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Assessment of Fire Risk of Indian Coals Using Artificial Neural Network Techniques

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Abstract Spontaneous heating of coal is a major problem in the global mining industry. It has been known to pose serious problems on account of coal loss due to fires and affects not only the coal production but also creates environmental pollution over the years. It is well known that the intrinsic properties and susceptibility indices play a vital role to assess the spontaneous heating susceptibility of coal. In this paper, best correlated parameters from the intrinsic properties with the susceptibility indices were used as input to the different Artificial Neural Network (ANN) techniques viz. Multilayer Perceptron (MLP), Functional Link Artificial Neural Network (FLANN), and Radial Basis Function (RBF) to predict in advance the fire risk of Indian coals. This can help the mine management to adopt appropriate strategies and effective action plans to prevent occurrence and spread of fire. From the proposed ANN techniques, it was observed that Szb provides better fire risk prediction with RBF model vis-à-vis MLP and FLANN.

Keywords: *coal; spontaneous heating, ANN, MLP, FLANN, RBF*

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1. Introduction

Coal is the most important and abundant fossil fuel in India. Coal is the source of about 27% of the world's primary energy consumption and it accounts for about 34% of electricity generated in the world. Hence, in recent years, much attention has been focused on coal as an alternative source of energy [45]. Coal is the dominant energy source in India and meets 55% of the country's primary commercial energy supply. Commercial primary energy consumption in India has grown by about 700% in the last four decades [7]. India is the third largest coal producing country in the world after China and USA [27]. Indian mines have a historical record of extensive fire activity for over hundred years. The fire problem in Indian mines is very complex because of involvement of different seams simultaneously. Such conditions do not exist elsewhere in the world [40]. Spontaneous combustion of coal generally causes mine fires in Indian coalfields despite various preventive measures have been extensively practiced. The spontaneous heating susceptibility of different coals varies over a wide range and it is important to predict their degree of proneness in advance for taking preventive measures against the occurrence of fires to avoid loss of lives and property, sterilization of coal reserves and environmental pollution and raise concerns about safety and economic aspects of mining, etc. [43].

Brief overview of the related works carried out by various researchers in India and other countries are summarized in the following subsection:

Pattnaik et al. [31] investigated intrinsic properties and a few susceptibility indices to characterize the Chirimiri coals of the SECL coalfields, India. Karmakar and Banerjee [15] worked on sixteen Indian coal samples using comparative experimental techniques to measure the susceptibility of coal to spontaneous combustion based on statistical regression analysis. Olpinski index being a convenient and rapid method, and can be used as an alternative to CPT method India. Smith et al. [50] designed and developed the sponcom program in the U.S Bureau of Mines for the assessment of the spontaneous combustion risk of an underground mining operation. It used the available information to make decisions based on a series of rules provided by the programmer. Panigrahi and Ray [48] analyzed 78 Indian coals and used MLP ANN model for obtaining optimum results based on the evaluation of the best combination of wet oxidation potential experimental conditions. Zhang et al. [51] employed feed forward 3-layer MLP model to express relationship between temperature and index gases (CO and C_2H_4) and forecasting the coal sponcom in the low-temperature range. Xiao and Tian [52] introduced genetic algorithm and back propogation neural network for the purpose of predicting the danger of coal layer spontaneous combustion based on the selection of three key influencing factors, namely, coal spontaneous combustion inclination, geology conditions and occurrence features of coal seam, and ventilation conditions. Panigrahi et al. [49] investigated Indian coals using susceptibility indices such as CPT, Wet oxidation method, Russian U-index, Szb, etc., and categorized and predicted spontaneous fire risk based on regression analysis. Literature work seems that most of the work carried out by researchers, academicians and coal companies in the world are based on experimental investigations, statistical analysis, mathematical models, and to limited extent ANN models etc. to predict the proneness of coal to spontaneous heating.

In this paper, an attempt has been made to carry out the statistical analysis among the different intrinsic properties (Proximate, Ultimate and Petrographic analysis) and the susceptibility indices (Crossing point temperature (CPT), Olpinski index free of ash (Szb), Wet oxidation Potential difference (ΔE), and Flammability temperature (FT)) to obtain the best correlated parameters. The high significant correlated parameters of ultimate analysis were used as an input to different ANN models such as MLP, FLANN, and RBF. The paper also highlights the performance analysis of different ANN models with different susceptibility indices to predict the fire risk of Indian coals.

