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ASSESSMENT OF INSTALLED POWER FOR INCLINED BELT CONVEYORS USING GENETIC ALGORITHM AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT: In this study, the installed power (P_{inst}, kW) of several inclined belt conveyors operating in the mining industry of Turkey was investigated through two soft computing algorithms (i.e., genetic expression programming (GEP) and artificial neural networks (ANN)). For this purpose, the most crucial belt (i.e., belt length (L), belt width (W), belt inclination (α)), operational (i.e., belt speed (V_b) and throughput (Q)) and infrastructural (belt weight (W_b) and idler weight (W_{id})) features of 42 belt conveyors were collected for each investigated belt conveyor. The collected data was transformed into a comprehensive dataset for soft computing analyses. Based on the GEP and ANN analyses, two robust predictive models were proposed to estimate the P_{inst}. The performance of the proposed models was evaluated using several statistical indicators, and the statistical evaluations demonstrated that the models yielded a correlation of determination (R^2) greater than 0.95. Nevertheless, the ANN-based model has slightly overperformed in predicting the P_{inst} values. In conclusion, the proposed models can be reliably used to estimate the P_{inst} for the investigated conveyor belts. In addition, the mathematical expressions of the proposed models were given in the present study to let users implement them more efficiently.

Keywords: *Belt conveyors, Mining, Installed power, Gene expression programming, Artificial neural networks*

Eğimli Bant Konveyörlerde Kurulu Gücün Genetik Algoritma ve Yapay Sinir Ağları Kullanılarak Tahmini

ÖZ: Bu çalışmada, madencilik endüstrisinde kullanılan bazı eğimli bant konveyörlerin kurulu gücü (P_{inst}, Kw) iki yapay zeka yöntemi (Genetik programlama (GEP) ve yapay sinir ağları (ANN) ile araştırılmıştır. Bu amaçla, 42 bant konveyöre ait en önemli bant (bant boyu, (L), bant genişliği (W), bant eğimi (α)), işletme (bant hızı, (V_b) ve taşıma kapasitesi (Q)) ve alt yapı (Bant ağırlığı (W_b), bant akış kasnak ağırlığı (W_{id})) özelliklerine ait veriler toplanmıştır. Toplanan veriler yapay zeka analizleri için bir veri seti haline dönüştürülmüş olup, GEP ve ANN yöntemlerini temel alan ve P_{inst} değerini tahmin edebilen iki kuvvetli tahmin modeli önerilmiştir. Önerilen modellerin performansları bazı istatistiksel göstergerler kullanılarak değerlendirilmiş olup, istatisiksel değerlendirmeler modellerin belirleme katsayısı (R^2) değerlerinin 0.95'ten yüksek olduğunu göstermiştir. Bununla birlikte, ANN yöntemini temel alan modelin P_{inst} değerlerini tahmin etmede hafif bir üstünlüğü mevcuttur. Sonuç olarak, önerilen modeller güvenilir bir biçimde P_{inst} değerlerini tahmin etmede kullanılabilir. Ayrıca çalışmada ifade edilen modellere ait matematiksel ifadeler kullanıcıların modelleri daha etkin bir şekilde kullanmaları adına bu çalışmada sunulmuştur.

Anahtar Kelimeler: *Bant konveyörler, Madencilik, Kurulu güç, Genetik programlama, Yapay sinir ağları*

1. INTRODUCTION

Belt conveyors are materials handling equipment that is widely used in several industries. They transport bulk materials from one side to another one in a plant or an industrial environment. Therefore, belt conveyors should continuously operate during their service life with optimum energy consumption. To achieve the maximum outputs from a belt conveyor, it is essential to note that variables such as throughput, operating time, motor horsepower, and the efficiency of components embedded in the belt conveyor system should be paid attention to sustainable material transportation.

A typical belt conveyor is illustrated in Figure 1. Of the variables described in Figure 1, the head pulley with gearbox and the electrical motor are one of the most critical variables for belt conveyor sustainability. Since the power consumption of belt conveyors plays a crucial role in engineering economics, it has been investigated in terms of equipment, operation, technology, and performance indicators, each of which has typical qualifications (Middelberg et al. 2009; Xia and Zhang 2010; Mhlongo et al. 2020).

