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A new conventional criterion for the performance evaluation of gang saw machines

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Abstract

The process of cutting dimension stones by gang saw machines plays a vital role in the productivity and efficiency of quarries and stone cutting factories. The maximum electrical current (MEC) is a key variable for assessing this process. This paper proposes two new models based on multiple linear regression (MLP) and a robust non-linear algorithm of gene expression programming (GEP) to predict MEC. To do so, the parameters of Mohs hardness (Mh), uniaxial compressive strength (UCS), Schimazek's F-abrasiveness factor (SF-a), Young's modulus (YM) and production rate (Pr) were measured as input parameters using laboratory tests. A statistical comparison was made between the developed models and a previous study. The GEP-based model was found to be a reliable and robust modelling approach for predicting MEC. Finally, according to the conducted parametric analysis, Mh was identified as the most influential parameter on MEC prediction.

Keywords: Gang saw machine; Carbonate rocks; Cutting dimension stones; Maximum electrical current; Gene expression programming; Multiple linear regression.

1. Introduction

The process of cutting dimension stones using the gang saw is one of the most significant topics of study in relation to the production process in quarries and stone cutting factories. The gang saw is one of the principal machines used for slab production in dimension-stone processing plants. Sawing performance evaluations, contribute to increases in the product quality, productivity and efficiency in quarries and stone cutting factories, which is why they are so important. Developing a high-performance predictive model will guarantee accurate cost estimations and planning in plants, assure a longer tool lifetime, reduce diamond tools' abrasion, and reduce electricity consumption. Some variables are involved in the cutting process, which affect the final cost and quality of the product [1-4]. Of all variables, the most important is the maximum electrical current (MEC). The maximum electrical current of the gang saw influences a relationship with production rate, machine and tools characteristics, operational properties and rock properties. Many researchers have attempted to study the relationships between sawability and rock properties. They have examined properties of rock, type and form of instruments, force or load being imposed, and other environmental parameters. These are shown in Table 1 [5-59]. Figure 1 indicates the frequency of the physical and mechanical characteristics of the rock used in sawability studies. With regard to Fig. 1, uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), Hardness (H), Abrasivity (A), and quartz content (Q_c) have been used widely in research works.

Table 1 Summary of sawability studies.

Researchers	Year	Saw type			Physical and mechanical properties											
		W	C	G	UCS	BTS	YM	IS	SS	BS	H	A	D	Gs	Q_c	N
Burgess and Birle [5]	1978		●											●	●	
Wright and Cassapi [6]	1985		●		●	●					●	●			●	
Birle and Ratterman [7]	1986		●								●					

Jennings and Wright [8]	1989		●	●	●					●				●	
Clausen et al. [9]	1996		●										●	●	
Wei et al. [10]	2003		●	●						●	●			●	
Eyuboglu et al. [11]	2003		●	●	●	●				●					
Zhang & Lu [12]	2003		●												●
Ersoy and Atici [13]	2004		●	●	●	●	●	●	●	●	●	●	●	●	
Kahraman et al. [14]	2004		●	●	●		●			●	●				
Gunaydin et al. [15]	2004		●	●	●		●								
Ozcelik et al. [16]	2004	●		●	●	●				●		●		●	
Buyuksagis and Goktan [17]	2005		●	●	●					●	●			●	
Ersoy et al. [18]	2005		●	●	●	●	●	●	●		●	●		●	
Delgado et al. [19]	2005		●							●				●	
Kahraman et al. [20]	2005		●					●						●	
Fener et al. [21]	2007		●	●	●		●			●	●				
Kahraman et al. [22]	2007		●	●	●							●		●	
Ozcelik [23]	2007	●		●	●					●				●	
Tutmez et al. [24]	2007		●	●	●		●			●	●				
Buyuksagis [25]	2007		●	●	●				●	●	●	●		●	
Mikaeil et al. [26]	2008	●		●										●	
Kahraman and Gunaydin [27]	2008		●							●		●			
Mikaeil et al. [28]	2011		●	●	●	●				●	●		●	●	
Mikaeil et al. [29]	2011		●	●	●					●	●				
Ataei et al. [30]	2011		●	●	●					●	●				
Mikaeil et al. [31]	2011		●	●	●										
Mikaeil et al. [32]	2011		●	●	●	●				●	●		●	●	
Mikaeil et al. [33]	2011		●	●	●	●				●	●		●	●	
Mikaeil et al. [34]	2011		●	●	●										
Ataei et al. [35]	2012	●		●	●					●	●		●	●	
Yurdakul and Akdas [36]	2012		●	●	●				●	●	●	●			
Ghaysari et al. [37]	2012	●											●		
Mikaeil et al. [38]	2013		●	●	●	●				●	●		●	●	
Sadegheslam et al. [39]	2013	●		●		●					●			●	
Mikaeil et al. [40]	2014		●	●	●										
Tumac [41]	2015		●							●	●				
Mikaeil et al. [42]	2015		●	●	●	●				●	●		●	●	
Mikaeil et al. [43]	2016	●		●	●	●				●	●		●	●	
Aryafar & Mikaeil [44]	2016		●	●	●	●				●	●		●	●	
Tumac [45]	2016		●	●	●						●	●			
Almasi et al. [46]	2017	●		●	●	●				●	●		●	●	
Almasi et al. [47]	2017	●		●	●	●				●	●		●	●	
Almasi et al. [48]	2017	●		●	●	●				●	●		●	●	

Kamran et al. [49]	2017	●			●	●	●				●	●		●	●	
Akhyani et al. [50]	2017		●		●	●	●				●	●		●	●	
Akhyani et al. [51]	2017		●		●	●	●				●	●		●	●	
Mikaeil et al. [52]	2017	●			●	●	●				●	●		●	●	
Mohammadi et al. [53]	2018			●	●						●	●			●	
Dormishi et al. [54]	2018			●	●	●					●	●			●	
Mikaeil et al. [55]	2018	●			●	●					●	●			●	
Mohammadi et al. [56]	2018			●	●						●	●				
Aryafar et al. [57]	2018		●		●	●	●				●	●		●	●	
Dormishi et al. [58]	2018			●	●	●	●				●	●		●	●	
Mikaeil et al. [59]	2018			●	●	●					●	●			●	
Aryafar et al. [60]	2018		●		●	●	●				●	●		●	●	
Tumac & Shaterpour [61]	2018		●		●	●					●	●	●	●		

W Wire saw; *C* Circular saw; *G* Gang and Chain saw, *UCS* Uniaxial compressive strength; *YM* Young's modulus; *BTS* Indirect Brazilian tensile strength; *IS* Impact strength; *SS* Shear strength; *BS* Bending strength; *H* Hardness; *A* Abrasivity; *D*, Density; *Gs* Grain size; *Qc* Quartz content; *N* other parameters.