2. Sample Collection and Preparation

Forty-nine non-coking and coking in-situ coal samples were collected from major coalfields of India viz. South Eastern Coalfield Limited (SECL), Singareni Collieries Company Limited (SCCL), Mahanadi Coalfield Limited (MCL), Western Coalfield Limited (WCL), North Eastern Coalfield Limited (NEC), Northern Coalfield Limited (NCL), Indian Iron and Steel Company (IISCO), Bharat Coking Coal Limited (BCCL) and Tata Iron and Steel Company Limited (TISCO) using channel sampling method. The collected coals were crushed and sieved as per the experimental requirements following Indian Standard IS: 436(Part-I/Section-I)–1964 [9].

Table 1. Classification of liability of coal to sponcom based on Olpinski index [Tripathy and Pal, 2001]

Szb(^{0}C/min)	Risk Rating
<80	Poorly susceptible
80-120	Moderately susceptible
>120	Highly susceptible

Table 2. Results of the parameters of proximate, ultimate and petrographic analysis of coal samples

Sl. No.	Coal samples	Proximate analysis			Ultimate analysis				Petrographic analysis		
		M %	A %	VM %	C %	H %	S %	O %	V%	L%	I%
1	SECL -1	7.63	14.10	32.42	83.75	4.74	0.38	9.64	18.91	5.85	53.04
2	SECL -2	3.16	25.60	35.21	81.53	5.15	0.42	11.34	17.00	6.12	52.97
3	SECL -3	6.41	16.45	24.59	80.79	4.59	0.32	12.84	32.87	5.35	49.50
4	SECL - 4	5.95	16.24	39.79	80.00	4.92	0.40	12.94	31.31	3.97	57.38
5	SECL -5	8.25	12.10	39.54	81.86	6.24	1.02	9.27	58.43	1.57	24.51
6	SECL -6	7.62	22.55	20.77	77.26	5.75	1.24	13.60	49.23	6.17	33.96
7	SECL -7	8.15	14.99	30.91	78.38	5.24	0.79	13.54	28.79	6.2	33.11
8	SECL -8	8.86	11.16	30.52	77.81	6.15	0.54	13.99	39. 76	4.71	29.26
9	SECL -9	12.57	17.11	33.66	79.94	4.48	1.04	14.18	29.14	9.03	53.19
10	SECL -10	8.21	19.30	28.14	78.52	5.82	0.52	13.27	30.57	11.41	48.01
11	SCCL-1	2.43	33.07	27.96	75.71	6.39	0.71	12.21	45.88	1.76	38.83
12	SCCL-2	2.13	25.94	33.42	82.32	5.55	0.76	9.94	45.72	1.67	38.29
13	SCCL-3	2.73	14.46	35.83	81.22	3.82	0.25	12.73	42.89	6.8	33.98
14	SCCL-4	3.76	25.68	34.13	79.67	4.11	0.45	13.54	42.3	6.32	34.39
15	SCCL-5	3.17	15.28	35.99	79.45	5.16	0.75	13.02	41.66	7.22	33.96
16	SCCL-6	3.66	37.84	25.88	78.84	4.89	1.01	14.71	50.35	4.62	27.79