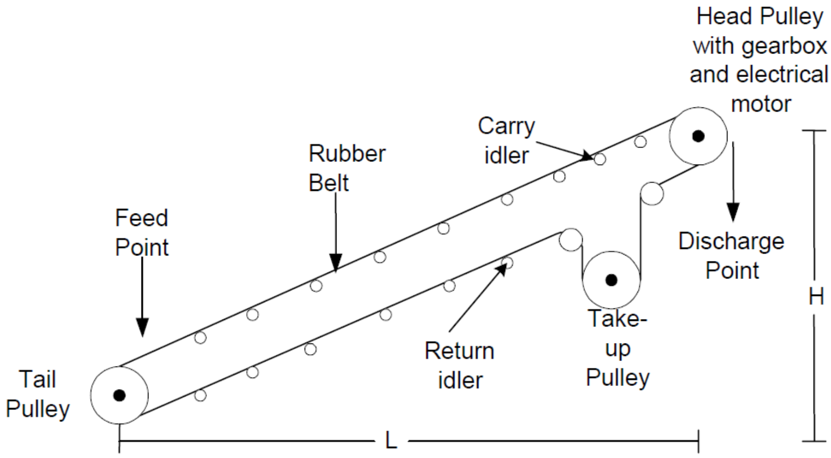

Figure 1. Simplified illustration of a typically inclined belt conveyor (Marx 2005).

Based on modern material transportation science and technology, the installed power of belt conveyors (P_{inst}, kW) has been studied through some methodologies. Therefore, fundamental factors acting directly on the power consumption of a belt conveyor have been widely documented. For instance, belt properties such as belt length (L), belt width (W), belt inclination (α), and belt speed (V_b) are directly associated with the P_{inst}.

Apart from these, belt weight (W_b), idler weight (W_{id}), and throughput (Q) can be declared as other independent parameters for evaluating power consumption (DIN 22101 2002; Dunlop-Fenner 2009; CEMA 2014).

Compared to the conventional ones, energy-saving belt conveyors equipped with multi drivers and soft starters have been designed to let the materials be transported over longer distances (Masaki et al., 2017). From this point of view, belt conveyor systems considering their infrastructures, are inevitable parts, especially in the mining industry.

For instance, Król et al. (2016) proposed a measurement methodology using strain gauges to determine the total mechanical power in underground and surface mining applications. Apart from these, soft computing algorithms were utilized to optimize or regulate the speed control of belt conveyors, which can reduce the total energy consumption (Espinosa et al., 2005; Leposava et al. 2012; Ali 2018).

Belt conveyors are typically made up of a viscoelastic material, which extends under tension. While running in different segments, the belt has to overcome various resistances, causing its tension to increase continuously. Correspondingly, the belt extends during service life, and its speed increases gradually (Yao and Zhang, 2020). Therefore, the maintenance interval of belt conveyors becomes important for sustainable material transportation.

In that context, the proper selection of electric motor propelling the whole belt conveyor system is of prime importance. For this purpose, conventional methods such as DIN 22101 (2002), Dunlop – Fenner (2009), and CEMA (2014) have been widely adopted to estimate P_{inst} for belt conveyors. However, these methods have time-consuming calculation steps (Köken et al., 2022). Therefore, instead of adopting conventional methods to estimate the P_{inst}, such attempts based on soft computing algorithms would be much more practical and straightforward.

For a practical evaluation of estimating the P_{inst} for the Turkish Mining Industry (TMI), two soft computing methods (i.e., genetic algorithm and artificial neural networks) were attempted in this study. For this purpose, a total of 42 inclined belt conveyors used in mining companies in Turkey were considered. The geometrical, conditional, and operational features were collected from each belt conveyor, and the collected data was transformed into a database for soft computing analyses.

Adopting the constructed database, two soft computing-based predictive models were proposed. The performance of the proposed models was compared using several statistical indicators, and it was concluded that the two proposed methods could be reliably used to evaluate the P_{inst} for the investigated belt conveyors.