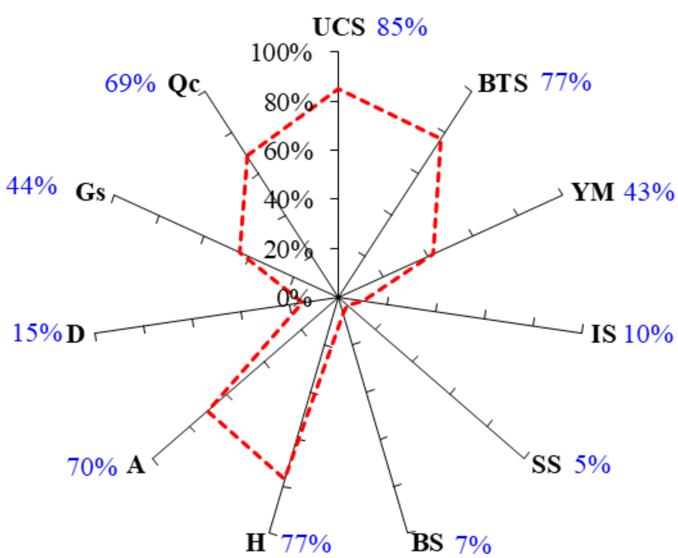

Fig. 1. Frequency of parameters studied in sawability research.

Dormishi et al. [54] investigated the relationship between texture coefficient and the energy consumption of gang saws in carbonate rock cutting processes. They studied 14 carbonate rock samples. Their results indicated that, in the three groups of carbonate rocks, there was a striking relationship between the texture coefficient and the energy consumption rate. Mikaeil et al. [55] investigated the effects of mechanical rock properties on cutting efficiency and wearing rate, and developed three intelligent models to estimate the wearing rate of diamond wire saws. Their results showed that ANFIS-SCM performed better than other predictive methods. Mohammadi et al. [56] developed a group method of data handling (GMDH) model to predict the production rate of the dimension stone cutting process. They conducted 98 laboratory tests on 7 carbonate rocks. In their study, some operational characteristics of the machines, and three important physical and mechanical characteristics of the rocks, were considered as inputs of the model, and the production rate as the output. Finally, they could predict the production rate with high accuracy. Aryafar et al. [57] assessed the performance of sawing machines using particle swarm optimisation (PSO) and artificial bee colony (ABC) algorithms as soft computing techniques. They evaluated physical and mechanical properties. The results showed that the applied soft computing techniques can be used to classify dimension stone in various complex conditions and uncertain systems. Dormishi et al. [58] carried out optimisation investigations of the process of cutting dimension rocks using two hybrid algorithms. For this purpose, 120 samples were tested on 12 carbonate rocks. They compiled a database containing the maximum electrical current of the gang saw machine during the process of cutting, the mechanical properties of the rock samples, and the production rate of the cutting machine. They proposed some models in their study based on ANFIS-DE and ANFIS-PSO algorithms for predicting the performance of gang saw machine. The results indicated the superiority of the proposed ANFIS–PSO model compared to ANFIS–DE model. Mikaeil et al. [59] investigated 12 quarries and provided a good correlation between the hourly production rate and the rock characteristics. Those characteristics included the Schmiazek abrasivity factor, the Mohs hardness, the uniaxial compressive strength and Young's modulus using the imperialist competitive algorithm and fuzzy C-means. As a result, the imperialist competitive algorithm was able to provide more precise results than the fuzzy clustering technique. Aryafar et al. [60] evaluated and predicted sawing performance using two data mining techniques (a genetic algorithm (GA) and a differential evolution algorithm) based on the sawing machine's vibration. In their study, 12 types of rocks, including granite, marble and travertine were selected and studied, and laboratory tests were conducted based on four physical and mechanical rock properties. The obtained results indicated the superiority of the GA to the differential algorithm in evaluating sawing performance. Tumac and Shaterpour-Mamaghani [61] used regression analyses for evaluating the sawability of large diameter circular saws. They considered some of the most essential physico-mechanical parameters of rock samples to predict the areal slab production rate of large-diameter circular saws. The proposed model provided reliable results for evaluating the sawability of large diameter circular saws. In another study, Taheri et al. [62] used multiple regression method to predict drilling rate based on rock properties.

Considering the all above-mentioned studies, most of the used techniques for evaluating the sawing performance are known as black-box techniques i.e. they suffer from the complex and vague internal structure and cannot provide an equation or visual pattern for the users. Hence, there is still a need to develop a multi-parameter, easy to use, and practical models to predict gang saw machines' performance precisely. This paper proposes new mathematical predictive models based on gene expression programming (GEP), as an evolutionary algorithm, and the multiple linear regression-based (MLR) analysis. For this purpose, 120 laboratory tests were conducted on three types of carbonate rocks, and the influential parameters on MEC were measured for further analysis. The results of the proposed models were compared, and a parametric sensitivity analysis was carried out on the selected model.

2. Experimental study and data collection

The field investigation was carried out in one of the dimension stone processing factories in Mahalat city, in Markazi Province, Iran. In this study, the blocks were extracted from 12 nearby quarries, and then were sent to the laboratory, where 120 samples were tested based on ISRM standards [63]. The laboratory tests were conducted on three groups of carbonate rocks, including travertine, marble and crystal marble. The crystal marble has fully crystalline texture, coarse grains, and less color variation, which distinguishes it from others. All these three types of carbonate rocks have suitable resistance to frost, heat, and humidity. According to Table 1 and Fig.1, the parameters of UCS, BTS, H, A, Q_c, G_s, and YM, respectively, are the most commonly used parameters for assessing the performance of gang saw machines. Abrasiveness, the wearing of material at a solid surface, affects the performance of sawing tools and is influenced by several components such as mineral composition, the hardness of minerals, grain shape, grain size, and grain angularity [59]. The Schimazek's F-abrasiveness (SF-a) is an important factor for measuring the rock abrasivity, which can be calculated by the following equation [59]:

$$SF-a = \frac{Q_C \times G_S \times BTS}{100} \quad (1)$$

As can be seen from Eq. 1, SF-a considers the influence of the parameters of quartz content (Q_c), grain size (G_s), and Brazilian tensile strength (BTS) directly. Hence, in this study, to decrease the complexity of the developed model using fewer independent variables, the SF-a was introduced as a representative parameter for abrasivity (A), Q_c, G_s, and BTS parameters. Finally, during the conducted tests in the laboratory, the parameters of Mohs hardness (Mh), uniaxial compressive strength (UCS), Schimazek's F-abrasiveness factor (SF-a), Young's modulus (YM), and production rate (Pr) (cutting rate per a meter length of rock) were measured as the representatives of the hardness, strength, wear, and machine operation, respectively. These five parameters also were considered as the inputs during modelling. As mentioned in Section 1, the maximum electrical current (MEC) is an important parameter evaluating the performance of gang saw machines. Therefore, this parameter was assigned as the output parameter. The compiled database can be found in Appendix A. Table 2 shows the descriptive statistics of the data used in this study. Figure 2 and Table 3 display the locations of the quarries that samples were collected from them and their characteristics, respectively.

