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EVALUATION OF THE CAPACITY OF APRON FEEDERS USED IN CRUSHING–SCREENING PLANTS BY RESPONSE SURFACE METHODOLOGY AND ARTIFICIAL INTELLIGENCE METHODS

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Abstract

In this study, the capacity (Q) of Apron feeders is investigated through response surface methodology (RSM) and some artificial intelligence methods. In this regard, a comprehensive field survey is performed to compile quantitative data on the common working conditions of Apron feeders used in the Turkish Mining Industry (TMI). Based on the collected data, RSM analyses are performed to reveal the factors affecting the Q of Apron feeders. Accordingly, hopper width (B), the height of the material layer conveyed (D), conveyor speed (V), and fill factor (φ) are determined to be the most critical factors for the Q. Several interaction and contour plots are presented to observe the variations in the Q values. Moreover, several predictive models are also introduced to estimate the Q of apron feeders based on artificial intelligence methods such as multivariate adaptive regression spline (MARS), adaptive neuro-fuzzy inference system (ANFIS), and artificial neural networks (ANN). The performance of the established predictive models is assessed based on scatter plots, and it is found that the predictive model based on RSM methodology provides relatively better results than the ones found on soft computing-based predictive models. The presented predictive models can be reliably used to estimate the Q of Apron feeders with high capacity. However, crushing–screening plant designers should be careful when using established predictive models for assessing low-capacity Apron feeders. Based on the findings obtained, the present study demonstrates the applicability of RSM methodology and several artificial intelligence methods for evaluating the Q of Apron feeders.
Keywords: Apron feeders, Crushing-screening plant, Response surface methodology, Artificial intelligence, Mining industry

APRON BESLEYİCİ KAPASİTESİNİN YÜZEY TEPKİ YÖNTEMİ VE BAZI YAPAY ZEKA YÖNTEMLERİ İLE DEĞERLENDİRİLMESİ

Özet

Bu çalışmada Apron besleyicilerin kapasitesi (Q), yüzey tepki yöntemi (RSM) ve bazı yapay zekâ yöntemleriyle araştırılmıştır. Bu bağlamda, Türk Madencilik Sektöründe (TMI) kullanılan Apron besleyicilerin yaygın çalışma koşullarına ilişkin niceliksel verilerin toplanması amacıyla kapsamlı bir saha araştırması yapılmıştır. Toplanan bu verilere göre, Apron besleyicilerin Q değerini etkileyen değiştirgelerin ortaya konması için RSM analizleri gerçekleştirilmiştir. Buna göre, besleyici hazne genişliği (B), taşınan malzemenin bant üzerindeki yüksekliği (D), konveyör hızı (V) ve doluluk faktörü (φ), Q değeri için en önemli faktörler olarak belirlenmiştir. Q değerlerindeki gözlemlemek için çeşitli etkileşim ve kontur grafikleri sunulmuştur. Ayrıca, apron besleyicilerin Q değerini tahmin için, çok değişkenli uyarlamalı regresyon analizi (MARS), uyarlamalı ağ tabanlı bulanık mantık çıkarım sistemi (ANFIS) ve yapay sinir ağları (ANN) gibi bazı yapay zekâ yöntemlerine dayılı bazı tahmin modelleri tanıtılmıştır. Kurulan tahmin modellerinin performansı dağılım grafiklerine göre değerlendirilmiş ve RSM metodolojisine dayalı tahmin modelinin, yapay zekâ tabanlı tahmin modellerine göre nispeten daha iyi sonuçlar sağladığı bulunmuştur. Sunulan tahmin modelleri, yüksek kapasiteli Apron besleyicilerin Q değerini tahmin etmek için güvenilir bir şekilde kullanılabilir. Ancak kırma-eleme tesisi tasarımcıları, düşük kapasiteli Apron besleyicileri değerlendirmek için sunulan tahmin modellerini kullanırken dikkatli olmalıdır. Elde edilen bulgulara dayanarak, bu çalışma, Apron besleyicilerinin Q değerini değerlendirmek için RSM metodolojisinin ve çeşitli yapay zekâ yöntemlerinin uygulanabilirliğini göstermiştir.
Anahtar Kelimeler: Apron besleyiciler, Kırma – eleme tesisi, Yüzey tepki yöntemi, Yapay zekâ, Madencilik endüstrisi

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1. Introduction

Conveyor belts and feeders are essential components in transferring a wide range of bulk materials from millimeter to meter scale. Feeders are of prime importance in crushing–screening, and ore-dressing plants to maintain the sustainability of mining applications. For this reason, they should ensure accurate and uniform discharge from storage to the upcoming system. Grizzly and apron feeders are commonly used to increase the capacity of primary crushing equipment (Fig 1.) The selection of the appropriate type of feeder depends on the properties of the bulk material being handled. (e.g., cohesiveness, maximum particle size, particle friability, propensity for dust generation) [1].

Aprons are mostly preferred when problems associated with blockage and adherence to bulk material are encountered. Mobile apron feeders can also be used for in-pit crushing and conveying (IPCC) systems [2–4].