17	SCCL-7	3.77	27.15	32.84	83.50	1.97	0.94	10.52	53.79	4.89	30.23
18	SCCL-8	3.69	17.41	40.40	81.84	5.46	0.85	10.26	52.15	4.12	25.69
19	SCCL-9	2.86	11.04	38.91	80.51	4.01	0.63	13.31	54.71	4.71	32.54
20	MCL-1	7.13	37.48	23.17	72.93	7.64	0.79	17.64	19. 24	6.7	28.99
21	MCL-2	6.42	35.25	25.76	74.09	7.47	1.18	15.54	18. 88	7.89	31.34
22	MCL-3	2.81	13.46	30.19	80.17	3.83	0.30	14.21	21.11	9.84	20.55
23	MCL-4	6.63	11.20	40.92	82.91	3.80	0.28	11.66	39.88	7.25	35.16
24	MCL-5	3.89	16.20	35.55	81.67	3.62	0.31	11.51	33.19	7.88	16
25	MCL-6	6.13	37.12	26.78	66.90	7.45	1.06	19.12	23.78	2.76	25.12
26	MCL-7	7.77	14.01	26.46	78.31	5.91	1.14	10.91	28.2	5.11	25.23
27	MCL-8	11.71	22.74	22.48	77.64	6.97	1.16	10.47	38.67	3.35	26.11
28	WCL-1	6.03	14.50	39.97	82.11	3.23	0.15	12.92	58.62	4.55	17.23
29	WCL-2	4.00	22.00	37.00	82.78	3.18	0.20	12.13	66.74	3.56	16.63
30	WCL-3	6.50	16.00	35.50	81.27	5.48	0.27	10.78	34.85	2.77	43.96
31	WCL-4	3.50	23.10	32.50	82.09	4.58	0.34	9.86	56.55	5.75	26.19
32	WCL-5	5.50	16.00	34.50	77.95	4.80	0.48	12.23	42.18	5.94	40.59
33	WCL-6	6.00	17.50	33.50	77.40	5.36	0.86	14.93	40.07	6.03	39.88
34	WCL-7	7.30	16.00	31.50	79.69	5.49	0.76	12.31	40.97	8.76	37.88
35	WCL-8	11.00	13.50	30.00	82.28	5.46	0.60	10.05	29.15	8.52	50.93
36	WCL-9	4.13	19.50	28.97	78.90	3.78	0.84	13.31	27.44	9.16	49.74
37	WCL-10	4.00	16.09	30.18	80.05	4.05	0.61	11.15	31.47	8.38	50.23
38	NEC-1	1.32	6.20	43.26	72.72	4.54	2.27	17.41	86.87	4.32	5.10
39	NEC-2	1.90	6.90	44.12	70.06	6.14	2.63	18.36	85.21	4.45	5.83
40	NEC-3	4.06	11.63	54.12	72.66	4.61	1.16	18.22	85.94	4.73	5.76
41	NEC-4	2.36	11.21	55.45	73.14	4.55	0.59	20.05	84.18	4.56	5.42
42	NEC-5	2.15	13.50	54.44	71.06	4.13	0.96	22.36	86.35	4.18	5.39
43	NEC-6	2.53	8.31	56.30	72.07	3.65	0.65	18.80	85.81	4.37	5.94
44	NCL-1	7.94	19.40	28.40	77.43	5.37	1.36	11.82	35.08	1.6	40.94
45	NCL-2	8.03	19.06	31.21	74.36	6.76	0.73	16.03	36. 87	0.67	41.32
46	IISCO-1	0.82	31.57	14.24	79.78	5.16	1.20	12.15	59.36	2.19	30.68
47	IISCO-2	0.97	27.96	16.58	72.12	5.92	0.82	15.21	58.33	2.17	31.92
48	BCCL-1	1.39	16.30	18.48	81.66	5.50	0.39	8.50	59.94	2.79	27.32
49	TISCO-1	1.44	15.05	17.86	82.26	5.62	0.51	9.06	62.29	3.39	28.68

