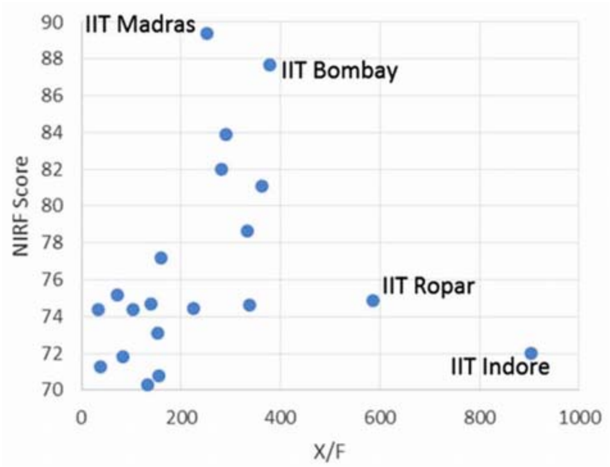

Figure 3. Scatter plot of NIRF score versus exergy per faculty (X/F).

The Pearson's correlations are also shown in Table 2 and Figures 1–3 show the key relationships between X/F, X and NIRF score as scatter plots. We see that the IITs at Bombay and Kharagpur stand out in terms of research excellence. Another insight is the excellent promise shown by the new IITs at Ropar-Rupnagar and Indore.

We use the bibliometric data that has been released through the NIRF 2016 rankings to see how the top twenty engineering institutions fare if only research excellence is considered as is done in major ranking exercises[1–4]. Unlike the NIRF score, which is one single number, we now decompose performance into a size-dependent exergy term and a size-independent productivity term. We see that the IITs at Bombay and Kharagpur stand out in terms of research excellence. Another insight is the excellent promise shown by the new IITs at Ropar-Rupnagar and Indore.

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Hierarchy of parameters influencing cutting performance of surface miner through artificial intelligence and statistical methods

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Applicability of a surface miner (SM) must be based on a careful assessment of intact rock and rock mass properties. A detailed literature review was made to identify different parameters influencing the performance of various types of cutting machines deployed in different parts of the world. The critical parameters influencing the production, diesel consumption and pick consumption of SM in Indian coal and limestone mines, were identified through artificial neural network (ANN) technique and screened by correlation coefficient analysis. Parameters that were common in both ANN and correlation analysis were grouped under critical category and others in semi-critical category.

Keywords: Surface miner, intact rock, rock mass, artificial neural network.

INTACT rock, rock mass and machine parameters are broad key parameters that play a key role in cutting performance. Cutting performance is generally evaluated by various parameters such as, production, specific energy, chip size of cut material, cutting force, pick wear, pick consumption, etc. The present study describes an approach to identify critical parameters that affect the performance of SM based on field data collection from various project areas in India. The purpose of identification of the influencing parameters is to understand their relevant importance in the performance of surface miner (SM) and subsequently use them for predicting its performance. Field investigations were conducted in six mines (three each in coal and limestone mines), spread across India representing varied rock mass parameters. The present study conducted under varied rock mass conditions was confined to SM application only. Artificial neural network (ANN) and correlation tools were used to arrive at critical parameters influencing performance of SM in Indian geo-mining conditions with respect to production, diesel consumption and pick consumption.

The following are the intact rock parameters: Rock density: Dry density is a key property that affects specific energy (SE) while cutting[1]. A rock with higher specific gravity or density will need higher SE in cutting. Kahraman

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et al.[2] correlated rock density to determine penetration rate of percussive drills. Kirsten[3] identified rock density as an influencing parameter in the excavatability assessment of the rock.

Moisture content: Moisture content affects the uniaxial compressive strength (UCS) of the rock[4]. Presence of moisture adversely affects mechanical cutting of those materials which turn sticky if wet, like consolidated soil, bentonite, and some types of claystone, shale, marl and siltstone.

UCS: Rock strength is one of the most important parameters evaluated in rock mechanics[5]. Evans[6] proposed a cutting theory that used UCS and tensile strength (TS) as input variables for determining cutting and normal force (vertical component of the cutting force). The SM manufacturers follow simple conjecture and use UCS of rocks as the only yardstick to define the cutting ability of their machines or to assess the cutting ability of rocks with respect to any given machine[7].

Brazilian tensile strength: The cutting force estimation model used by Evans[8] for coal, taking TS as the main criteria, found wider acceptance for predicting cutting forces in brittle materials. Thuro[9] took TS as one of the rock properties for predicting drillability. Murthy *et al.*[10] considered TS for cuttability assessment of road header (RH).