In practical applications of handling bulk materials, apron feeders help feed large tonnages of bulk materials and are capable of withstanding high-impact loads [5]. Nevertheless, apron feeders are not capable of holding back flooding materials; hence, tons of bulk materials within a silo could be discharged in a couple of minutes [6]. From this point of view, the appropriate use of apron feeders must be accompanied by a feeding hooper [1].

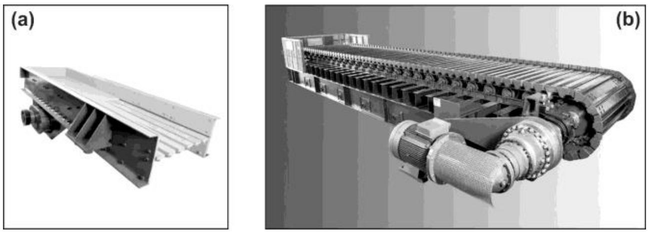

Fig 1. Typical feeders used in crushing–screening plants a) Grizzly feeder b) Apron feeder.

On the other hand, grizzly feeders may be an alternative to apron feeders when handling bulk materials with high amounts of dust and dirty materials. Regarding engineering economics, grizzly feeders are cheaper than apron feeders. In most crushing screening plants, apron feeders are typically located before primary crushing equipment [7–9]. An example of this phenomenon is illustrated in Fig 2. They are also located under a stockpile of ore-dressing plants [10 –12].

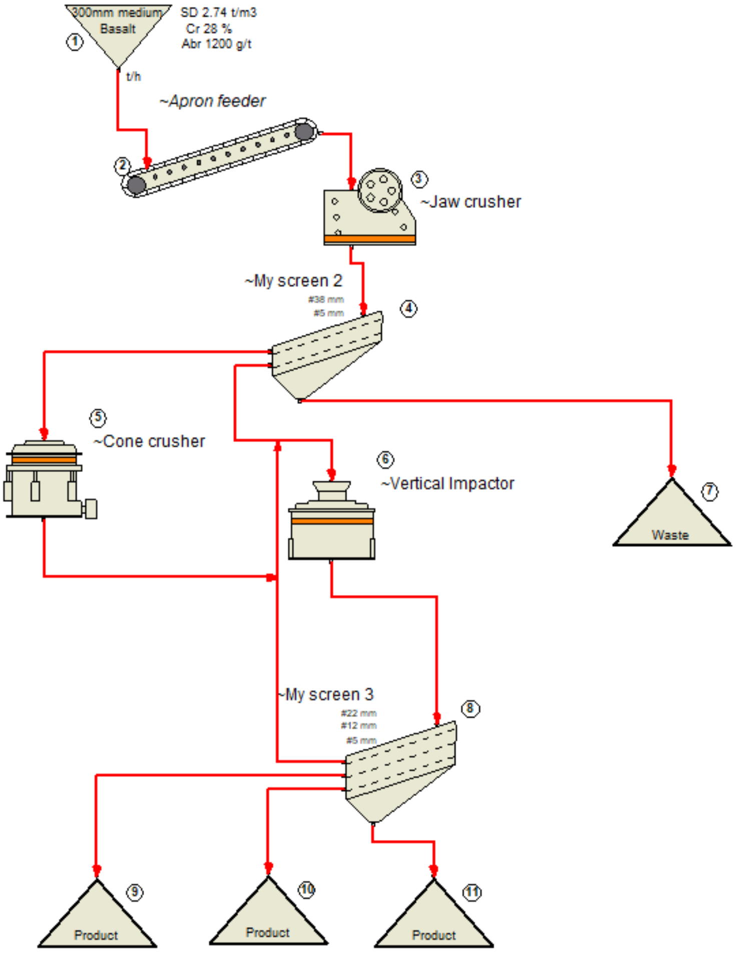

Fig 2. A typical flow diagram of a crushing–screening plant to produce concrete aggregates in Turkey.

Apron feeders are usually made up of metal pans and operate horizontally or at inclines up to 25° [13]. They have been designed by considering a chain drive system, and the efficiency of apron feeders is based upon the stability of this chain drive system. In that context, Huo et al. [14] concluded that the number of teeth and pitch in sprockets is one of the most important factors when dealing with vibration problems.

Table 1 provides a solid basis for the factors affecting the capacity and efficiency of apron feeders. However, as far as the author's knowledge, in the literature, there is no referenced academic paper revealing the common working conditions of apron feeders used in mining engineering applications.

Table 1. Factors affecting the efficiency of apron feeders (Modified after Roberts [15])

- Hopper/feeder flow pattern
- Flow properties of bulk material
- Hopper shape (i.e., conical, trapezoidal etc.)
- Wall friction characteristics between bulk material and hopper wall and skirt plates
- Inclination and filling ratio of apron feeder

Specific to crushing-screening plants, selecting appropriate apron feeders is mainly conducted based on the previous experiences of the ones who are responsible for the crushing-screening plant. Another approach to evaluate the capacity of apron feeders (Q) is that it is generally linked to the capacity of primary crushing equipment (jaw or gyratory crushers) and the characteristics of the material being conveyed. Nevertheless, the capacity of primary crushing equipment is associated with several factors, such as the size and physicomechanical properties of the feeding material, configuration and working conditions of the crushing equipment and the flowchart of the crushing-screening plant [16–20]. This means that the selection of appropriate apron feeders is a complex issue that requires technical guidance and objective evaluations based on real-field data. Engineering judgements based on the previous experiences of the appliers may be somewhat subjective and site-specific. In addition, they are not repeatable, limiting their broader usage.