NB: Coking coal samples – IISCO-1, IISCO-2, BCCL-1 and TISCO-1, and the rest are non-coking coal samples.

3. Experimental Investigations

To assess the liability of coals to spontaneous combustion, it is important to investigate the intrinsic properties by proximate, ultimate, and petrographic analysis as well as determination of susceptibility indices viz., CPT, Szb, ΔE, and FT. Parameters of proximate analysis such as moisture (M), volatile matter (VM), and ash (A); elements of ultimate analysis viz., carbon, hydrogen, sulphur, and oxygen; and macerals of petrographic analysis such as vitrinite (V), liptinite (L), and inertinite (I) can be ascertained using the standard procedure [8,10,11,12,13,34] and the results are summarized in Table 2.

Susceptibility indices play a vital role to assess the spontaneous combustion of coal. In this paper, susceptibility indices such as CPT, Szb, ΔE, and FT was determined using standard procedure [1,3,15,27,28,29,42], and the results are depicted in Table 3.

Table 3. Results of CPT, Szb, ΔE, and FT

Sample	CPT ^{0}C	Szb ^{0}C/min	ΔE mV	FT ^{0}C
SECL -1	175	68	132	550
SECL -2	182	74	159	555
SECL -3	156	85	135	540
SECL -4	178	70	130	545
SECL -5	158	99	165	540
SECL -6	163	77.36	133	535
SECL -7	176	69.14	152	575
SECL -8	182	63.26	125	580
SECL -9	154	107.89	116	525
SECL -10	188	65.42	140	580
SCCL-1	175	73	140	520
SCCL-2	180	67	155	500
SCCL-3	153	111	159	530
SCCL-4	179	55	151	510
SCCL-5	164	77	136	510
SCCL-6	168	78	150	500
SCCL-7	166	59	143	510
SCCL-8	157	105.74	125	530
SCCL-9	172	74.28	144	525
MCL-1	154	98	73	500
MCL-2	158	104	82	515
MCL-3	151	109	59	525
MCL-4	142	105	104	500
MCL-5	152	110	92	540
MCL-6	168	78	81	535
MCL-7	148	117.61	75	480
MCL-8	164	58.23	95	540
WCL-1	155	98	131	550
WCL-2	149	112	141	540
WCL-3	142	107	139	535
WCL-4	147	89	145	540
WCL-5	157	98	72	560
WCL-6	148	93	68	540
WCL-7	165	59.08	114	540
WCL-8	155	108.95	94	530
WCL-9	153	116.48	178	520
WCL-10	143	118.73	144	475
NEC-1	150	109	56	520
NEC-2	153	118	65	545
NEC-3	152	111.88	68	515
NEC-4	151	115.58	72	500
NEC-5	154	113.16	69	520
NEC-6	176	68.69	87	570
NCL-1	141	151	182	490
NCL-2	146	170	148	530
IISCO-1	180	45	46	570
IISCO-2	165	70	48	560
BCCL-1	178	64.55	55	575
TISCO-1	192	58.06	67	590

4. Statistical Analysis

Statistical correlation analysis (univariate) reveals that the parameters of ultimate (C, H, and O) analysis show significant correlation with all investigated susceptibility indices (CPT, Szb, ΔE, and FT) as compared to other independent variables (Table 4).

Table 4. Correlation analysis between intrinsic properties and the susceptibility indices

Sl. No.	Susceptibility indices → / Intrinsic properties ↓	CPT	Sz_b	ΔE	FT
1	**M**	0.98	0.85	0.91	0.98
2	**VM**	0.95	0.95	0.91	0.98
3	**A**	0.92	0.85	0.88	0.91
4	**C**	0.99	0.95	0.95	0.99
5	**H**	0.97	0.95	0.90	0.97
6	**O**	0.96	0.95	0.90	0.97
7	**V**	0.94	0.90	0.86	0.94
8	**L**	0.54	0.55	0.93	0.54
9	**I**	0.92	0.88	0.93	0.92

Multivariate analysis has also been carried out on combined parameters of the intrinsic properties such as parameters of proximate analysis (M, VM, and A), elements of ultimate analysis (C, H, and O), and the macerals of petrographic analysis (V, L, and I), and all investigated susceptibility indices. From Table 5, it can be inferred that CPT, Szb, ΔE, and FT show significant correlation with the elements of ultimate analysis(C, H, and O) based on correlation coefficient (r), standard error (SE), and variance (σ) as compared to the other parameters (Proximate and Petrographic analysis). Hence, these parameters (C, H, and O) can be used as input to ANN models to predict the proneness of coal to spontaneous combustion.

Table 5. Multivariate analysis between intrinsic properties and the susceptibility indices

Sl. No.	Independent variable	Multivariate analysis	CPT	Szb	ΔE	FT
1.	**M, VM, and A**	**r**	0.98	0.95	0.94	0.98
		SE	0.28	0.27	0.39	0.89
		Mean	1.61	0.9	1.13	5.32
		Variance	0.01	0.06	0.14	0.07
2.	**C, H, and O**	**r**	0.99	0.96	0.95	0.99
		SE	0.13	0.25	0.38	0.27
		Mean	1.61	0.90	1.13	5.32
		Variance	0.01	0.06	0.14	0.07
3.	**V, L, and I**	**r**	0.97	0.93	0.91	0.97
		SE	0.36	0.32	0.48	1.13
		Mean	1.61	0.9	1.13	5.32
		Variance	0.01	0.06	0.14	0.07

5. Artificial Neural Network Models

An ANN is an efficient information processing system and performs various tasks such as pattern matching and classification, optimization function, approximation, vector quantization, and data clustering [41,47]. In the model specification, ANN requires no knowledge of the data source but, since they often contain many weights that must be estimated [3]. In this paper, three ANN models such as MLP, FLANN, and RBF were applied to predict fire risk of Indian coals.

5.1. Cross-validation Method

Cross-validation is a statistical learning method to evaluate and compare the models by partitioning the data into two portions. One portion of the set is used to train or learn the model, and the rest of the data is used to validate the model. K-fold cross-validation is the basic form of cross validation [21,32]. In K-fold cross-validation, the data are first partitioned into K equal (or nearly equally) sized portions or folds. For each of the K model, K-1 folds are used for training and the remaining one fold is used for testing purpose. In this paper, 5-folds cross-validation was used for designing and comparing the models.