Point load strength index (PLSI): Point load test is useful for strength classification of intact rocks. Hadjigeorgiu and Scoble[11] developed an excavation index classification scheme by considering PLSI as one of the parameters. Dey and Ghose[12] considered PLSI as one of the key influencing parameters for determination of cuttability of SM.

Seismic wave velocity: In the field of rock mechanics, seismic refraction method is the most popular method and is useful in rock mass characterization in surface mines helping in the selection of an excavation system[13]. The measurement of P-wave velocity is a significant way to determine the mechanical parameters of a rock mass[14].

Abrasiveness: More abrasive a rock, more wear and tear it causes on cutting tools of the machine thus affecting its cutting performance adversely. Origliasso *et al.*[15] considered rock abrasivity as one of the key influencing parameters for cuttability determination of SM. Thuro and Plinninger[16] discussed the application of the Cerchar Abrasivity Index (CAI) in the estimation of tool wear rates for hard rock operations. Murthy *et al.*[17] considered CAI as one of the parameters to develop cuttability index of SM.

Petrography: Roxborough[18] stressed that rock mineralogy, particularly its quartz content, is often of crucial significance to cutting. Howarth and Rowlands[19] developed a model to predict drillability. This model depends on textural properties of the rock such as grain shape and orientation, degree of grain interlocking, and packing density. According to Tiryaki and Dikmen[1], pick forces are expected to increase in linear rock cutting as the texture coefficient increases.

The following are the rock mass parameter: Discontinuities: Presence of joints and other structural features like bedding planes, cleats, slips, etc. in high frequency along with their length and degree of openness assist the cutting process, especially when they are favourably oriented with respect to the direction of cutting. Evans and Pomeroy[20] demonstrated that the orientation of cleats to the direction of cutting can have an important influence on cutter performance with drag picks.

Roxborough and Phillips[21] reported that less SE of about 0.22 MJ/bcm is required when the cutting direction of picks is parallel to coal cleats (cleat orientation = 0°) as shown in Figure 1.

Rock quality designation (RQD): Kirsten[3] identified RQD for determining excavatability of the rock. Bilgin *et al.*[22] used RQD to estimate the advance rate of a RH. Murthy *et al.*[17] developed a relation between block RQD and production by SM.

Schmidt rebound hardness number (RN): Shimada and Matsui[23] used rock impact hardness number for prediction of drivage/drilling rate. Goktan and Gunes[24] determined Schmidt hammer rebound number for predicting cutting rates for a RH. According to Adebayo[25], RN exhibited a strong correlation with the cutting rate.

Rock mass rating (RMR): Many models were developed relating RH performance to rock mass properties such as RMR and RQD values[26]. Bilgin *et al.*[27] utilized UCS, RQD and machine power to predict the instantaneous cutting rate.

Based on the above literature review, it may be summarized that machine cutting performance is influenced significantly by intact rock and rock mass properties (Figure 2). Some of the relations developed by researchers on cutting performance under varied conditions with rock parameters are given in Table 1.

Performance of SM depends on machine configuration such as cutting tool configuration (rake angle, attack angle, clearance angle and tip angle, pick lacing, type of pick, number of picks, tip material), drum weight, drum

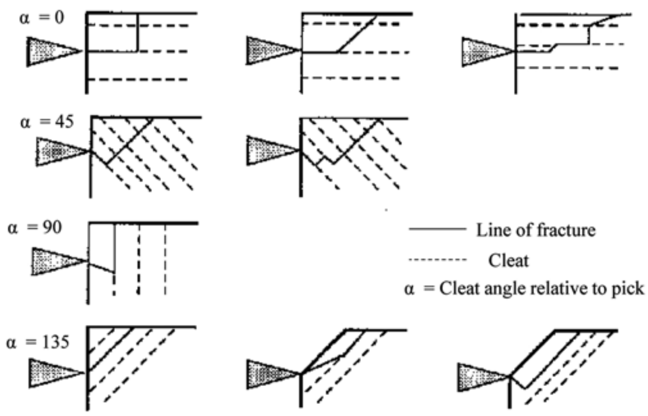


Figure 1. Types of fracture in cleated coals[21].