The primary motivation for preparing this research article is that the Q of apron feeders is mainly assumed to be the capacity of the primary crushing equipment in most crushing–screening plants. In other cases, for example, in ore dressing plants, the Q of apron feeders is assumed to be the capacity of the silo, stockpile, or the throughput of the upcoming transfer component. However, they are not the case.
The Q of apron feeders is changeable based on their working conditions. To reveal the variations in Q values due to varying working conditions, a comprehensive field survey was conducted to obtain a database on varying working conditions of some apron feeders used in the Turkish Mining Industry (TMI). The database includes quantitative information on the hopper width (B), the height of the material layer to be conveyed (D), bulk density of the material being conveyed (ρ_s), conveyor speed (V), the inclination of the apron feeder (λ), characterised feed size (F_{80}) and the fill factor (φ).

In this research article, international readers will find an exact implementation of the sole quantitative approach provided by Metso [21] for calculating the Q of apron feeders. Based on the comprehensive field survey, the Q values are predicted depending upon varying working conditions. The relationships between the collected input parameters and Q values are investigated through the response surface methodology (RSM). Based on the RSM methodology, several interaction and contour plots are prepared to reveal the variations in the Q values. Furthermore, based on some soft computing methods, novel predictive models are also proposed to estimate the Q of apron feeders.

2. Materials and Methods

A comprehensive field survey was conducted to reveal common working conditions of apron feeders used in the TMI. Based on the field survey, including 54 crushing-screening and ore-dressing plants in Turkey, the common working conditions for apron feeders were determined (Table 2).

Table 2. Descriptive statistics of the parameters adopted in this study.

Parameter	Range	Mean	Std. dev.	n
B (m)	0.6–3.5	2.09	0.83	54
D (m)	0.10–0.6	0.34	0.14	54
λ (°)	3–20	8.19	4.27	54
F_{80} (mm)	42.23–255.8	140.13	53.24	54
ρ_s (g/cm^3)	1.2–1.8	1.52	0.17	54
V (m/min)	3–15	8.99	3.35	54
φ	0.2–0.8	0.48	0.17	54
Q (t/h)	24.3–850.5	290.6	242.4	54

Note: Design type: Box-Behnken, Design mode: Quadratic, Data transformation technique: square root ($y' = \sqrt{y}$)

The Q was calculated for each case based on the equations given above [Eqs 1–4]. After the determination of Q, RSM analyses were performed to present some design charts for evaluating Q. After the RSM analyses, several soft computing analyses were also performed to estimate the Q of apron feeders.

$$Q = 60 \otimes B \otimes D \otimes \rho_s \otimes V \otimes \varphi \quad [1]$$

where Q is feed capacity (t/h), B is hopper width (m), D is the height of the material layer to be conveyed (m), ρ_s is the bulk density of the material being conveyed (t/m^3), V is the conveyor speed (m/min), and φ is the fill factor [21].

The V of apron feeders was measured using a stopwatch. The D was determined based on the average material height on the apron feeder. The ρ_s was determined by considering TS EN 1097–3 [22]. The φ was also calculated by the following equations:

$$f_1 = -0.0005\lambda^2 + 0.0012\lambda + 0.9954 \quad [2]$$

Where λ is the inclination of the apron feeder (°)

$$f_2 = 3.90B^{-0.22} \quad [3]$$

Where B is the hopper width (mm)

$$\varphi = \frac{f_1 \otimes f_2 \otimes F_{80}}{200} \quad [4]$$

Where F_{80} is the characterized feed size on the feeder (mm)

The main motivation for attempting soft computing methods is that apart from the approach by Metso [21], there are no quantitative approaches to evaluate the Q of apron feeders in the literature. Herein, it should also be mentioned that the determination of Q (Eqs 1–4) for apron feeders necessitates some redundant and labour-intensive input parameters like ρ_s. From this point of view, several predictive models to estimate the Q of apron feeders may also enable a more comprehensive comparison of the results based on varying working conditions. At this point, soft computing analyses become helpful. They may also eliminate some input parameters and propose more practical and accessible predictive models for evaluating Q. In this context, adaptive fuzzy logic inference systems (ANFIS), artificial neural networks (ANN), and multiple adaptive regression splines (MARS) were adopted as soft computing methodologies.

3. RSM Analyses

The Response Surface Methodology (RSM) is an effective technique that can be used to develop, improve, and optimize processes or products. [23]. This method helps identify the main factors that have a significant impact on the outcome and reveals any potential interactions with other variables [24].
In this study, RSM analyses were performed using Design Expert software. The Box-Behnken design method was adopted in the RSM analyses.