Table 2 Descriptive statistics of the parameters used in the model development.

Parameters	Abbreviation	Min.	Max.	Mean	Std. deviation	Variance
Uniaxial compressive strength (MPa)	UCS	50.5	72	62.025	6.467	41.824
Mohs hardness	Mh	2.2	4.3	3.138	0.647	0.419
Young's modulus (GPa)	YM	14.5	32	22.225	4.968	24.679
SF-a (N/mm)	SF-a	0.020	0.167	0.064	0.044	0.002
Production rate (Cm/hr)	Pr	8	37	22	9.198	84.600
Maximum electrical current (A)	MEC	81	118	97.908	8.388	70.367

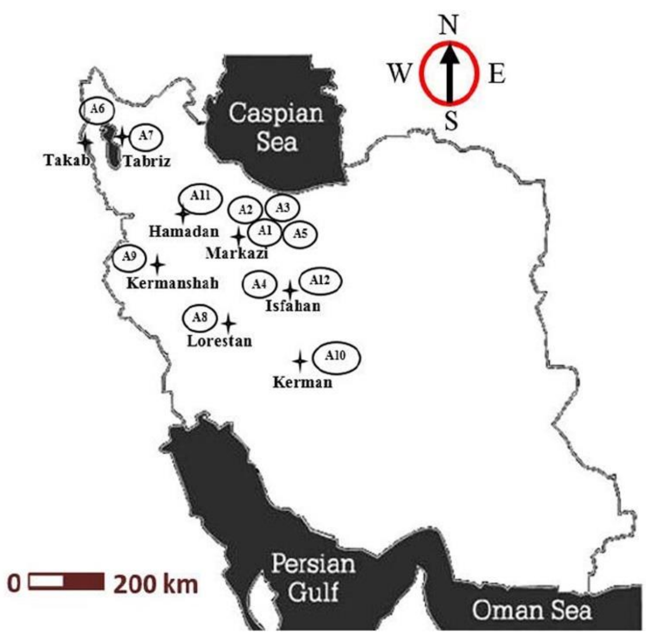

Fig. 2. The location of quarries.

Table 3 Information related to the quarries and average MEC.

Quarry ID	Commercial name	Name of quarry	Average MEC (A)
A1	Hajiabad Travertine	Hajiabad	98.3
A2	Darebokhari Travertine	Kohbar	96.1
A3	Atashkoh Travertine	Atashkoh	104
A4	Chocolate Travertine	Kashan	86.9
A5	Abbas Abad Travertine	Abbas Abad	97
A6	Takab Travertine	Takab	93.7
A7	Azarshahr Travertine	Azarshahr	88.1
A8	Khalkhal Travertine	Khalkhal	85.5
A9	Harsin Marble	Harsin	110.3
A10	Kerman Marble	Mirzaei	105.5
A11	Ghorveh Crystal	Ghorveh	104
A12	Laybid Crystal	Laybid	105.5

In this study, the gang saw machine was used to cut the dimension stones. Figure 3 and Table 4 show the gang saw machine used in this study, and its machine operating properties, respectively. We created Q-Q (quantile-quantile) plots of all parameters to gain insights into the collected datasets (see Fig. 4). A Q-Q plot is a graphical method that allows us to compare two cumulative distribution functions (CDF), e.g. CDF of the datasets and CDF of the normal distribution. Where the datasets have a normal distribution, the points in the Q-Q plot will lie approximately on the line $y = x$. Otherwise, the plots will deviate from the line. Except for P_r and MEC which slightly show a normal distribution, other parameters do not follow a normal distribution.

Fig. 3. Gang saw machine used in this study.

Table 4 Machine operating characteristics.

Characteristic	Unit	Value
Blade run	mm	750
Cutting width	mm	1440
Cutting length	mm	3300
Cutting height	mm	1950
Blade length	mm	4400
Max. no. blades	-	50
Main engine power	kW	55
Total weight of machine	t	47