Table 1. Relations of cutting performance on rock parameters

Rock parameter	Relation	Test condition	Reference
Density	PR = –0.8 ρ + 3.25 (r = 0.60)	Percussive drill	Kahraman *et al.*[2]
	SE = –68.44 + 33.11ρ (r^2 = 0.74)	Laboratory	Tiryaki and Dikmen[1]
	Wg = 5e^{-5PD} + 0.011 for feldspar granite (r^2 = 0.778)	Laboratory	Adebayo[28]
Moisture content	SE = –2.58lnMC + 13.79 (r^2 = 0.85)	Laboratory	Mammen *et al.*[29]
UCS	Pr = 1004.9 – 558.73log(σ_c) (r^2 = 0.94)	SM	Kramadibrata and Shimada[30]
	ICR = 25.694e$^{-0.0206\sigma_c}$, RQD > 50 (r^2 = 0.54)	RH (71 kW)	Bilgin *et al.*[27]
	ICR = 19.773e$^{-0.008\sigma_c}$, RQD < 50 (r^2 = 0.19)	RH (71 kW)	Bilgin *et al.*[27]
	CR = –0.443σ_c + 43.97 (r^2 = 0.86)	RH	Copur *et al.*[31]
	CR = 75.7 – 14.3lnσ_c (r^2 = 0.62)	RH (132 kW)	Thuro and Plinninger[32]
	PR = –0.0079σc + 1.67 (r = 0.97)	Percussive drill	Kahraman *et al.*[2]
	SE = 3.6 + 0.17σc (r^2 = 0.52)	Laboratory	Tiryaki and Dikmen[1]
	ICR = 444.35$\sigma_c^{-0.8377}$ (r^2 = 0.29)	Laboratory	Adebayo[25]
TS	$F_c = \dfrac{16\pi d^2 \sigma_t^2}{\cos^2(\varphi/2)\sigma_c}$ (point attack picks)	Laboratory	Evans[8]
	PR = –0.083σ_t + 1.68 (r = 0.91)	Percussive drill	Kahraman *et al.*[2]
	ICR = 67.128 $\sigma_t^{-0.6578}$ (r^2 = 0.65)	RH	Kelles[33]
	SE = 0.67 + 3.12σ_t (r^2 = 0.89)	Laboratory	Tiryaki and Dikmen[1]
PLSI	PR = –0.096I$_s$ + 1.6 (r = 0.8)	Percussive drill	Kahraman *et al.*[2]
	SE = 1.28 + 5.06I$_s$ (r^2 = 0.68)	Laboratory	Tiryaki and Dikmen[1]
	P = 1237.8I$_s^{0.308}$ (r^2 = 0.91)	SM	Meena *et al.*[34]
Abrassiveness	CAI = 0.6 + 3.32F	Laboratory	Lislerud[35]
	CR = –0.528 SiO_2 + 50.08 (r^2 = 0.86)	Laboratory	Adebayo[25]
	Wg = 0.002SiO_2 – 0.126 for feldspar granite (r^2 = 0.83)	Laboratory	Adebayo[28]
Petrography	SE = 21.86 – 0.32flds (r^2 = 0.60)	Laboratory	Tiryaki and Dikmen[1]
	SE = 4.27 + 2.21te (r^2 = 0.56)	Laboratory	Tiryaki and Dikmen[1]
RQD	RMCI = σ_c(RQD/100)$^{2/3}$	RH	Bilgin *et al.*[27]
	ICR = 50.222RQD$^{-0.5654}$ (r^2 = 0.60), σ_c = 90–100 MPa	RH (71 kW)	Bilgin *et al.*[27]
RN	PR =–0.037RN + 1.60 (r^2 = 0.90)	Percussive drill	Kahraman *et al.*[2]
	CR = –0.6405RN + 43.1 (r^2 = 0.73)	RH (90 kW)	Goktan and Gunes[24]
	SE = –14.1 + 0.68RN (r^2 = 0.79)	Laboratory	Tiryaki and Dikmen[1]
	CR = –0.922RN + 62.62 (r^2 = 0.86)	Laboratory	Adebayo[25]

ρ = Density (g/m^3); σ_c = Uniaxial compressive strength (MPa); σ_t = Brazilian tensile strength (MPa); MC = Moisture content (%); flds = Feldspar (%); SiO_2 = Silica (%); te = Texture coefficient; RN = Rebound hardness number; RQD = Rock quality designation; Is = Point load strength index; PD = Packing density = Summed length of grains measured along traverse/length of traverse (%); SE = Specific energy (MJ/m^3); Wg = Bit wear rate (mm/m); PR = Penetration rate (m/min); CR = Cutting rate (m^3/h); ICR = Instantaneous cutting rate (m^3/h); Pr = Production (bank cm/h); F = Wear index = (QD σ_t/100), Q = Equivalent quartz (%); D = Mean quartz grain size (mm); RMCI = Rock mass cuttability index.

width (DW), engine power (EP), nature of coolant for tips, etc. Operational conditions of machine play an important role in production. The production capacities of SM depend on face length, depth of cut, machine speed, DW, etc. The various machine parameters influencing production performance are broadly categorized into cutting tool configuration, specifications of cutting drum, EP, project strategy and operational experience as shown in Figure 3.