Quadratic data processing was employed for the dataset, and before performing the analyses, the database was transformed by adopting a square root technique ($y' = \sqrt{y}$). RSM analysis results demonstrated that the parameters of B, D, V, and φ are highly correlated with the Q. On the other hand, the ρ_s has a lower impact on the Q. The interactions of these parameters can also be considered according to the ANOVA analysis results (Table 3). Based on the RSM analyses, the Q can be estimated using Eq 5.

$$Q = \begin{pmatrix} -2.22 - 2.94B - 6.16D + 5.32\rho_s - 0.28V \\ -5.95\varphi + 6.97BD + 0.27BV + 4.74B\varphi \\ +1.57DV + 27.84D\varphi + 1.07V\varphi \\ -15.83D^2 - 0.02V^2 - 6.18\varphi^2 \end{pmatrix}^2 \quad [5]$$

Based on the RSM methodology, several design charts are developed to illustrate possible interactions and reveal the variations in Q values due to varying working conditions. In the first part, interaction plots are given in Fig 3. The most important interactions were obtained between the coupling variables of D–V and B–φ. These parameters mainly control the variations in the Q values and can be regarded as one of the most essential working conditions of apron feeders. Contour plots are also prepared for specific working conditions to estimate the Q (Fig 4). Accordingly, the Q can be easily estimated using such contour plots for definite working conditions. However, when needed, different contour plots can also be easily generated based on the RSM methodology.

Table 3. ANOVA analysis results of the parameters used in the proposed RSM model.

Parameter	F value	P value	Statistically significance
B	855.18	<0.0001	Significant
D	876.61	<0.0001	Significant
ρ_s	56.76	<0.0001	Significant
V	738.93	<0.0001	Significant
φ	575.93	<0.0001	Significant
BD	35.56	<0.0001	Significant
BV	30.17	<0.0001	Significant
Bφ	23.69	<0.0001	Significant
DV	30.89	<0.0001	Significant
Dφ	24.26	<0.0001	Significant
Vφ	20.58	<0.0001	Significant
D^2	13.47	0.0009	Significant
V^2	8.58	0.0063	Significant
φ^2	4.25	0.0478	Significant

Note: P values less than 0.05 indicate that model terms are significant.

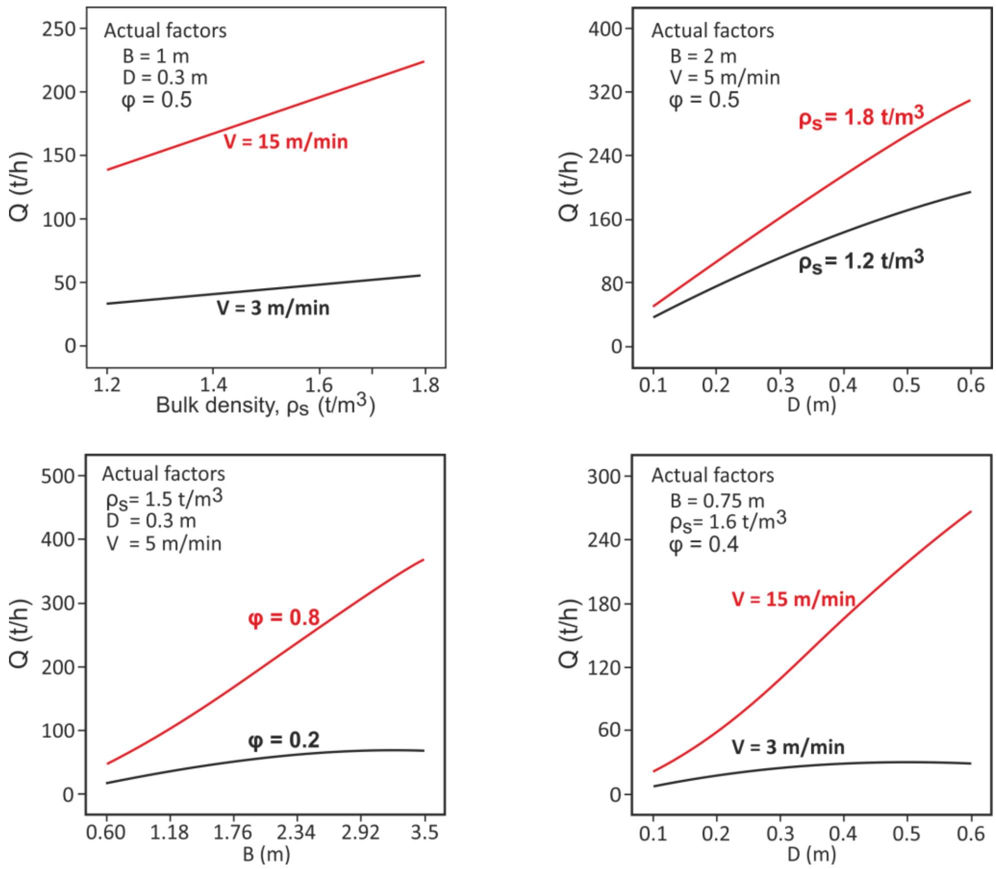

Fig 3. Interaction plots based on different input parameters.