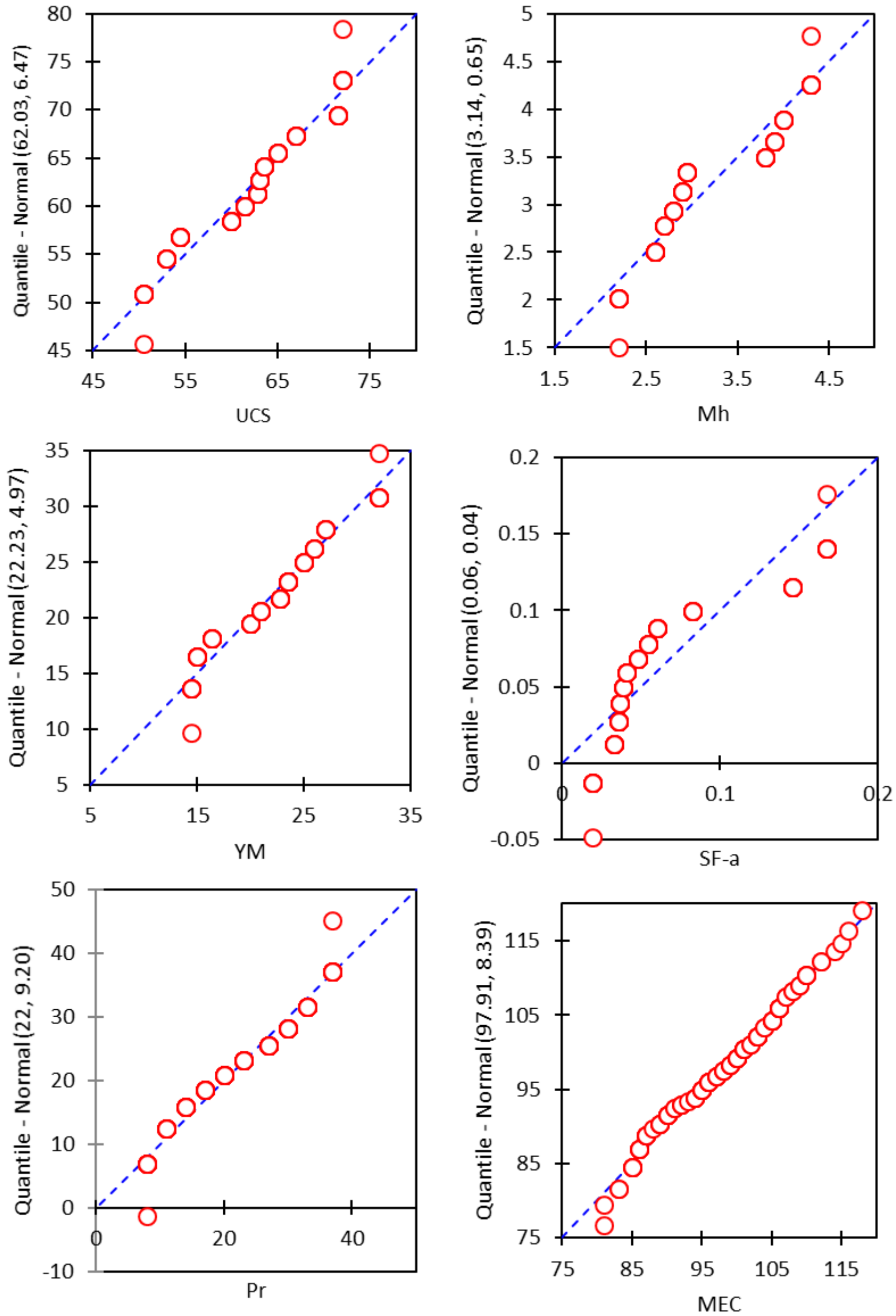

Fig. 4. Q-Q plot of the parameters.

3. Overview of gene expression programming

Gene expression programming (GEP) is a subset of meta-heuristic algorithms first invented by Ferreira [64]. It is a renowned technique for complex, non-linear modelling. Gene expression programming deals with a population of individuals, evaluate them based on fitness values and applies some genetic operators to achieve a desirable solution [65, 66]. Each individual in GEP exhibits characteristics of its siblings (i.e. GA and genetic programming (GP)). Contrary to the parse tree representation in GP, GEP employs linear strings [65-67]. These solutions are then expressed as non-linear entities of different sizes and shapes, or as expression trees (ETs). In GEP, a combination of terminals (i.e. input parameters and constant values) and functions (e.g. $+, -, \times, \div, Log, \sqrt{}$, etc.) forms the structure of chromosomes (possible solutions). Each chromosome in GEP consists of one or more genes, and each gene consists of two main components: A head and a tail. The former contains both the terminals and functions, while the latter only contains the functions [68, 69]. An example of a single-gene chromosome can be presented as follows:

$$+./.Sqrt.\times.c.-.a.b.d.5 \quad (2)$$

where a, b, c and d are input parameters; and 5 is a constant value.

This kind of expression in GEP is referred to as Karva notation or a K-expression, which can be transformed into the ET according to the defined rules by Ferreira [64] (Fig. 5).

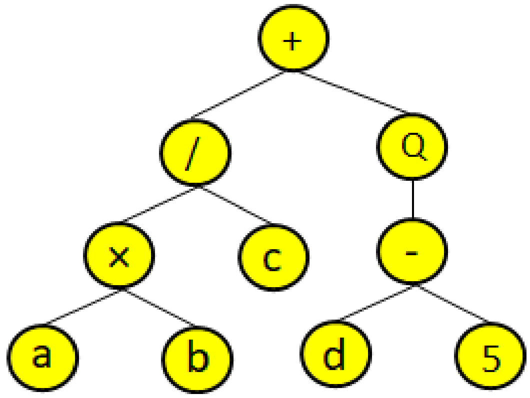

Fig. 5. Expression tree (Q is the second root).

Finally, the innate mathematical relationship of the above-mentioned ET can be extracted as follows:

$$\frac{a \times b}{c} + \sqrt{d - 5} \tag{3}$$

In summary, the GEP algorithm starts with stochastically generated, a predefined number of chromosomes. These chromosomes are then expressed as ETs, and their fitness is checked based on a fitness function. If the desired solution is not obtained, the algorithm continues. The best of initial population is selected by a selection operator such as roulette-wheel sampling method to copy into the next generation, and the remainder is subjected to the specific genetic operators (i.e. mutation, inversion, transposition, and recombination). The newborn (modified) chromosomes are assessed again according to the preceding procedure. The algorithm will stop when it reaches the stopping criterion (maximum number of generations, or a specific fitness value). The process of GEP modelling is displayed schematically in Fig. 6. Further information regarding the GEP mechanism and related genetic operators can be found in many studies [64, 70, 71].

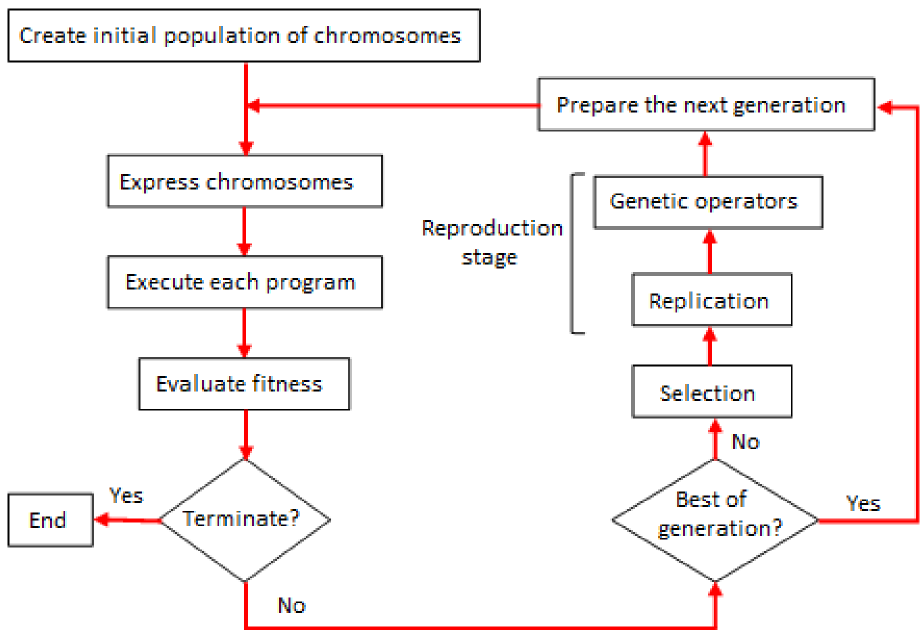

Fig. 6. GEP flowchart [70].