5.2. Performance Evaluation Parameters

To assess the performance of prediction models, the most widely used evaluation criterion is the Mean Magnitude of Relative Error (MMRE) [18,44]. Further, determination of software accuracy for a designed model by using performance evaluation parameters [37,46] such as: Mean Absolute Error (MAE), MMRE, Root Mean Square Error (RMSE), and Standard Error of the Mean (SEM). This is usually computed following standard evaluation processes such as cross-validation [19,20].

• ***Mean Absolute Error (MAE)***

It determines how close the values of predicted and actual differ.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}(|\, y_i^{'} - y_i \,|) \tag{1}$$

Where, n is the number of samples, y_i is the actual value, and $y_i^{'}$ is predicted value.

• ***Magnitude of Relative Error (MRE)***

The MRE for each observation i can be obtained as:

$$\mathrm{MRE}_i = \frac{|\,\text{Actual Effort}_i - \text{Predicted Effort}_i\,|}{\text{Actual Effort}_i} \tag{2}$$

• ***Mean Magnitude of Relative Error (MMRE)***

The mean magnitude of relative error (MMRE) can be achieved through the summation of MRE over N observations

$$\mathrm{MMRE} = \sum_{1}^{N} \mathrm{MRE}_i \tag{3}$$

• ***Root Mean Square Error (RMSE)***

It determines the differences in the values of predicted and actual differ.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^{'}\right)^2} \tag{4}$$

• ***Standard Error of the Mean (SEM)***

It is the deviation of predicted value from the actual.

$$\mathrm{SEM} = \frac{SD}{\sqrt{n}} \tag{5}$$

Where, SD is the sample standard deviation, and n is the number of samples.

5.3. Multilayer Perceptron (MLP)

The multilayer perceptron propagates the input signal through the network in a forward direction, layer-by-layer basis. This system has been applied successfully to solve some difficult and diverse problems by training in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm [4,5,6,16]. The structure of MLP is shown in Figure 1. MLP is widely used for pattern classification, recognition, prediction and approximation.

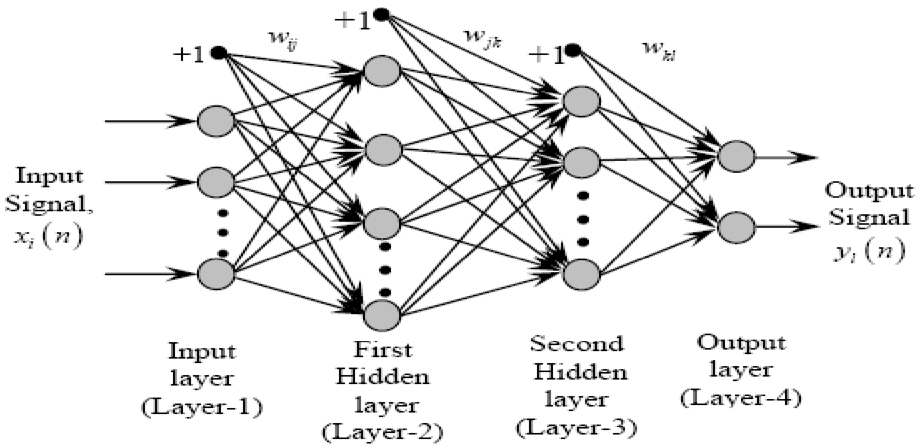

Figure 1. Structure of MLP

If P_1 is the number of neurons in the first hidden layer, each element of the output vector of first hidden layer can be calculated as:

$$f_j = \varphi_j\left[\sum_{i=1}^{N} w_{ij}x_i(n) + b_j\right], \quad i = 1,2,3,\ldots\ldots, N, \; j = 1,2,3,\ldots\ldots, P_1 \tag{6}$$

Where, bj - the bias to the neurons of the first hidden layer; N - the number of inputs; φ - the nonlinear activation function in the first hidden layer.

The time index, n has been dropped to make the equations simpler.

Let P_2 be the number of neurons in the second hidden layer. The output (f_k) of this layer can be expressed as:

$$f_k = \varphi_k\left[\sum_{j=1}^{P_1} w_{jk}f_j + b_k\right], k = 1,2,3,\ldots\ldots, P_2 \tag{7}$$

Where, b_k - the bias to the neurons of the second hidden layer.

The output of the final output layer can be calculated as:

$$y_1(n) = \varphi_l\left[\sum_{k=1}^{P_2} w_{kl} f_k + b_l\right], l = 1,2,3,......., P_3 \quad (8)$$

Where, b_l - the bias to the neuron of the final layer;
P_3 - the number of neurons in the output layer.