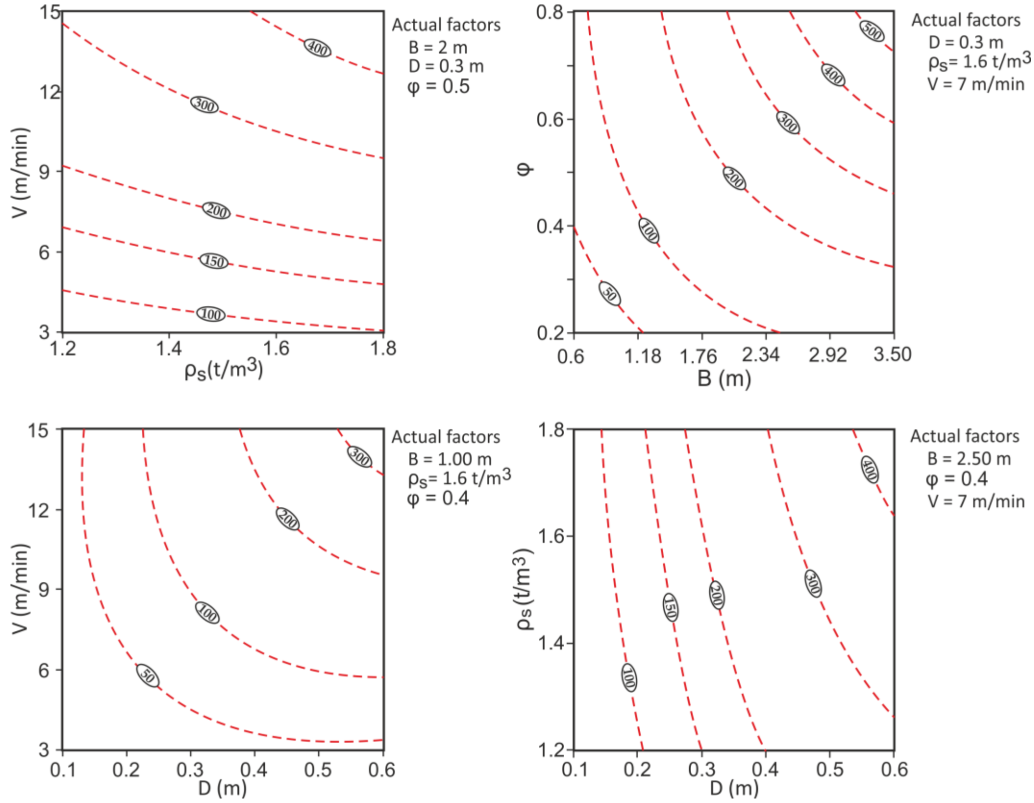

Fig 4. Contour plots based on different working conditions.

4. Soft Computing Analyses

4.1. Multivariate adaptive regression spline (MARS)

The MARS (Multivariate Adaptive Regression Splines) was initially suggested by Friedman [25] as a nonparametric regression technique. In typical MARS models, there are two steps in developing the predictive model: the forward pass and the backward pass. In the forward pass, MARS models are defined with constant basis functions (BFs). On the other hand, the backward pass connects the BFs with linear regression models. In this study, a novel MARS model was introduced to estimate the Q of Apron feeders. The MARS analyses were performed using the software R, and the MARS model is defined by the following equations:

$$Q = 0.368 + 50.23BF3 + 34.08BF4 + 1242.79BF6 \quad [6]$$

$$BF1 = \max(0; B - 0.6) \quad [7]$$

$$BF2 = \max(0; V - 3) \otimes BF1 \quad [8]$$

$$BF3 = \max(0; D - 0.1) \otimes BF2 \quad [9]$$

$$BF4 = \max(0; \varphi - 0.2) \otimes BF2 \quad [10]$$

$$BF5 = \max(0; D - 0.1) \quad [11]$$

$$BF6 = \max(0; \varphi - 0.2) \otimes BF5 \quad [12]$$

4.2. Adaptive neuro-fuzzy inference system (ANFIS)

Due to its advantages, researchers have adopted ANFIS to build predictive models for various engineering applications. The main advantage of ANFIS is that it can be declared as a hybrid learning process based on artificial neural networks and fuzzy logic inference systems. For this reason, ANFIS can provide robust predictive models to estimate the desired output [26]. The ANFIS analyses were performed in the MATLAB environment, where the Sugeno fuzzy reasoning algorithm, which relied on novel membership functions, was used in this case.

The input parameters of D, V, φ and B were adopted in the ANFIS analyses (Fig 5a). The number of the membership functions was changed until the minimum error was achieved. Accordingly, nine Gaussian membership functions were defined for each input parameter (Fig 5b). Nine if-then rules propelled the ANFIS model in parallel with the number of membership functions (Fig 5c). Based on the established ANFIS models, a typical nonlinear surface plot was obtained to represent the variations in Q values (Fig 5d).