2. DATA COLLECTION METHOD

In this study, a comprehensive data collection method was carried out. More profoundly, the most important geometrical (i.e., L, W, α), operational (i.e., Q and V_b), and infrastructural (i.e., W_b, W_{id}) features were collected from each investigated belt conveyor. Under all these circumstances, the motor horsepower propelling each belt conveyor system was acquired, inspecting the identity card of each electric motor propelling belt conveyor system. The throughput (Q) of each belt conveyor was determined by Eq 1 as follows;

$$Q = 3.6 \times A_{mf} \times V_b \times \rho \tag{1}$$

where A_{mf} is the cross-section area of material flow (m^2) (DIN 22101 2002; CEMA 2014), ρ is the bulk density of the transported material (kg/m^3), and Q is ton/h in unit.

For determining A_{mf} in Eq 1, the methods proposed by DIN 22101 (2002) and CEMA (2014) were considered together, and average values obtained from these two methods were adopted as the A_{mf} for generalized material flow during material transportation. In addition, the V_b was measured using a stopwatch, observing the belt's material flow of one complete material transportation. Typically inclined belt conveyors considered in this study are given in Figure 2.

Based on the above-mentioned explanations, a comprehensive database was obtained to establish such predictive models for the evaluation of P_{inst}. Case studies and descriptive statistics of the variables considered in this study are listed in Table 1 and Table 2, respectively. From the descriptive statistics, one could notice that the investigated belt conveyors have a wide range of operational features that enable successful soft computing analyses, which are given in the following section.

3. SOFT COMPUTING ANALYSES

3.1. Gene expression programming (GEP)

The GEP is an evolutionary-based algorithm that produces an explicit mathematical formula between dependent and independent variables. The GEP was first developed by Ferreira (2001) and for the past two decades, the GEP has gained popularity among researchers in various engineering fields. In this section, novel applications of GEP were introduced to establish strong predictive models for the evaluation of P_{inst}. For this purpose, the GeneXpro software was used to implement various GEP models. In these models, the number of chromosomes, head sizes, and gene sizes were set to 30, 7, and 3, respectively.

The linking function was the addition, and root means squared error (RMSE) was regarded as the fitness function. As a result of the GEP analyses, the sub-expression trees obtained from the GEP analyses are given in Figure 3.

Figure 2. Typical inclined belt conveyors considered in this study.

3.2. Artificial neural networks (ANN)

The artificial neural network (ANN) has been widely adopted to predict dependent variables based on complex datasets. It is a well-accepted method in most engineering-related problems. In this study, the neural network toolbox (nntool) was utilized to establish several neural networks in the MATLAB environment. The dataset was randomly divided into training (70/100) and testing/validating (30/100) parts. Various possible network architectures with variable hidden layers and neurons were attempted to determine the most reliable structural combination. For estimating the P_{inst}, the most convenient ANN architecture was found to be 7–5–1. (Figure 4). To increase training efficiency, the dataset (Table 1) was normalized using the following equation (Singh et al. 2012; Lawal and Idris 2020).

$$V_N = 2\left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}\right) - 1 \tag{6}$$

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

The explicit mathematic formulae of the sub-expression trees are also presented in Eqs 2 – 4.

$$S_1 = \frac{\left(\frac{-9.10\times Q}{10^3} + 2.0745\right)\times \alpha}{-5.2630}\times V_b \tag{2}$$

$$S_2 = -7.9893 + \ln\left(V_b\right) + 0.3356L \tag{3}$$

$$S_3 = \frac{\ln\left(V_b^{\,2}\right) - \frac{W}{Q - Slp} + Slp}{2} \tag{4}$$

Table 1. Case studies considered in this study.