4. Prediction of MEC

4.1. Function development for MEC based on GEP

We used a GEP-based model to obtain a meaningful relationship between the maximum electrical current (MEC) and six other input parameters. Unlike the common non-linear multiple regressions (NLMRs), for which the operator needs to define a predefined structure (i.e. logarithmic, power, exponential, and polynomial structures), the GEP algorithm can search all of the possible combinations of input parameters and functions intelligently. So, there is no need to develop NLMRs separately. A GEP-based model will also automatically check the influence of various ratios of input parameters on the generated solutions. Therefore, there is no need to consider the ratios of parameters as separate inputs. We used GeneXproTools 4.0 software for function finding in this study. At first, we divided all 120 primary datasets into two groups: Training (96 cases) and testing (24 cases). The root mean squared error (RMSE) with parsimony pressure was used to evaluate the fitness of randomly generated chromosomes. The parsimony pressure is an option in GeneXproTools that puts a little pressure on the size of the evolving solutions, allowing it to discover more compact models. The next stage in GEP modelling is to allocate optimum values to the controlling parameters (i.e. the head size, the number of genes, the number of chromosomes, and genetic operators). In this study, we adjusted these parameters based on previously suggested values, after using a trial-and-error approach [67]. Ferreira [64] proved that the number of genes plays a significant role in the success rate of the GEP as it increases from 1 to 3. Therefore, we fixed the number of genes at 3.

The trial-and-error procedure showed that the GEP's performance does not meaningfully improve in either training or testing stages when the number of genes and head size was greater than 3 and 9, respectively. It was attempted to enhance the quality of solutions by taking advantage of a combination of genetic operators comprising mutation, inversion, transposition, and recombination, with specific rates as modifiers. Applying multi-genic chromosomes in GEP modelling requires the operator to assign a linking function to link the genes and provide complete solutions. The addition operator (+) was used in this study as the linking function, since it provided more appropriate results than others (i.e. $-, \times, \div$, etc.). The software was allowed to consider random, numerical constants (i.e. 2 constants per gene) in the range of [-10, 10] to extend the search space of the algorithm and its capability if needed. Table 5 gives the summary of obtained optimum values for GEP parameters. Eventually, the software was executed for 5000 generations with a population size of 80, and the results were recorded.

Table 5 Parameters of the GEP model.

Type of setting	Parameter	Value/quality
General setting	Terminal set	UCS, Mh, YM, SF-a, Pr
	Function set	$+, -, \times, \div, \sqrt{}, Exp, \text{^}2, \text{^}3, \sqrt[3]{}, Sin, Cos, Tan, Atan$
	Fitness function	RMSE
	Population size	80
	Generation number	5000
	Linking function	+
Genetic operators	Mutation	0.06
	Inversion	0.13
	IS transposition	0.11
	RIS transposition	0.12
	Gene transposition	0.13
	One-point recombination	0.3
	Two-point recombination	0.3
	Gene recombination	0.1

Sin sine, *Cos* cosine, *Tan* tangent, *Atan* arctangent

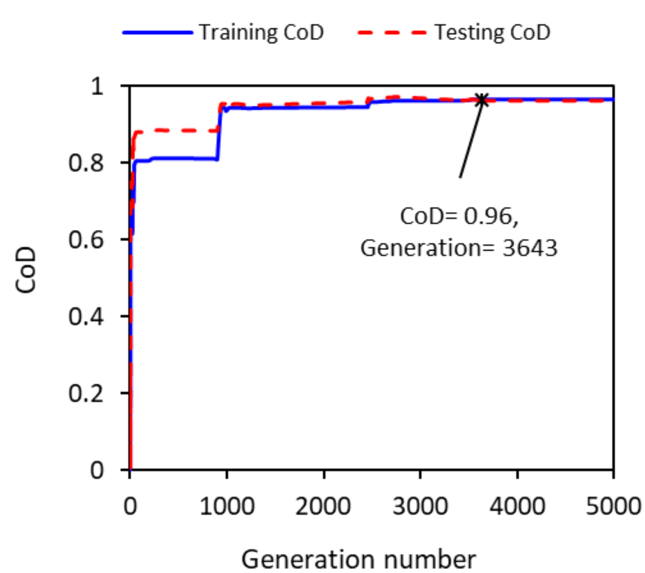

Fig. 7. Variation of CoD with generation number in training and testing stages.

The values of the coefficient of determination (CoD), an accuracy index, were measured during the training and testing stages to check the progress of the GEP modelling process. As shown in Fig. 7, an up-trend of CoDs can be seen until generation No. 3643. This happened in both training and testing stages simultaneously. At this generation, the CoDs converge to a value of 0.96, and no change is observed in CoDs after this. The GEP modelling was stopped at this generation, and the corresponding chromosome (individual) was identified as the best solution. The K-expression of the selected chromosome was listed in Table 6. Subsequently, this chromosome was transformed to ETs so that it could be formulated readily. Figure 8 shows the sub-ETs corresponding to each gene of the preceding K-expression. As mentioned before, these genes are connected by the multiplication (×) function and create a large tree. Finally, the GEP-based predictor can be formulated as follows:

$$MEC = Atan(Mh) \times (2.92389 + \frac{tan(YM^2 - SF_a)}{\sqrt{YM} + YM}) \times Ln\left(\left((-2.41333 + Pr + UCS)^3 + (UCS^3 \times 6.602112 \times SF - a)\right)^2\right) \quad (4)$$

Table 6 K-expression of the best chromosome.

Gene No.	K-expression (without non-coding region)	Constants	
		C0	C1
1	`Atan.d1`	-	-
2	`+.c0./.tan.+.-.Sqrt.d2.^2.d3.d2.d2`	2.92389	-
3	`Ln.^2.+.^3.*.+.^3.*.+.d0.d0.c0.d3.c1.d4`	6.602112	-2.41333

d0 UCS, *d1* Mh, *d2* YM, *d3* SF-a, *d4* Pr, *3Rt* ∛, *Sqrt* √.