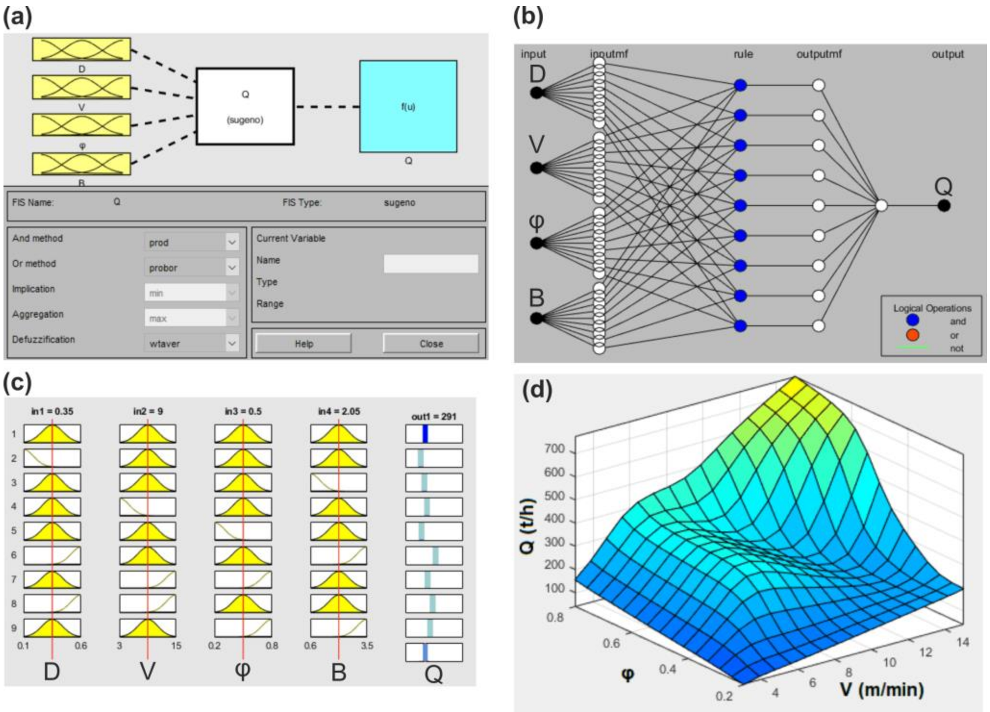

Fig 5. ANFIS outputs a) Input parameters b) ANFIS model structure c) Membership functions d) A typical surface plot based on φ and V.

4.3. Artificial neural networks (ANN)

ANN can analyze the data, learn from it and save the experience-based knowledge for further predictions

[27, 28]. A feedforward backpropagation algorithm is adopted in most ANN models. In this study, various ANN analyses were conducted based on the input parameters of D, V, φ, and B. The ANN architecture adopted in this study is given in Fig 6. Accordingly, there were four inputs, four hidden layers and one output (Q). Eq 12 was used to normalize the database between −1 and 1 before the ANN analyses. The preprocessing was necessary to overcome overfitting problems.

$$V_n = 2 \otimes \frac{(x_i - x_{\min})}{(x_{\max} - x_{\min})} - 1 \quad [13]$$

where x_i is the parameter to be normalized, x_{min}, and x_{max} are the minimum and maximum values in the dataset.

There were four input parameters, four hidden layers and one output (Q) (Fig 6).

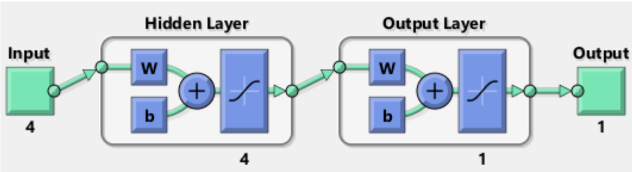

Fig 6. ANN architecture adopted in this study.

As a result of the ANN analyses, a novel predictive model with definite mathematical formulas is introduced. The mathematical expressions (Eqs 14–18) were revealed by using the deterministic approach by Das [29]. Consequently, the Q can be estimated by the following equations:

$$Q = 413.1\tanh\left(\sum_{i=1}^{4} A_i + 0.26\right) + 437.4 \quad [14]$$

$$A_1 = 2.3036\tanh\left(0.48625D^n + 0.15943V^n - 0.00398\varphi^n - 0.09985B^n - 0.42875\right) \quad [15]$$

$$A_2 = 1.1872\tanh\left(0.58571D^n + 0.79546V^n + 1.0211\varphi^n + 1.4506B^n - 1.7929\right) \quad [16]$$

$$A_3 = 0.8776\tanh\left(-0.94728D^n + 0.79498V^n + 1.059\varphi^n + 2.3657B^n + 1.3942\right) \quad [17]$$

$$A_3 = 0.65722\tanh\left(0.67463D^n - 0.96148V^n + 1.0151\varphi^n - 0.65478B^n + 2.2545\right) \quad [18]$$

Normalization functions

$$D^n = 4D - 1.4 \quad [19]$$

$$V^n = 0.1667V - 1.5 \quad [20]$$

$$\varphi^n = 3.3333\varphi - 1.6667 \quad [21]$$

$$B^n = 0.6897B - 1.4138 \quad [22]$$

5. Results and Discussion

Based on the RSM and soft computing analysis results, it was found that the D, V, φ and B are the most critical factors for evaluating the Q of Apron feeders. The ρ_s and some interactions also influence the Q (Table 3). Several predictive models are proposed in Section 4 based on the input parameters of D, V, φ and B.