Literature review is an excellent means to identify and provide base information of parameters influencing the cutting performance of machines. Several mathematical models were developed for different cutting machines to understand their performance with respect to intact rock and rock mass parameters. The models mainly covered rock cutting by picks, SE, cuttability and production prediction by different machines as shown in Table 2.

Fourteen distinct intact rock, rock mass and machine parameters were identified from literature to assess the cutting performance of mechanical excavators in general. UCS was considered as the most dominant parameter due to its consistency in predicting machine performance and hence, was used by many researchers.

The critical parameters were also identified by ANN technique-based on relative importance and sensitivity. The relative importance and sensitivity are represented by

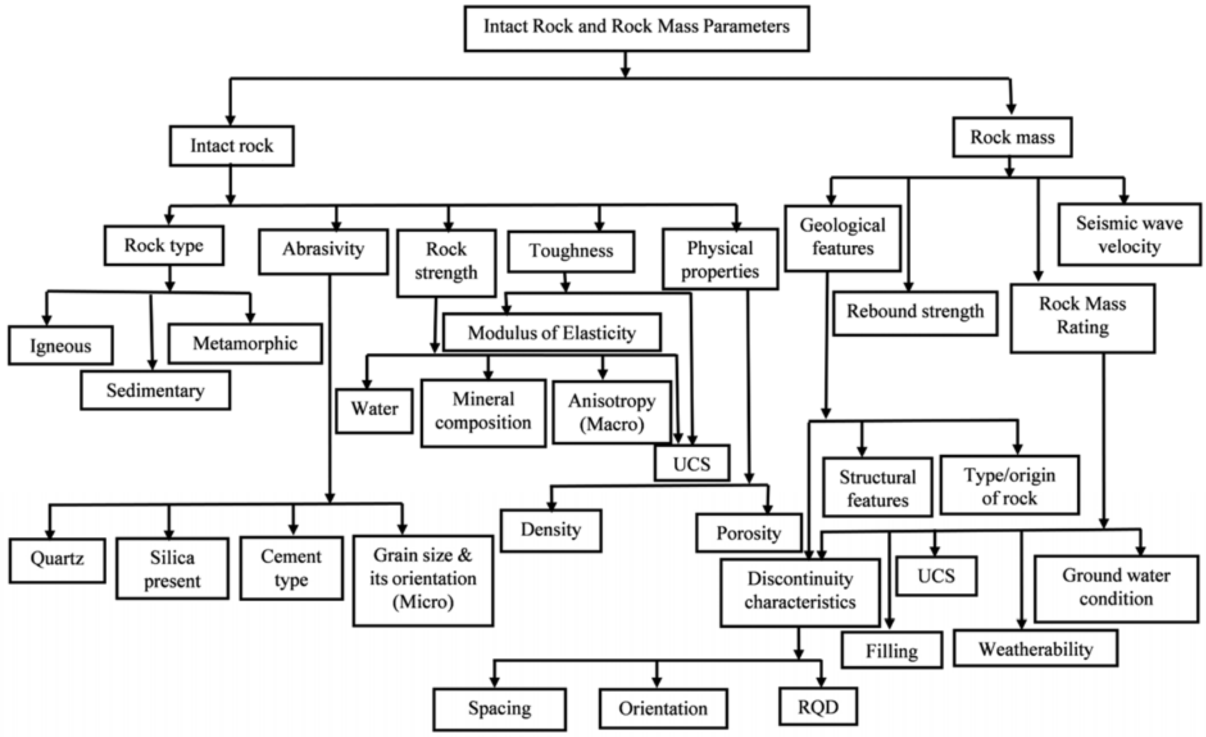


Figure 2. Intact rock and rock mass parameters influencing machine performance.

