80} and O_e were found to be the most important parameters for the evaluation of Q.

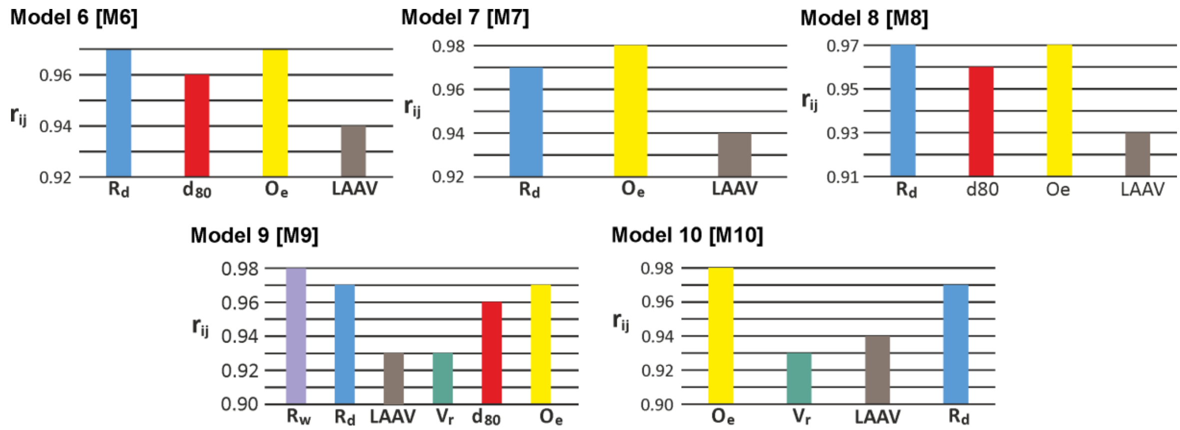

Figure 5. Sensivity analysis results of the proposed models.

5. Conclusions

The present study introduces several predictive models to estimate the Q of HSI-type crushers from various crushing – screening plants in Turkey. For this purpose, a comprehensive database was generated based on the collected data (Table 1, 2). Regression, ANN and MARS analyses were carried out using the independent variables of R_w, R_d, V_r, d_{80}, O_e, and LAAV.

Regression analysis results indicated that the M6–M8 could be reliably used to estimate the Q of HSI type crushers. Nevertheless, M4 and M5 models can also be welcome for simple evaluations on the Q. In addition, the established proposed MARS model (Table 7) was found to present a lower performance than the models of M8 and M9. The ANN-based predictive model (M9) outperformed the other models established in this study. The mathematical formulae of the M9 model are also given to let users implement them more efficiently.

These formulations (Table 6) can be easily coded into any computational language that saves time and reliably estimates the Q of various HSI-type crushers. The sensitivity analyses also revealed the effectiveness of the input parameters used in the proposed models are changeable when the model architecture varies. From this perspective, the number of case studies should be increased to achieve generalized inferences on modeling the Q of various HSI-type crushers as a function of different operational conditions.

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Conflict of 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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