Fig 7 also shows the scatter plots of the proposed predictive models. Accordingly, the correlation of determination value (R^2) was found to be between 0.92 and 0.97, which shows their relative success. When focusing on the scatter plots in Fig 7, the RSM model (Eq 5) seems to be the best predictive model.

Although this model seems a bit complicated, it is required to observe the variations in Q due to varying working conditions (See Fig 3, Fig 4). On the other hand, since the proposed soft computing-based models did not consider the ρ_s as an input parameter, they seem more practical than the method of Metso [21]. However, the proposed methods should be improved by measuring the factors affecting the losses of Q during material transportation. Table 4 lists some outputs obtained from the RSM and soft computing analyses. When considering these results, it was found that in most cases, the traditional method (Metso) provides higher Q values than those found on the RSM methodology and other soft computing methods. Some possible underlying reasons for this phenomenon can be listed as follows:

- Incomplete information: Soft computing methods utilize existing data to make predictions. Predictions can be slightly different when the available data is incomplete or not representative. In this context, the number of case studies should be improved to enhance the capability of the proposed prediction models.
- Limited model complexity: Soft computing methods are often designed to be computationally interpretable but may not capture the full complexity due to a lack of adequate information or inputs. Additional input parameters may be beneficial here.

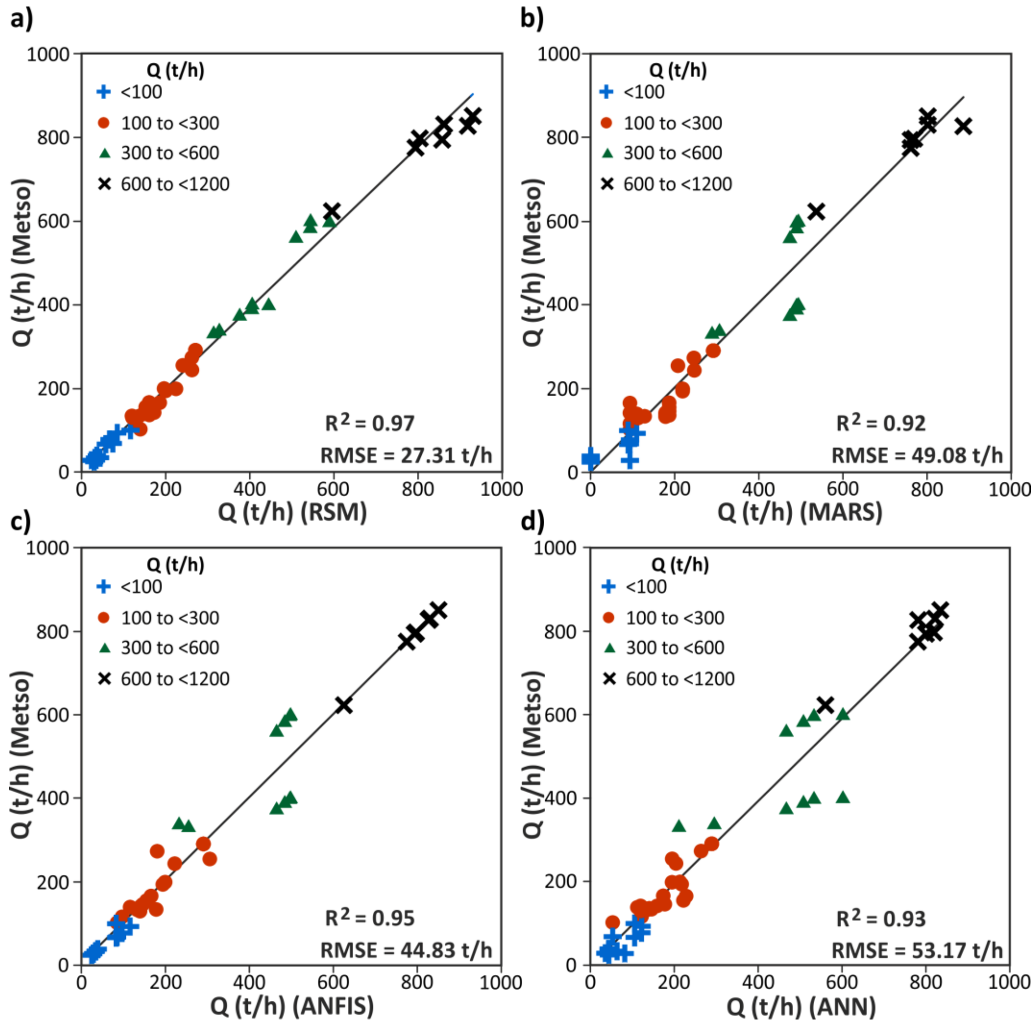

Fig 7. Scatter plots of the proposed predictive models a) RSM b) MARS c) ANFIS d) ANN.