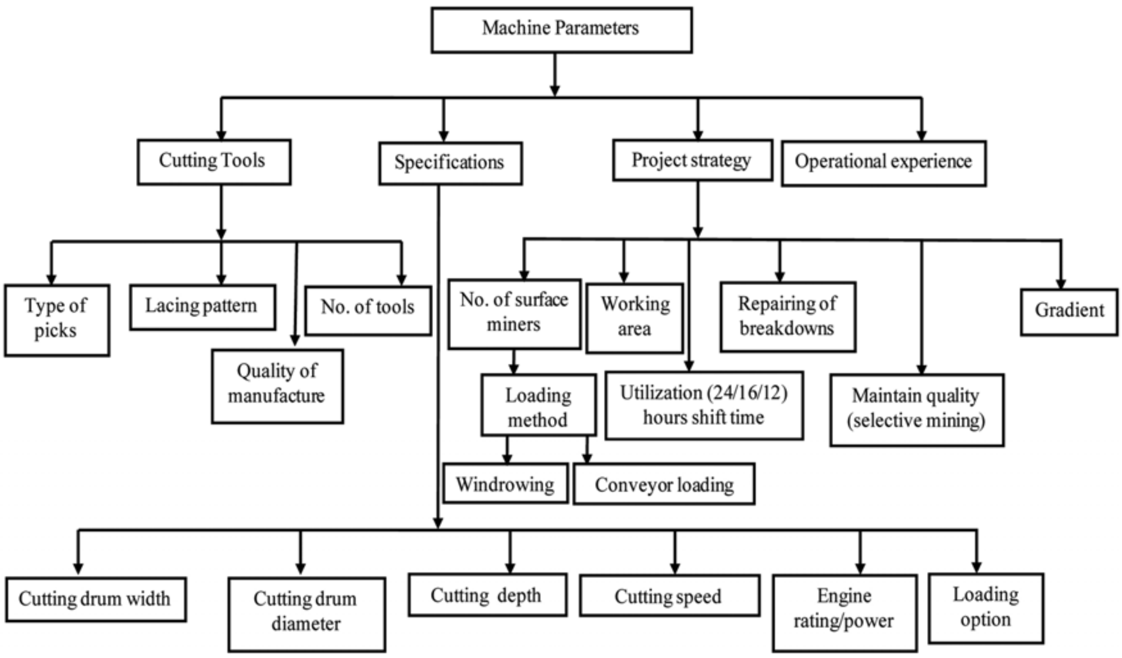


Figure 3. Machine parameters influencing production performance.

weights of different input parameters in the networks. EasyNN software (demo version) was used for analysis. It grows multi-layer neural networks from the data in a grid. The neural network input and output layers are created to match the grid input and output columns. Hidden layers connecting the input and output layers can then be grown to hold the optimum number of nodes. Each node contains a neuron and its connection addresses.

Neural networks allow the training data to understand the grid and they can use the validating data in the grid to

Table 2. Parameters used in empirical relationships for predicting machine performance

Parameters → Models ↓	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Evans[8]	◙	◙												
Barendsen[36]	◙													
Atkinson[13]								◙						
Franklin *et al.*[37]									◙					
Kirsten[3]						◙	◙							
Singh *et al.*[38]	◙									◙				
Farmer[39]	◙									◙		◙		
Roxborough[18]	◙													
Bilgin *et al.*[22]	◙						◙							
Gehring[40]	◙					◙						◙		◙
Hadjigeorgiu and Scoble[11]					◙				◙					
Jones and Kramadibrata[41]	◙													
Kramadibrata and Shimada[30]	◙	◙	◙			◙				◙	◙	◙		
Tiryaki and Dikmen[1]		◙												
Murthy *et al.*[17]				◙				◙				◙	◙	◙
Dey and Ghose[42]						◙			◙		◙	◙		
Kahraman *et al.*[2]			◙											
Total	9	3	2	1	1	4	2	2	3	3	2	5	1	2

1, UCS; 2, TS; 3, Density; 4, Silica percentage (SI); 5, Ground structure/weathering condition; 6, Joints; 7, RQD; 8, Seismic velocity; 9, PLSI; 10, E; 11, Abrasivity; 12, Machine/cutter head power; 13, Machine specifications; 14, Operational condition.

Table 3. Critical parameters identified by ANN

Performance Properties	Production (t/h)	Diesel consumption per 1000 *t* (l)	Pick consumption per 1000 *t* (nos)
Intact rock and rock mass parameters	*In situ P*-wave velocity (IV_p)	RN	Rock density
	Laboratory *P*-wave velocity (LV_p)	SI	SI
	CAI	*E*	UCS
	Rock density	Rock density	*E*
	SI	LV_p	Brittleness index (BI)
	TS	IV_p	TS
Machine parameters	EP	–	Depth of cut
	DW		EP