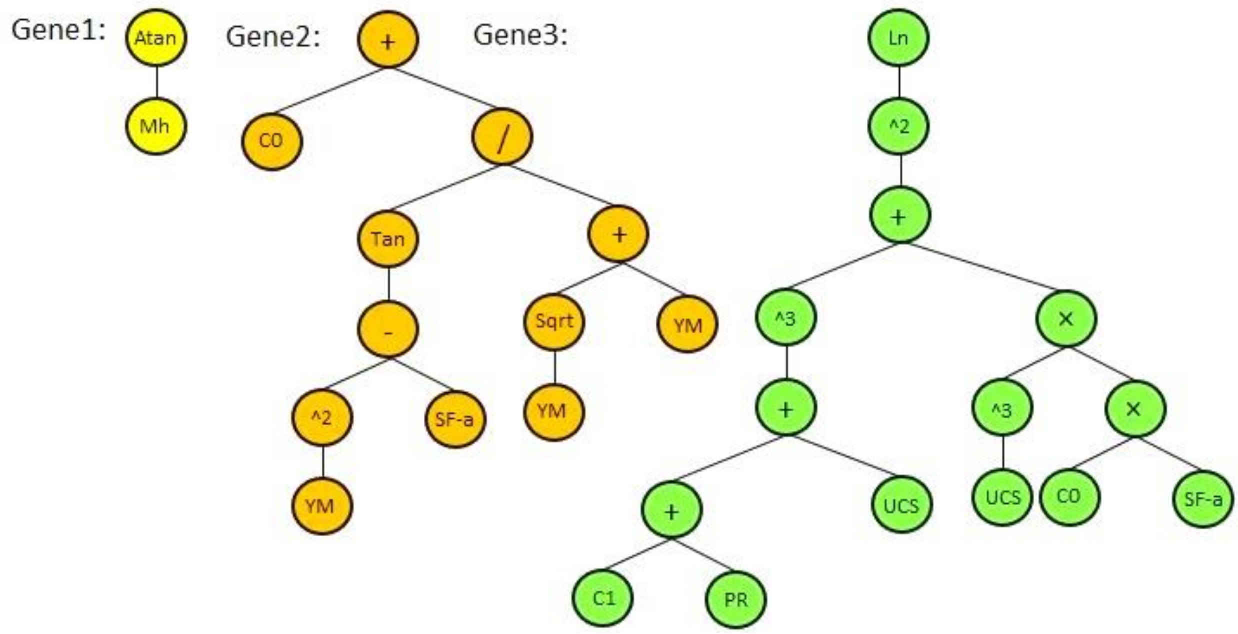

Fig. 8. ET of the GEP model.

4.2. Function development for MEC based on regression analysis

Multiple linear regression (MLR) analysis has been widely used in geoscience, especially in rock mechanics problems [72, 73] to establish a relationship between several independent parameters and a dependent one, by fitting a linear equation to the measured datasets as follows:

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \tag{5}$$

where a_0 and $a_1, a_2, \ldots, a_n$ are the intercept and regression coefficients, respectively, which are calculated using the least squares technique; $x_1, x_2, \ldots, x_n$ are the independent parameters and y is the dependent one.

In this study, SPSS V.21 software was used to develop an MLR model considering five input parameters—UCS, Mh, YM, and Pr and MEC—as the output. Similar to GEP, training datasets were fed to the software and the respective MLR model was obtained as follows:

$$MEC = 19.943 + 1.134UCS + 3.355Mh - 0.471YM + 24.360SF - a + 0.281PR \qquad (6)$$

The developed MLR model was used to predict the MEC for the testing datasets as well.

5. The MEC prediction models' goodness-of-fit

To assess the models' goodness-of-fit, several performance indices were used, including the coefficient of determination (CoD), the root-mean-square error (RMSE), and the variance accounted for (VAF). The CoD represents the proportion of total output variations explained by the model and prepares a judging index of how well the model predicts the real outputs. The higher the value of CoD, the greater the model's accuracy. The RMSE is a measure of standard deviation of the prediction errors (residuals). The ideal value for RMSE is 0. The VAF shows the contribution of the datasets that have been used in the model's construction, and range from 0 % to 100 %, with the ideal value of 100 %. The following equations can calculate these three indices:

$$CoD = 1 - \frac{\sum_{i=1}^{n}(x_{imeas} - x_{ipred})^2}{\sum_{i=1}^{n}(x_{imeas} - \bar{x})^2} \qquad (7)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(x_{imeas} - x_{ipred})^2} \qquad (8)$$

$$VAF = [1 - \frac{var(x_{imeas} - x_{ipred})}{var(x_{imeas})}] \times 100 \qquad (9)$$

where x_{imeas}, x_{ipred}, $\bar{x}$, and n are the measured value, predicted value, mean value of the x_i, and the number of datasets, respectively.

Table 7 shows the obtained values of the indices above for both GEP and MLR models in both training and testing stages. The high values of CoD and VAF, and the low value of RMSE show the superiority of a predictor. As seen in Table 7, both models of GEP and MLR can predict MEC with high accuracy and low estimation errors. However, GEP performs better, and its results are more reliable when compared with MLR in both training and testing stages. The predicted values of the maximum electrical current by GEP is plotted against the measured values in Fig. 9. The errors in estimation can be defined as the distance between the data points and the 1:1 diagonal line ($y = x$). Locating the points on this line gives the exact prediction. According to Fig. 9, the datasets are uniformly scattered around the diagonal line in both training and testing stages. This demonstrates that the GEP model is good enough in predicting MEC value precisely.

Table 7 Statistical performance of the models in training and testing stages.

Index	Training		Testing	
	GEP	MLR	GEP	MLR
CoD	0.964	0.871	0.961	0.937
RMSE	1.586	2.942	1.938	2.396
VAF (%)	96.264	87.130	95.408	93.682

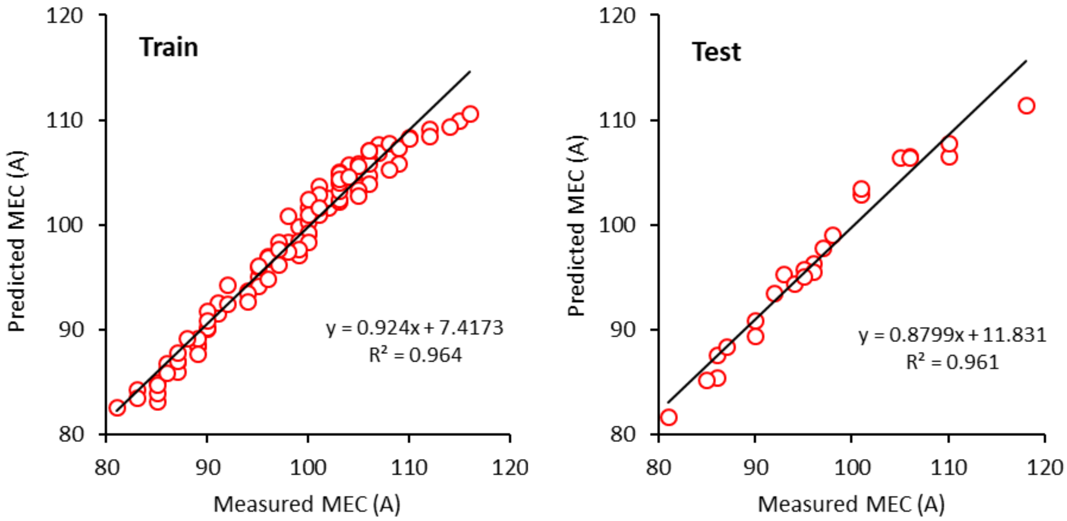

Fig. 9. Measured versus predicted MEC values using GEP model in training and testing stages.