So, the output of the MLP neural network can be expressed as:

$$y_1(n) = \varphi_n[\sum_{k=1}^{P_2} w_{kl}\varphi_k(\sum_{j=1}^{P_1} w_{jk}\varphi_j \{\sum_{i=1}^{N} w_{ij} x_i(n) + b_j\} + b_k) + b_l] \quad (9)$$

5.3.1. Back-Propagation (BP) Algorithm

It is the most popular MLP network learning the algorithm. The parameters of the neural network can be updated in both sequential and batch mode operation and the least mean square (LMS) technique is used for the minimization of error [22,35,38].

5.3.1.1. Algorithm for Training MLP Based Fire Risk Model

The algorithm for training MLP [5,14] based fire risk model has been represented as follows:

Step 1: Select the total number of layers as m and the number n_i (i=1, 2, . . . , m−1) of the neurons in each hidden layer.

Step 2: Randomly select the initial values of the weight vectors $w^m_{i,j}$ for i=1,2, . . . n_i and m=2 (number of layers).

$$w^m_{i,j} \leftarrow \text{Rand}\left(w^m_{i,j}(0)\right) \quad (10)$$

Step 3: Randomly select the initial values of the bias vectors $b^m_{i,j}$ for i=1,2, . . . n_i and m=2 .

$$b^m_{i,j} \leftarrow \text{Rand}\left(b^m_{i,j}(0)\right) \quad (11)$$

Step 4: Calculation of the neural outputs of the hidden layer and the equation can be represented as:

$$a^m_{i,j} = \varphi\left(\left(w^1_{i,j}\right) * x_k + \text{bias}\right) \quad (12)$$

Where, φ - the transfer function;
$w^1_{i,j}$ - weight associated with the neuron

Step 5: Calculation of the neural outputs of the output layer and the equation obtained as:

$$Y_j = \varphi\left(\left(W^2_{i,j}\right) * a^m_{j} + \text{bias}\right) \quad (13)$$

Where, $W^2_{i,j}$ - weight associated with the neuron

Step 6: The final output $y_l(n)$ at the output neuron was compared with the desired output *d*(*n*) and the resulting error signal $e_l(n)$ was obtained as:

$$e_l(n) = d(n) - y_l(n) \quad (14)$$

Step 7: Total error obtained by addition of error signals of all neurons in the output layer

$$\xi(n) = \frac{1}{n}\sum_{i=1}^{n} e^2(n) \quad (15)$$

Step 8: The Sensitivity calculation for the output layer is the derivative of activation function of output layer and can be represented as:

$$S_1 = \dot{f}^2\left(n^2\right) = \frac{d}{dn}(n) = 1 \quad (16)$$

Step 9: The Sensitivity of hidden layer is the derivative of activation function of hidden layer and can be represented as:

$$\begin{aligned} S_2 &= \dot{f}^1(n) = \frac{d}{dn}\left[\frac{1}{1+\exp^{-n}}\right] \\ &= \left[1 - \frac{1}{1+\exp^{-n}}\right] * \left[\frac{1}{1+\exp^{-n}}\right] \\ &= \left(1 - a^m_{i,j}\right) * a^m_{i,j} \end{aligned} \quad (17)$$

Step 10: The weights of the respective layers are adjusted using the following relationship:

a) Updating the weight for output layer:

$$W^1_{i,j}(\text{new}) = W^1_{i,j}(\text{old}) + \eta S^1_J \quad (18)$$

b) Updating the weight for hidden layer:

$$W^2_{i,j}(\text{new}) = W^2_{i,j}(\text{old}) + \eta S^2_J (a^1_{i,j}) \quad (19)$$

Where, η is the momentum parameter of the system.

Step 11: The above process was repeated for steps 4 - 10. The weights and the bias were updated using the iterative method until the error signal reaches minimum. For measuring the degree of matching, the mean square error (MSE) was taken as a performance measurement.

Step 12: After the completion of training of input data, the weights were fixed and the network can be used for future prediction.

5.4. Functional Link Artificial Neural Network (FLANN)

In FLANN, the hidden layers are removed, and the structure offers less computational complexity and higher convergence speed than MLP because of its single-layer structure. The mathematical expression and computational calculation was evaluated [22,30,36], and the structure has been represented in Figure 2.