- Parameter selection or tuning: Soft computing methods use input parameters to establish a predictive model; however, if these parameters are not correctly tuned or normalized, prediction accuracy may vary slightly. In this context, it is believed that there is no problem when normalizing (See Eq 13) the input parameters.
- Overfitting or underfitting: Soft computing models may suffer from overfitting or underfitting, resulting in lower prediction accuracy. Some problems may arise because some apron feeders have similar outputs despite having different working conditions.
- Complexity of the problem: Some problems may be inherently complex to model. At this point, the traditional method of Metso [21] was aimed to be simplified by excluding the input parameter of ρ_s. However, it seems that although the ρ_s has a slight impact on the Q, it may become a critical input parameter when assessing the Q of low-capacity-apron feeders.

Considering the coefficient of variations (CoV) in Table 4, it is clear that the CoV increases for low-capacity apron feeders. On the other hand, it dramatically decreases when considering high-capacity apron feeders. Based on this observation, it can be inferred that the proposed predictive models can be reliably used to estimate the Q of apron feeders with high capacity. Conversely, for low-capacity apron feeders, the use of introduced methods (Metso, RSM and other soft computing-based predictive models) may be limited and it is recommended to use all these methods together under this circumstance.

Table 4. Some outputs regarding Q of apron feeders based on definite working conditions.

Working Condition	Q (Metso)	Q (RSM)	Q (MARS)	Q (ANFIS)	Q (ANN)	Q(Average)	CoV (%)
D= 0.25 m ρ_s= 1.74 g/cm^3 V= 8.2 m/min, φ= 0.56 B=2.75 m	329.59	314.03	288.87	255.01	211.19	279.74	15.21
D= 0.18 m ρ_s= 1.60 g/cm^3 V= 7.5 m/min, φ= 0.40 B=2.50m	129.6	120.98	112.88	139.48	119.91	124.57	7.34
D= 0.40 m ρ_s= 1.68 g/cm^3 V= 10.6m/min, φ= 0.34 B=1.88m	273.19	262.18	245.57	180.41	263.95	245.06	13.68
D= 0.29m ρ_s= 1.75 g/cm^3, V= 6.7 m/min, φ= 0.48, B=2.60m	254.61	240.74	207.72	305.72	195.10	240.78	16.17
D= 0.32m ρ_s= 1.74 g/cm^3 V= 9.0 m/min, φ=0.74 B=2.80m	622.99	595.17	536.80	625.16	560.38	588.10	5.91
D= 0.35m ρ_s= 1.58 g/cm^3 V= 7.6 m/min, φ= 0.43 B=3.10m	336.14	327.50	306.38	232.53	295.43	299.60	12.19
D = 0.44m ρ_s = 1.65 g/cm^3 V = 10.5m/min, φ= 0.39 B=1.54m	243.48	262.37	246.70	222.17	204.19	235.78	8.62
D = 0.23m ρ_s = 1.46 g/cm^3 V = 11.5 m/min φ= 0.35 B =1.65m	133.81	119.76	128.50	177.96	145.70	141.15	14.33
D = 0.15m ρ_s = 1.25 g/cm^3 V = 8 m/min φ= 0.25 B =1.50m	33.75	24.99	22.44	28.70	51.49	32.27	32.01
D = 0.28m ρ_s = 1.30 g/cm^3 V = 12 m/min φ= 0.3 B =2.5m	196.56	190.40	235.62	157.62	187.50	193.54	12.89
D = 0.32m ρ_s = 1.55 g/cm^3 V = 14 m/min φ= 0.45 B =1.85m	346.85	326.69	337.81	208.54	355.99	315.17	17.19

6. Conclusions

The variations in Q of apron feeders are investigated using the RSM methodology and some soft computing techniques in this study. A comprehensive field survey was conducted to gather quantitative data on apron feeders used in the TMI. (Table 2). Detailed RSM analyses are then performed to obtain the factors affecting the Q.

As a result of the RSM analyses, it is found that the B, D, V and φ are highly correlated with the Q. Consequently, several interaction and contour plots are developed for definite working conditions (Fig 3, Fig 4). Moreover, soft computing analyses are performed to build some predictive models for evaluating the Q of apron feeders. Consequently, three robust predictive models are established based on soft computing analyses.

When comparing the performance of soft computing-based predictive models, the ANFIS-based predictive model provides more accurate results than the ones found on MARS and ANN. The performance of the proposed predictive models is also assessed by some scatter plots, and it is determined that the best predictive model is based on the RSM methodology.

Nevertheless, soft computing-based predictive models can be reliably used to estimate the Q of apron feeders with high capacity. These models seem more practical than the traditional method of Metso as they did not consider ρ_s, which is hard to determine in laboratory studies. On the other hand, crushing-screening plant designers should be careful when using the introduced methods for low-capacity apron feeders.

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8. References

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