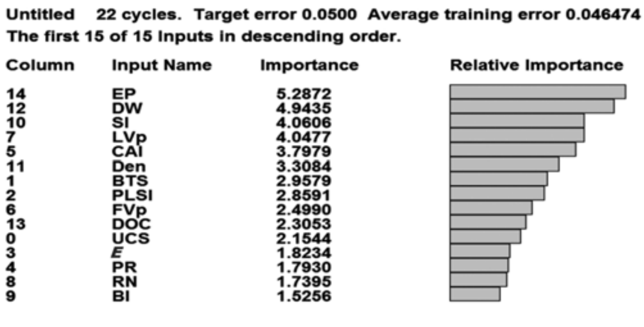


Figure 4. Relative importance of parameters with respect to production.

self-validate at the same time. During training, software assigns a weightage to the various inter-related parameters and attempts to limit the error. This process is repeated until the error converges to set limits. The final weightages are obtained after training. After the training neural networks can be tested using the querying data in the grid, using the interactive query facilities or using querying data in separate files. The values for each parameter were investigated with respect to production, diesel and pick consumption per 1000 *t* and are shown correspondingly in Figures 4–9.

The top five intact rock and rock mass parameters exclusive of machine parameters based on highest relative importance and sensitivity were identified as critical parameters. The outcome of this analysis is depicted in Table 3. Analysis by ANN being qualitative in nature does not yield any numerical relationship with actual machine performance. Thus, developing mathematical models relating the critical parameters is important for further refining and screening. Hence, regression analysis amongst different parameters was carried out.

The correlation coefficients, between critical intact rock and rock mass parameters and the performance of SM in Indian geo-mining conditions, were determined

Table 4. Correlation coefficients relating machine performance with intact rock, rock mass and machine parameters

Parameter	σ_c	σ_t	I_s	E	ν	CAI	IV_p	LV_p	RN	BI	SI	ρ	DW	DOC	EP	TPH	DCT	PCT
σ_c	1.00	0.79	0.65	0.39	–0.28	0.35	0.01	0.27	–0.18	–0.12	0.12	0.07	–0.09	–0.17	–0.14	–0.12	0.10	–0.07
σ_t	0.79	1.00	0.67	0.45	–0.37	0.63	0.07	0.40	–0.06	–0.59	0.28	0.12	–0.14	–0.14	–0.14	–0.22	0.24	0.07
I_s	0.65	0.67	1.00	0.70	–0.23	0.56	0.34	0.58	–0.47	–0.21	0.52	0.45	–0.10	–0.20	–0.15	–0.27	0.48	0.33
E	0.39	0.45	0.70	1.00	0.04	0.65	0.66	0.90	–0.60	–0.13	0.90	0.84	–0.52	–0.51	–0.56	–0.74	0.88	0.77
ν	–0.28	–0.37	–0.23	0.04	1.00	–0.16	0.13	–0.04	–0.01	0.27	0.17	0.19	–0.01	–0.12	–0.03	0.01	0.07	0.19
CAI	0.35	0.63	0.56	0.65	–0.16	1.00	0.55	0.76	–0.22	–0.38	0.65	0.59	–0.43	–0.41	–0.44	–0.61	0.63	0.46
IV_p	0.01	0.07	0.34	0.66	0.13	0.55	1.00	0.80	–0.40	0.08	0.69	0.86	–0.46	–0.59	–0.49	–0.67	0.67	0.60
LV_p	0.27	0.40	0.58	0.90	–0.04	0.76	0.80	1.00	–0.57	–0.14	0.87	0.89	–0.56	–0.59	–0.58	–0.81	0.89	0.75
RN	–0.18	–0.06	–0.47	–0.60	–0.01	–0.22	–0.40	–0.57	1.00	–0.30	–0.54	–0.67	0.29	0.49	0.32	–0.48	0.64	0.49
BI	–0.12	–0.59	–0.21	–0.13	0.27	–0.38	0.08	–0.14	–0.30	1.00	–0.18	0.12	–0.08	–0.21	–0.11	–0.02	–0.11	–0.11
SI	0.12	0.28	0.52	0.90	0.17	0.65	0.69	0.87	–0.54	–0.18	1.00	0.83	–0.51	–0.42	–0.52	–0.75	0.94	0.92
γ	0.07	0.12	0.45	0.84	0.19	0.59	0.86	0.89	–0.67	0.12	0.83	1.00	–0.48	–0.67	–0.51	–0.76	0.86	0.76
DW	–0.09	–0.14	–0.10	–0.52	–0.01	–0.43	–0.46	–0.56	0.29	–0.08	–0.51	–0.48	1.00	0.66	0.99	0.90	–0.59	–0.41
DOC	–0.17	–0.14	–0.20	–0.51	–0.12	–0.41	–0.59	–0.59	0.49	–0.21	–0.42	–0.67	0.66	1.00	0.71	0.71	–0.51	–0.27
EP	–0.14	–0.14	–0.15	–0.56	–0.03	–0.44	–0.49	–0.58	0.32	–0.11	–0.52	–0.51	0.99	0.71	1.00	0.89	–0.59	–0.40
TPH	–0.12	–0.22	–0.27	–0.74	0.01	–0.61	–0.67	–0.81	–0.48	–0.02	–0.75	–0.76	0.90	0.71	0.89	1.00	–0.82	–0.67
DCT	0.10	0.24	0.48	0.88	0.07	0.63	0.67	0.89	0.64	–0.11	0.94	0.86	–0.59	–0.51	–0.59	–0.82	1.00	0.92
PCT	–0.07	0.07	0.33	0.77	0.19	0.46	0.60	0.75	0.49	–0.11	0.92	0.76	–0.41	–0.27	–0.40	–0.67	0.92	1.00