Let X is the input vector of size N×1 which represents N as the number of elements; the k^{th} element, and has been expressed as:

$$X(K) = x_k, 1 \le K \le N \quad (20)$$

Each element undergoes trigonometric expansion to form M elements such that the resultant matrix [30] has the dimension of N×M and can be represented as:

$$s_i = \begin{Bmatrix} x_k & \text{for } i = 1 \\ \sin(l\pi x_k) & \text{for } i = 2,4,\ldots, M \\ \cos(l\pi x_k) & \text{for } i = 3,5,\ldots, M+1 \end{Bmatrix} \quad (21)$$

The bias input is unity and the enhanced pattern can be obtained by the trigonometric function X = $[x_1 \cos(\pi x_1) \sin(\pi x_1) \cdots x_2 \cos(\pi x_2) \sin(\pi x_2) \cdots x_1 x_2]^T$ for the prediction purpose. The back propagation algorithm, which is used to train the network, becomes very simple because of the absence of hidden layers.

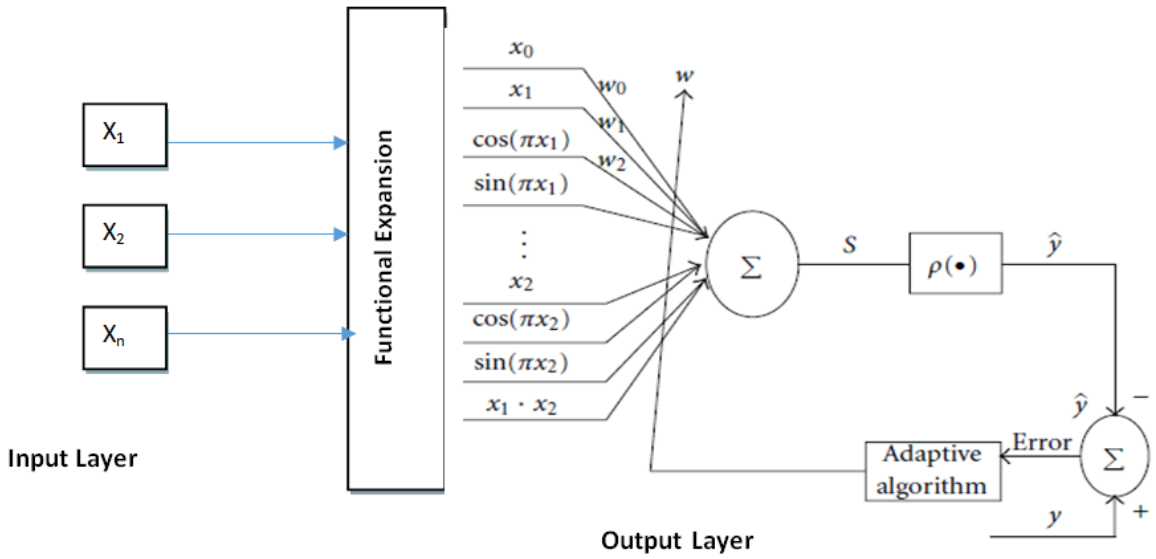

Figure 2. Structure of FLANN [25]

5.4.1. Algorithm for Training FLANN Fire Risk Model

The algorithm for training FLANN [24] based fire risk model has been represented as follows:

Step 1: Initialize the inputs x_i, (i = 1, . . . , n).

Step 2: Randomly select the initial values of the weight vectors w_i, for i = 1, 2, . . . l, where i is the number of functional elements.

Step 3: All the weights w_i were initialized to random number and given as

$$w_i \leftarrow \mathrm{Rand}(w_i(0)) \tag{22}$$

Step 4: The functional block can be represented as:

$$\mathrm{Xi} = \begin{bmatrix} 1, x_1, \sin(\pi x_1), \cos(\pi x_1), \\ x_2, \sin(\pi x_2), \cos(\pi x_2)... \end{bmatrix} \tag{23}$$

Step 5: The output was calculated as follows:

$$O_i = \sum_{i=1}^{N} w_i * X_i \tag{24}$$

Step 6: The error was calculated as $e_i = d_i - O_i$. It may be seen that the network produces a scalar output.

Step 7: The weight matrix was updated using the following relationship:

$$w_i(k+1) = w_i(k) + \alpha e_i(k)\, X_i(k) \tag{25}$$

Where, k - the time index;

α - the momentum parameter.

Step 8: If error ≤ ε (error limit), then go to Step 9 otherwise, go to Step 3.

Step 9: After the completion of learning, the weights were fixed, and the network can be used for testing.