Case	Belt length. L (m)	Belt slope. α (°)	Throughput. Q (t/h)	Belt width. W (mm)	Belt speed. V_b (m/s)	Belt weight. W_b (kg/m)	Idler weight. W_{id} (kg/m)	Installed power. Pinst (kW)
1	65	15	284	900	1.32	16.8	5.7	22.0
2	47	8	304	1000	1.74	18.3	6.2	15.0
3	53	10	472	900	2.10	16.5	5.7	22.0
4	33	7	525	1200	2.42	22.0	7.7	15.0
5	51	10	614	900	1.91	16.7	6.6	30.0
6	40	17	383	1000	0.98	18.6	7.1	22.0
7	40	10	279	900	1.55	16.5	5.7	11.0
8	54	11	383	1000	1.62	18.3	6.2	22.0
9	49	8	183	1200	2.03	22.0	7.7	11.0
10	52	9	345	900	1.57	16.5	5.7	15.0
11	33	16	441	1000	1.51	18.3	6.2	18.5
12	47	13	319	1000	2.55	18.3	6.2	18.5
13	65	11	353	1000	1.62	18.3	6.2	22.0
14	36	15	354	1000	2.09	18.3	6.2	22.0
15	52	13	293	1000	2.47	18.3	6.2	18.5
16	48	10	399	1000	2.09	18.3	6.2	18.5
17	47	8	157	1000	0.91	18.3	6.2	7.5
18	34	10	278	900	1.24	16.5	5.7	9.2
19	55	10	340	1200	2.58	22.0	7.8	18.5
20	43	9	313	900	1.53	16.5	5.7	15.0
21	49	13	290	1000	2.24	18.3	6.2	18.5
22	58	11	320	1200	2.06	22.0	7.8	22.0
23	58	11	383	1000	2.83	18.3	6.2	30.0
24	32	9	256	1000	2.00	18.3	6.2	9.2
25	59	11	439	1000	1.01	21.3	7.1	22.0
26	53	15	429	1000	2.44	18.3	6.6	30.0
27	33	8	523	900	1.69	16.5	6.6	15.0
28	41	19	148	1000	0.39	18.6	7.7	9.2
29	58	13	96	1200	0.31	19.8	7.8	7.5
30	42	12	416	1200	1.53	22.0	7.8	18.5
31	50	11	397	1000	2.66	18.3	6.2	22.0
32	40	14	375	1000	1.96	18.3	6.2	18.5
33	52	6	160	900	0.59	16.5	6.1	5.5
34	43	8	311	1000	1.54	18.3	6.2	11.0
35	45	8	189	1000	1.32	18.3	6.2	7.5
36	41	13	79	1000	0.32	16.5	6.2	4.0
37	48	9	801	1200	2.30	22.0	7.8	37.0
38	52	12	458	1000	2.35	18.3	6.2	30.0
39	41	22	327	900	2.17	16.5	5.7	22.0
40	53	15	311	1000	1.02	18.7	6.7	18.5
41	71	15	504	1000	2.50	18.3	6.2	45.0
42	55	10	338	1000	2.18	18.3	6.2	18.5

Based on the subexpression formulations given herein, the P_{inst} can be predicted by Eq 5.

$$P_{inst(GEP)} = 1.0377\sum_{i=1}^{3} S_i - 0.2148 \quad (5)$$

Based on the above-mentioned ANN architecture, the P_{inst} can be estimated using Eq 7. The subequations of the proposed ANN model are listed in Table 3.

$$P_{inst(ANN)} = 20.5\tanh\left(\sum_{i=1}^{5} A_i + 0.10968\right) + 24.5 \quad (7)$$

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

Variable	Unit	Minimum	Mean	Maximum	Std. deviation	Number of observation
L	M	32.00	48.05	71.00	9.27	42
α	°	6.00	11.54	22.00	3.35	42
Q	t/h	79.00	346.9	801.00	136.5	42
W	mm	900.00	1009.50	1200.00	95.8	42
V_b	m/s	0.310	1.744	2.830	0.660	42
W_b	kg/m	16.50	18.50	22.00	0.27	42
W_{id}	kg/m	5.70	6.49	7.80	0.69	42
P_{inst}	kW	4.00	18.44	45.00	8.45	42