DOC, Depth of cut; TPH, Production in tonnes per hour; DCT, Diesel consumption per 1000*t*; PCT, Pick consumption per 1000*t*.

Associative relationship with rock parameters

Associative relationship with production

Associative relationship with PCT.

Associative relationship with DCT.

Table 5. Critical and semi-critical parameters influencing performance of SM

Performance Criticality	Production (t/h)	Diesel consumption per 1000 t (l)	Pick consumption per 1000 t (nos)
Critical	IV_p	RN	Rock density
	LV_p	E	E
	Rock density	LV_p	SI
	CAI	SI	
	EP	IV_p	
	DW		
	SI		
Semi-critical	E	CAI	UCS
	TS	Rock density	TS
			BI
			LV_p
			Depth of cut
			EP

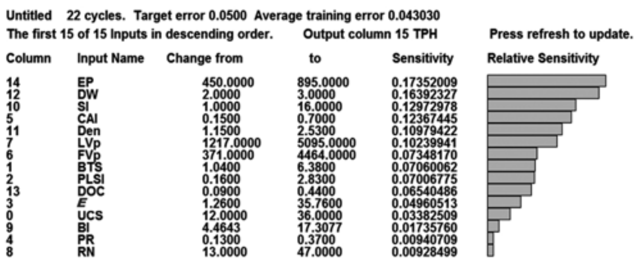


Figure 5. Relative sensitivity of parameters with respect to production.

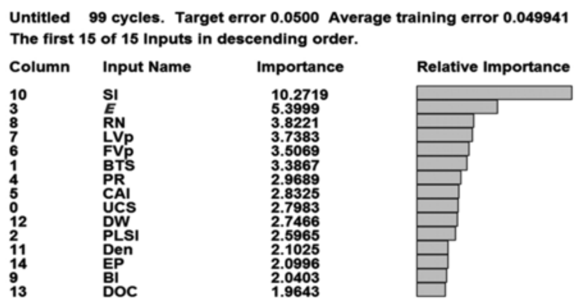
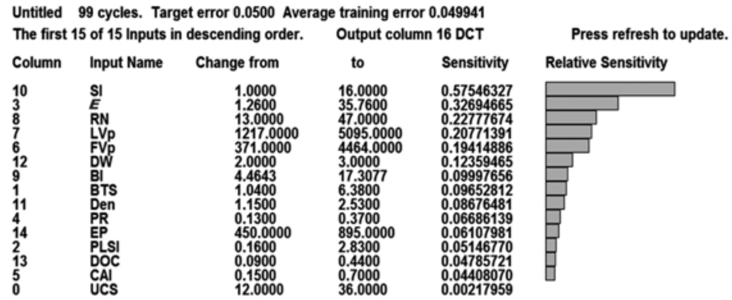


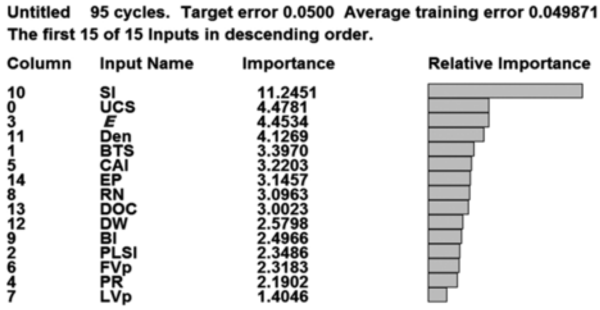
Figure 6. Relative importance of parameters with respect to diesel consumption.