6. Comparison of the developed models with a previous study

The prediction performance of the proposed models (i.e. GEP and MLR) were compared with the results obtained from a study conducted by Dormishi et al. [59] using the same database and input parameters. In that study, two hybrid algorithms of ANFIS-based particle swarm optimisation (ANFIS-PSO) and ANFIS-based differential evolution (ANFIS-DE) were used to predict the maximum electrical current (MEC). Three performance indices of CoD, RMSE, and VAF based on all datasets were calculated in their study to assess the accuracy of the models (see Table 8). To provide similar comparison conditions for that study and the current study, we calculated the performance indices of the proposed model based on the whole of the training and testing datasets. The results are given in Table 8. It is evident in this table that, all f models exhibit high performance in predicting MEC. However, ANFIS-PSO and GEP provide more striking results compared to others. Although ANFIS-PSO shows relatively better values for performance indices, it is a black-box method, and cannot provide a practical output for users. That is, it fails to provide any mathematical equations or graphical outputs. This means it will not be convenient for engineers to use in the field, and researchers cannot use the results of this algorithm in further studies. Gene expression programming, by following an apparent structure and providing a mathematical equation to predict the goal parameters, overcomes the aforementioned problem.

Table 8 Performance indices for different models based on whole datasets.

Model	Index		
	CoD	RMSE	VAF (%)
ANFIS-PSO	0.997	0.500	99.650
ANFIS-DE	0.940	2.310	93.290
GEP	0.963	1.662	96.073
MLR	0.886	2.814	88.564

7. Parametric analysis

To further validate the developed GEP-based model, we performed a parametric analysis to investigate the influence of each input parameter on the maximum electrical current (MEC). To do this, we considered the datasets of the first quarry (i.e. A1: Hajiabad Travertine). It should be noted that although YM is one of the most important mechanical properties, in this study, UCS was considered to be representative of the rock mechanical characteristic [74, 75]. To conduct a parametric analysis, we selected the laboratory test results of the A1 quarry, and determined the maximum electrical current (MEC) consumed based upon the proposed model. Then, by changing the range of values of one of the inputs, and fixing others in their average values, the corresponding changes of the MEC were recorded. Figure 10 displays the results of the parametric analysis. According to this figure, the parameters of Mh and then UCS are the most influential parameters.

On the other hand, SF-a and then Pr have less influence on MEC. By increasing and decreasing the Mh value by 20 %, the MEC of the developed model experienced an almost 4 % and 6 % increase and decrease, respectively. However, this amount of change for the UCS parameter can increase and decrease the amount MEC by about 3.37 % and 3.95 %, respectively. By increasing and decreasing the Pr value by 20 %, the values of MEC have an equal and inverse changes (i.e. $\pm$1.01%). It is worth mentioning that SF-a has a direct relationship with quartz content and grain size; hence, the changes of SF-a influence wearing rate. As shown in Fig. 10, this parameter, however, has a negligible influence on MEC, as MEC is related to the energy required for rock cutting. As a matter of fact, a parameter may do not show a meaningful relationship solely with the output parameter, while it can be an influential component in a combination of other parameters in a non-linear form. In the end, it is necessary to mention that the developed models in this study are based on the collected datasets and a specific range of values for different parameters. So, for future applications, if the input parameters are out of these ranges, the proposed models should be adjusted again.

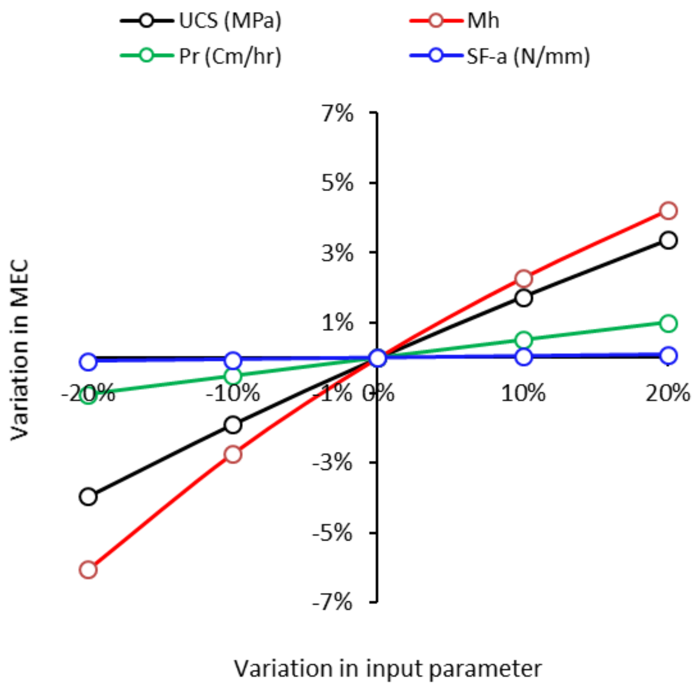

Fig. 10. Parametric analysis of MEC based on the GEP model.

8. Summary and conclusions

Evaluating the maximum electrical current (MEC) of gang saw machine is crucial in quarries and stone cutting factories. This study employed gene expression programming (GEP) as an evolutionary algorithm and a multiple linear regression-based model (MLR) to predict the maximum electrical current of gang saw machines. The 120 carbonate rock samples were collected from 12 quarries and prepared for experimental study. Laboratory tests were conducted to measure different properties of the rocks, including Mohs hardness, the uniaxial compressive strength, Schimazek's F-abrasiveness factor, and Young's modulus. Moreover, the production rate is also used as an input parameter. The following conclusions can be drawn from this study:

1. The prediction performances of the developed equations, using MLR and GEP methods, were compared with each other. The GEP model with statistical indices values of CoD =0.964, RMSE= 1.586, and VAF= 96.264 in the training stage, and CoD =0.961, RMSE= 1.938, and VAF= 95.408 in the testing stage demonstrated higher performance in predicting MEC when compared to MLR results, i.e. CoD=0.871, RMSE=2.942, VAF=87.130 in the training stage, and CoD=0.937, RMSE=2.396, and VAF=93.682 in the testing stage.

2. The GEP model was found to be superior to two hybrid algorithms of ANFIS-based particle swarm optimisation and ANFIS-based differential evolution models in terms of prediction accuracy. Besides, compared with other soft computing techniques, GEP could provide a clear mathematical equation to predict MEC which proves that GEP can deal with uncertain conditions in rock mechanic issues, and such models can be used easily in practice.

3. According to the results of the parametric analysis, Mh showed the most influence on the MEC prediction according to the developed GEP-based model. The parameters of UCS, Pr and SF-a are the next influential factors, respectively.

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Appendix A

Table A.1 Datasets measured in this study.