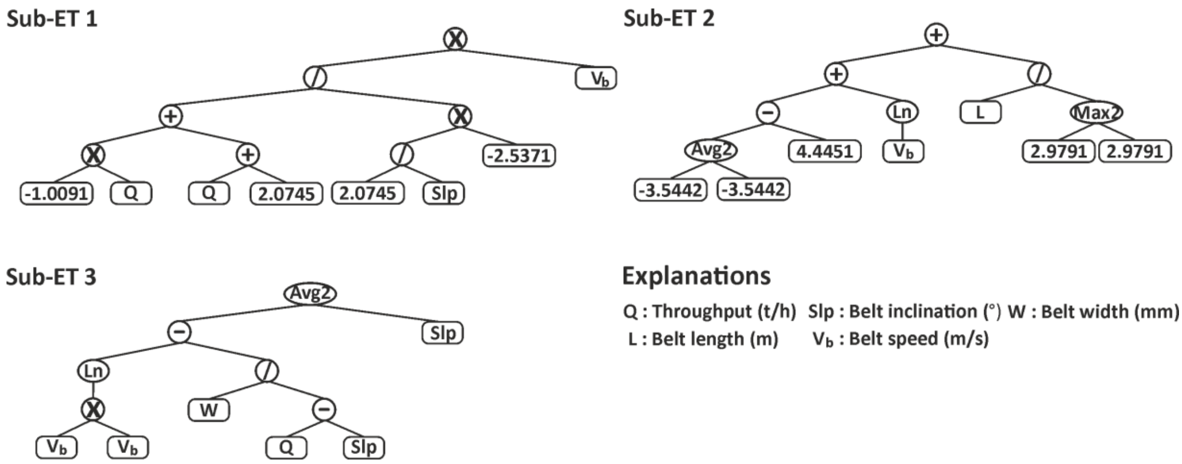

Figure 3. Sub expression trees for the developed GEP model.

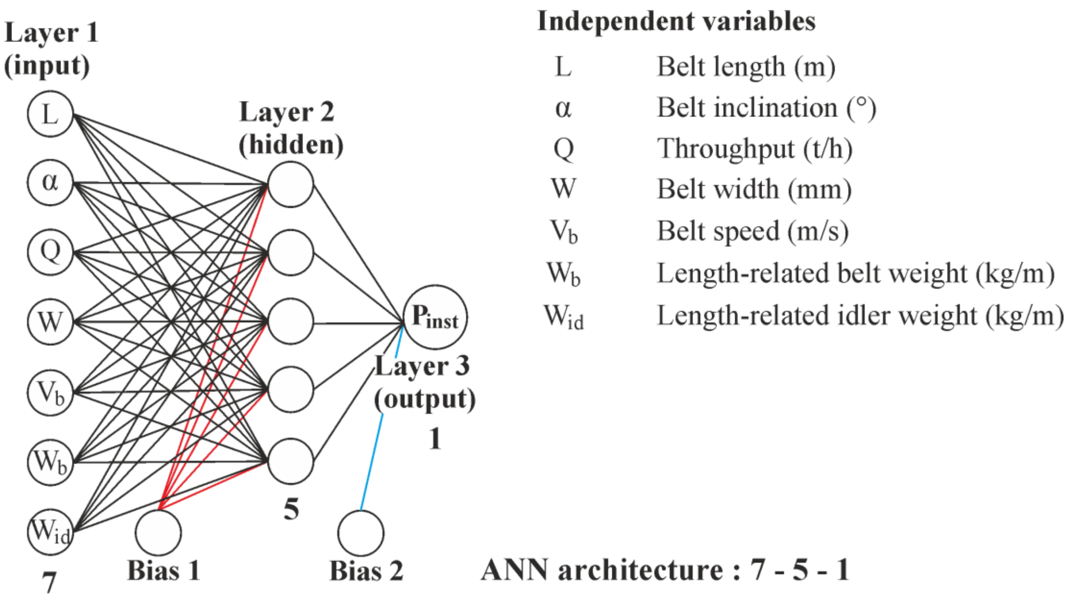

Figure 4. ANN architecture adopted in this study.