Untitled 99 cycles. Target error 0.0500 Average training error 0.049941
The first 15 of 15 Inputs in descending order. Output column 16 DCT Press refresh to update.

Column	Input Name	Change from	to	Sensitivity
10	SI	1.0000	16.0000	0.57546327
3	*E*	1.2600	35.7600	0.32694665
8	RN	13.0000	47.0000	0.22777674
7	LVp	1217.0000	5095.0000	0.20771391
6	FVp	371.0000	4464.0000	0.19414886
12	DW	2.0000	3.0000	0.12359465
9	BI	4.4643	17.3077	0.09997656
1	BTS	1.0400	6.3800	0.09652812
11	Den	1.1500	2.5300	0.08676481
4	PR	0.1300	0.3700	0.06686139
14	EP	450.0000	895.0000	0.06107981
2	PLSI	0.1600	2.8300	0.05146770
13	DOC	0.0900	0.4400	0.04785721
5	CAI	0.1500	0.7000	0.04408070
0	UCS	12.0000	36.0000	0.00217959

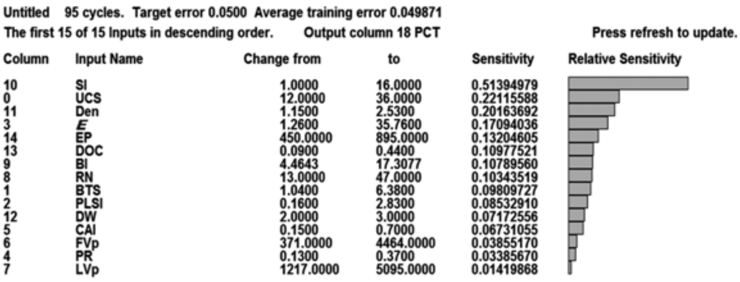
Figure 7. Relative sensitivity of parameters with respect to diesel consumption.



Untitled 95 cycles. Target error 0.0500 Average training error 0.049871
The first 15 of 15 Inputs in descending order.

Column	Input Name	Importance
10	SI	11.2451
0	UCS	4.4781
3	*E*	4.4534
11	Den	4.1269
1	BTS	3.3970
5	CAI	3.2203
14	EP	3.1457
8	RN	3.0963
13	DOC	3.0023
12	DW	2.5798
9	BI	2.4966
2	PLSI	2.3486
6	FVp	2.3183
4	PR	2.1902
7	LVp	1.4046

Figure 8. Relative importance of parameters with respect to pick consumption.



Untitled 95 cycles. Target error 0.0500 Average training error 0.049871
The first 15 of 15 Inputs in descending order. Output column 18 PCT Press refresh to update.

Column	Input Name	Change from	to	Sensitivity
10	SI	1.0000	16.0000	0.51394979
0	UCS	12.0000	36.0000	0.22115588
11	Den	1.1500	2.5300	0.20163692
3	*E*	1.2600	35.7600	0.17094036
14	EP	450.0000	895.0000	0.13204605
13	DOC	0.0900	0.4400	0.10977521
9	BI	4.4643	17.3077	0.10789560
8	RN	13.0000	47.0000	0.10343519
1	BTS	1.0400	6.3800	0.09809727
2	PLSI	0.1600	2.8300	0.08532910
12	DW	2.0000	3.0000	0.07172556
5	CAI	0.1500	0.7000	0.06731055
6	FVp	371.0000	4464.0000	0.03855170
4	PR	0.1300	0.3700	0.03385670
7	LVp	1217.0000	5095.0000	0.01419868

Figure 9. Relative sensitivity of parameters with respect to pick consumption.

(Table 4). The correlation coefficients of different parameters above ±0.6 were highlighted in the table with colour codes. Both ANN and correlation analysis have resulted in identifying more or less the same parameters for production, diesel and pick consumption estimation. Parameters that were common in both ANN and correlation analysis were grouped under critical category and others in semi-critical category as given in Table 5.

Parameters that have a bearing on the performance of a cutting machine were initially collated from literature review. Among the identified fourteen distinct intact rock, rock mass and machine parameters, UCS was found to be the most frequently used parameter for assessment of cutting performance of mechanical excavators. ANN analysis was subsequently used to identify the relative importance and sensitivity of different parameters influencing production, diesel and pick consumption of SM for coal and limestone mines of India.

The correlation analysis of each parameter with machine performance further helped in scrutinizing and screening the parameters into critical and semi-critical categories. All these identified parameters need to be taken into account in the development of acquiescent predictive models of the performance of SM in different rock mass conditions.

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