No.	Sample Type	UCS (MPa)	Mh	YM (GPa)	SF-a (N/mm)	Pr (Cm/hr)	MEC (A)
1	A2	63	2.95	23.5	0.0831	37	99
2	A5	67	2.7	27	0.0364	37	100

3	A5	67	2.7	27	0.0364	27	99
4	A11	65	3.8	25	0.1674	37	107
5	A12	63.5	3.9	23.5	0.1458	11	102
6	A11	65	3.8	25	0.1674	33	107
7	A7	53	2.9	15	0.0385	33	91
8	A6	60	2.6	20	0.0196	20	92
9	A11	65	3.8	25	0.1674	17	103
10	A9	71.5	4.3	26	0.0605	11	104
11	A1	61.5	2.9	21	0.0361	37	102
12	A6	60	2.6	20	0.0196	37	98
13	A4	54.5	2.2	14.5	0.0479	8	85
14	A4	54.5	2.2	14.5	0.0479	20	86
15	A2	63	2.95	23.5	0.0831	23	96
16	A3	62.8	2.8	22.8	0.0407	27	105
17	A6	60	2.6	20	0.0196	14	91
18	A6	60	2.6	20	0.0196	30	96
19	A11	65	3.8	25	0.1674	23	105
20	A12	63.5	3.9	23.5	0.1458	14	103
21	A12	63.5	3.9	23.5	0.1458	27	106
22	A12	63.5	3.9	23.5	0.1458	23	106
23	A10	72	4	32	0.0550	11	101
24	A4	54.5	2.2	14.5	0.0479	37	90
25	A4	54.5	2.2	14.5	0.0479	11	85
26	A9	71.5	4.3	26	0.0605	30	115
27	A7	53	2.9	15	0.0385	8	85
28	A10	72	4	32	0.0550	30	108
29	A2	63	2.95	23.5	0.0831	30	97
30	A6	60	2.6	20	0.0196	23	95
31	A1	61.5	2.9	21	0.0361	14	96
32	A8	50.5	2.6	16.4	0.0334	11	81
33	A3	62.8	2.8	22.8	0.0407	14	103
34	A4	54.5	2.2	14.5	0.0479	23	87
35	A8	50.5	2.6	16.4	0.0334	17	83

36	A2	63	2.95	23.5	0.0831	8	94
37	A6	60	2.6	20	0.0196	11	90
38	A8	50.5	2.6	16.4	0.0334	33	89
39	A8	50.5	2.6	16.4	0.0334	23	87
40	A3	62.8	2.8	22.8	0.0407	17	103
41	A1	61.5	2.9	21	0.0361	27	100
42	A4	54.5	2.2	14.5	0.0479	14	85
43	A10	72	4	32	0.0550	33	110
44	A10	72	4	32	0.0550	23	106
45	A1	61.5	2.9	21	0.0361	23	100
46	A7	53	2.9	15	0.0385	27	90
47	A12	63.5	3.9	23.5	0.1458	8	101
48	A7	53	2.9	15	0.0385	14	86
49	A8	50.5	2.6	16.4	0.0334	27	87
50	A4	54.5	2.2	14.5	0.0479	30	89
51	A3	62.8	2.8	22.8	0.0407	20	103
52	A4	54.5	2.2	14.5	0.0479	33	89
53	A11	65	3.8	25	0.1674	11	101
54	A1	61.5	2.9	21	0.0361	20	99
55	A9	71.5	4.3	26	0.0605	33	116
56	A4	54.5	2.2	14.5	0.0479	27	87
57	A5	67	2.7	27	0.0364	33	100
58	A12	63.5	3.9	23.5	0.1458	20	105
59	A9	71.5	4.3	26	0.0605	8	103
60	A7	53	2.9	15	0.0385	30	90
61	A7	53	2.9	15	0.0385	37	92
62	A5	67	2.7	27	0.0364	14	95
63	A5	67	2.7	27	0.0364	17	96
64	A11	65	3.8	25	0.1674	27	106
65	A3	62.8	2.8	22.8	0.0407	33	109
66	A3	62.8	2.8	22.8	0.0407	23	103
67	A3	62.8	2.8	22.8	0.0407	11	100
68	A6	60	2.6	20	0.0196	27	95

69	A1	61.5	2.9	21	0.0361	30	100
70	A12	63.5	3.9	23.5	0.1458	33	109
71	A5	67	2.7	27	0.0364	23	97
72	A12	63.5	3.9	23.5	0.1458	30	108
73	A3	62.8	2.8	22.8	0.0407	37	110
74	A1	61.5	2.9	21	0.0361	11	95
75	A10	72	4	32	0.0550	17	103
76	A10	72	4	32	0.0550	20	105
77	A11	65	3.8	25	0.1674	8	100
78	A10	72	4	32	0.0550	14	103
79	A12	63.5	3.9	23.5	0.1458	17	105
80	A5	67	2.7	27	0.0364	30	99
81	A6	60	2.6	20	0.0196	33	98
82	A10	72	4	32	0.0550	37	112
83	A7	53	2.9	15	0.0385	11	86
84	A9	71.5	4.3	26	0.0605	17	106
85	A5	67	2.7	27	0.0364	11	94
86	A9	71.5	4.3	26	0.0605	23	112
87	A8	50.5	2.6	16.4	0.0334	30	89
88	A1	61.5	2.9	21	0.0361	33	101
89	A3	62.8	2.8	22.8	0.0407	8	98
90	A8	50.5	2.6	16.4	0.0334	14	83
91	A1	61.5	2.9	21	0.0361	17	97
92	A5	67	2.7	27	0.0364	8	94
93	A9	71.5	4.3	26	0.0605	27	114
94	A10	72	4	32	0.0550	27	106
95	A11	65	3.8	25	0.1674	20	104
96	A7	53	2.9	15	0.0385	23	88
97	A8	50.5	2.6	16.4	0.0334	8	81
98	A2	63	2.95	23.5	0.0831	20	96
99	A2	63	2.95	23.5	0.0831	33	98
100	A6	60	2.6	20	0.0196	17	92
101	A6	60	2.6	20	0.0196	8	90

102	A2	63	2.95	23.5	0.0831	17	95
103	A3	62.8	2.8	22.8	0.0407	30	106
104	A1	61.5	2.9	21	0.0361	8	93
105	A2	63	2.95	23.5	0.0831	27	97
106	A9	71.5	4.3	26	0.0605	14	105
107	A10	72	4	32	0.0550	8	101
108	A11	65	3.8	25	0.1674	30	106
109	A5	67	2.7	27	0.0364	20	96
110	A4	54.5	2.2	14.5	0.0479	17	86
111	A2	63	2.95	23.5	0.0831	11	94
112	A8	50.5	2.6	16.4	0.0334	37	90
113	A7	53	2.9	15	0.0385	17	86
114	A12	63.5	3.9	23.5	0.1458	37	110
115	A2	63	2.95	23.5	0.0831	14	95
116	A7	53	2.9	15	0.0385	20	87
117	A11	65	3.8	25	0.1674	14	101
118	A9	71.5	4.3	26	0.0605	20	110
119	A9	71.5	4.3	26	0.0605	37	118
120	A8	50.5	2.6	16.4	0.0334	20	85

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