Table 3. Sub-equations for the developed ANN model

$A_1 = 0.66923\tanh(1.2678\,{}^{n}L + 0.97159\,{}^{n}\alpha + 2.2611\,{}^{n}Q + 0.44283\,{}^{n}W + 0.12\,{}^{n}V_b + 0.43722\,{}^{n}W_b - 0.1698\,{}^{n}W_{id} - 0.44501)$
$A_2 = -0.33578\tanh(1.4031\,{}^{n}L - 1.2798\,{}^{n}\alpha - 0.2072\,{}^{n}Q + 2.2191\,{}^{n}W - 1.20\,{}^{n}V_b + 1.6728\,{}^{n}W_b + 0.5712\,{}^{n}W_{id} - 0.21013)$
$A_3 = 0.044501\tanh(0.75634\,{}^{n}L - 0.88286\,{}^{n}\alpha - 0.49325\,{}^{n}Q + 1.1719\,{}^{n}W + 1.94\,{}^{n}V_b + 0.87464\,{}^{n}W_b + 0.92297\,{}^{n}W_{id} - 1.6244)$
$A_4 = 1.1508\tanh(0.3072\,{}^{n}L + 0.44506\,{}^{n}\alpha + 0.6536\,{}^{n}Q - 0.35161\,{}^{n}W + 0.14\,{}^{n}V_b + 1.0646\,{}^{n}W_b - 0.26455\,{}^{n}W_{id} + 1.0625)$
$A_5 = -0.71\tanh(0.28099\,{}^{n}L + 0.87214\,{}^{n}\alpha - 0.90376\,{}^{n}Q + 0.58785\,{}^{n}W + 0.30\,{}^{n}V_b + 0.81128\,{}^{n}W_b + 0.1762\,{}^{n}W_{id} + 2.7264)$
Normalization functions
${}^{n}L = 0.051L - 2.615$ ${}^{n}\alpha = 0.1268\alpha - 1.7901$ ${}^{n}Q = 0.0028Q - 1.2191$ ${}^{n}W = 0.0067W - 7$
${}^{n}V_b = 0.7946V_b - 1.2463$ ${}^{n}W_b = 0.3636W_b - 7$ ${}^{n}W_{id} = 0.9524W_{id} - 6.4286$

4. PERFORMANCE OF THE PROPOSED MODELS

The comparison of the predictive models was made using a simple computational code generated through Matlab 2020b (Appendix A). Accordingly, the predicted and measured P_{inst} values are plotted in Figure 5. The proposed GEP and ANN-based predictive models yielded a correlation of determination value (R^2) greater than 0.95.

Consequently, it is clear that the predicted P_{inst} values are in high conformity with the actual (operating) P_{inst} values. In the proposed GEP and ANN models, the most important independent variables (i.e., L, α, Q, W, V_b, W_b, and W_{id}) acting on the P_{inst} were considered (Figure 4). These independent variables were previously adopted by the conventional methods suggested by DIN 22101 (2002) and CEMA (2014).

The performance of the models was also evaluated using various statistical indices such as root means squared error (RMSE), mean absolute percentage error (MAPE), and the variance accounted for (VAF). The equations to calculate these indices are given in Eqs. 8 – 10.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(o_i - e_i)^2}{n}} \qquad (8)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|o_i - e_i\right| \qquad (9)$$

$$VAF = \left(1 - \frac{\text{var}(o_i - e_i)}{\text{var}(o_i)}\right) \times 100 \tag{10}$$

where o_i is the observed data, e_i is the estimated data, and n is the number of observations.

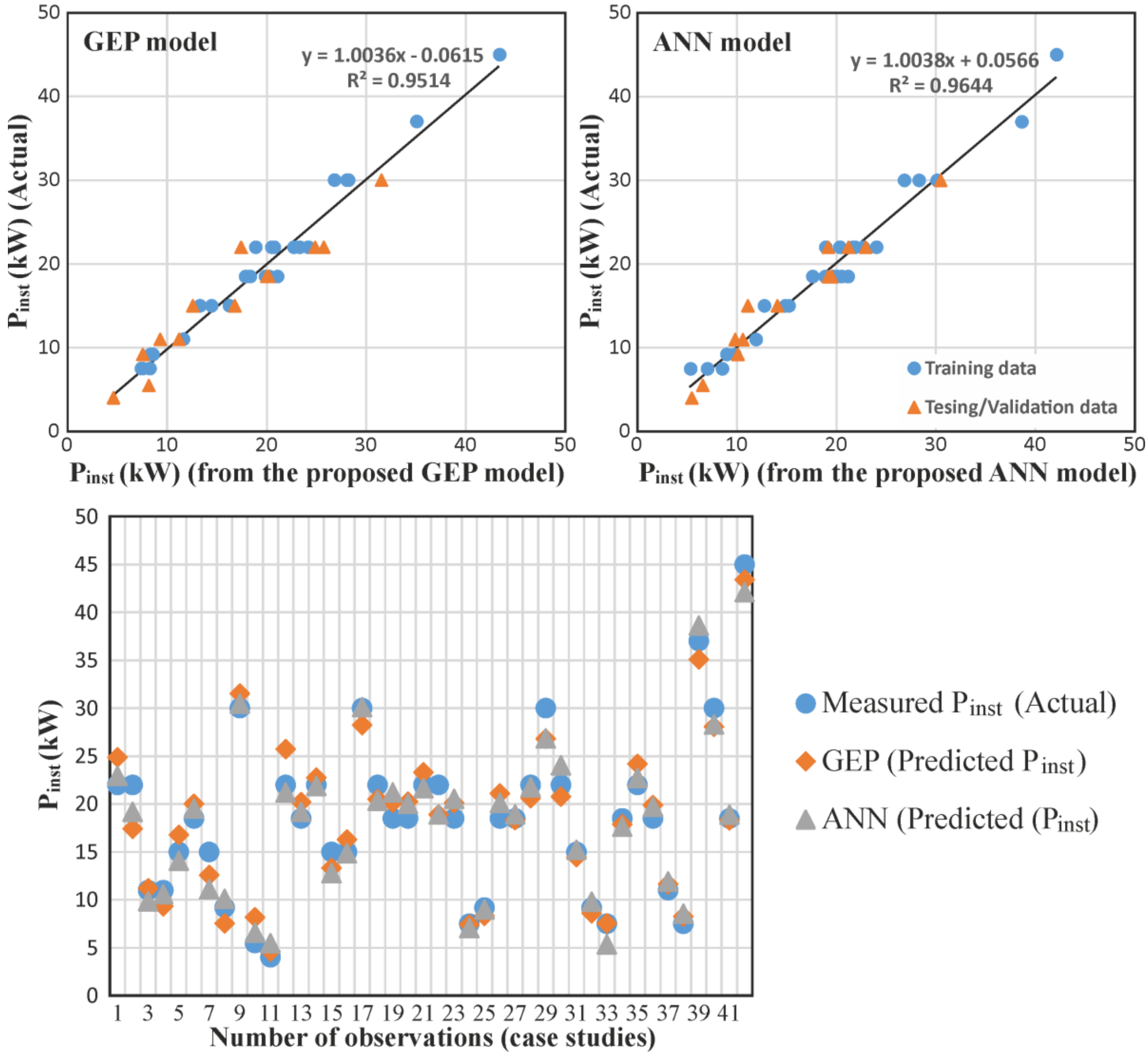

Figure 5. Comparison of the predicted and Measured P_{inst} values

The performance evaluation of the proposed models is given in Table 4. Higher VAF and lower RMSE and MAPE values indicate relatively more successful models. In this direction, when comparing the proposed predictive models to one another, it is logical to suppose that there is no remarkable superiority over the established models. Nevertheless, the ANN-based model (Eq 7) has a slight advantage in predicting the P_{inst} (Table 4). In any case, it is recommended to use the proposed predictive models together for the evaluation of P_{inst} since the conventional methods to estimate the P_{inst} is time-consuming.

Table 4. Performance evaluation of the predictive models

Predictive model	R2	RMSE	MAPE	VAF
GEP	0.9514	1.8416	1.5526	95.1341
ANN	0.9644	1.5812	1.2632	96.4360

Last but not least, the investigated belt conveyors have no energy-saving equipment such as soft starters, frequency converters, belt cleaners, or dust emission equipment, so the proposed models can only be valid for the evaluation of belt conveyors without having such equipment. Therefore there is still a need to analyze belt conveyors equipped with the above-mentioned equipment. It was reported by Jeftenic et al. (2009) and Mushiri (2016) that energy-saving equipment embedded into the belt conveyor systems had prolonged the maintenance interval of the whole belt conveyor system. Therefore, one can claim that the proper selection of motor horsepower could be overestimated when ignoring such equipment.

5. CONCLUSION

In this study, soft computing algorithms were attempted to estimate the P_{inst} of belt conveyors used in the TMI. For this purpose, a total of 42 belt conveyors were considered to establish a comprehensive database for soft computing analyses. Most important geometrical, operational and infrastructural features were collected from each investigated belt conveyor. Based on the GEP and ANN analyses, two robust predictive models were proposed. The proposed models yielded an R^2 greater than 0.95. The performance of the models was also compared with each other, and it was concluded that, there is no clear superiority over the proposed models for the evaluation of P_{inst}. However, the ANN-based model slightly overperformed the other model. Therefore, these two methods can be reliably used to estimate the P_{inst} values for the investigated belt conveyors. It is thought that the proposed models can save time and provide adequate and practical information for estimating the P_{inst} of inclined belt conveyors in the TMI. Since the conventional methods to estimate the P_{inst} is time-consuming, the explicit mathematical formulations of the proposed models were coded in the Matlab environment that can be easily implemented for practical evaluations in this study. From this approach, the present study can be declared a case study showing the applicability of soft computing tools for inclined belt conveyors used in the TMI.

6. ACKNOWLEDGEMENT

The author is greatly indebted to anonymous mining companies who provided their facilities during data gathering and shared the quantitative data of the investigated belt conveyors.

7. 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 document.

Appendix A

Matlab codes for the evaluation of P_{inst}.

```
%Input parameters
Q=input('throughput (t/h):');
Slp=input('slope (degree):');
W=input('belt width (mm):');
L=input('belt length (m):');
Vb=input('Belt speed (m/s):');
Wb=input('Belt weight per unit (kg/m):');
Wid=input('Idler weight per unit (kg/m):');
```

```
%ANN Model
% Normalization functions for the ANN model
nL=0.051*L-2.615;
nSlp=0.1268*Slp-1.7901;
nQ=0.0028*Q-1.2191;
nW=0.0067*W-7;
nVb=0.7946*Vb-1.2463;
nWb=0.3636*Wb-7;
nWid=0.9524*Wid-6.4286;

%Sub equation systems for the ANN model
A1=0.66923*tanh(1.2678*nL+0.97159*nSlp+2.2611*nQ+0.44283*nW+0.12*nVb+0.43722*nWb-0.1698*nWid-
0.44501);
A2=-0.33578*tanh(1.4031*nL-1.2798*nSlp-0.2072*nQ+2.2191*nW-1.20*nVb+1.6728*nWb+0.5712*nWid-
0.21013);
A3=0.044501*tanh(0.75634*nL-0.88286*nSlp-
0.49325*nQ+1.1719*nW+1.94*nVb+0.87464*nWb+0.92297*nWid-1.6244);
A4=1.1508*tanh(0.3072*nL+0.44506*nSlp+0.6536*nQ-0.35161*nW+0.14*nVb+1.0646*nWb-
0.26455*nWid+1.0625);
A5=-0.71*tanh(0.28099*nL+0.87214*nSlp-
0.90376*nQ+0.58785*nW+0.30*nVb+0.81128*nWb+0.1762*nWid+2.7264);
Pann=20.5*tanh(A1+A2+A3+A4+A5+0.10968)+24.5

%GEP model
% Sub equation systems for the GEP model
S1=((-9.1*10^-3*Q+2.0745)*Slp/-5.2630)*Vb;
S2=-7.9893+log(Vb)+0.3356*L;
S3=((log(Vb.^2))-W/(Q-Slp)+Slp)/2;
Pgep=1.0377*(S1+S2+S3)-0.2148
```

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