5.5. Radial Basis Function (RBF)

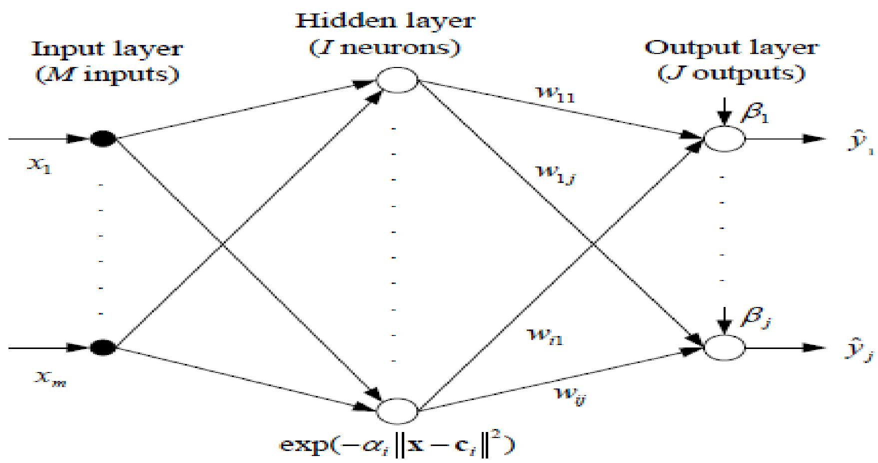

Figure 3. Network architecture of RBF [17]

The idea of RBF network derives from the theory of function approximation. RBF networks are very popular curve fitting, time series prediction, and control and classification problems. The architecture of the RBF network is quite simple. An input layer consisting of sources node; a hidden layer in which each neuron computes its output using a radial basis function, that being in general a Gaussian function, and an output layer that builds a linear weighted sum of hidden neuron outputs and supplies the response of the network (effort) [37]. An RBF network has only output neuron.The structure of RBF has been depicted in Figure 3.

Gradient Descent **(**GD) [39] is a first-order derivative-based optimization algorithm used for finding a local minimum of a function. The algorithm takes steps proportional to the negative of the gradient of the function at the current point. The output of an RBF network [39] has been written as:

$$\hat{y} = \begin{bmatrix} w_{11} & w_{11} & . & . & w_{1J} \\ w_{21} & w_{21} & . & . & w_{2J} \\ . & . & . & . & . \\ . & . & . & . & . \\ w_{J1} & . & . & . & w_{IJ} \end{bmatrix} \cdot \begin{bmatrix} 1 \\ \varphi(\|\mathbf{x}-\mathbf{c}_1\|^2) \\ . \\ . \\ \varphi(\|\mathbf{x}-\mathbf{c}_I\|^2 \end{bmatrix} \quad (26)$$

and

$$\hat{Y} = W.H \quad (27)$$

Where, the weight matrix is represented as W, and ϕ matrix is represented as H.

GD algorithm can be implemented to minimize the error after defining the error function:

$$E = \sum (Y - \hat{Y})^2 \quad (28)$$

Where, Y is the desired output.

RBF can be optimized by adjusting the weights and center vectors by iteratively computing the partials and performing the following updates:

$$w_{ij} = w_{ij} - \eta \frac{\partial E}{\partial w_{ij}} \quad (29)$$

$$c_i = c_i - \eta \frac{\partial E}{\partial c_i} \quad (30)$$

Where, η is the step size [39].

5.5.1. Algorithm for Training RBF Network Based Fire Risk Model

The algorithm for training RBF network [41] based fire risk model has been represented as:

Step 1: Set the weights to small random values.

Step 2: Perform steps 3-9 when the stopping condition is false.

Step 3: Perform steps 4-8 for each input.

Step 4: Each data unit (x_i for all i = 1 to n) receives input signals and transmits to the next hidden layer unit.

Step 5: Calculate the radial basis function.

Step 6: Select the centers for the radial basis function. The centers are selected from the set of input vectors. It should be noted that a sufficient number of centers have to be chosen to ensure adequate sampling of the input vector space.

Step 7: Calculate the output from the hidden layer unit:

$$v_i(x_i) = \frac{\exp\left[-\sum_{j=1}^{r}(x_{ji} - \hat{x}_{ji})^2\right]}{\sigma_i^2} \quad (31)$$

Where, x_{ji} - the center of the RBF unit for input variables;

σ_i - the width of the i^{th} RBF unit;

x_{ji} - the j^{th} variable of an input pattern.

Step 8: Calculate the output of the neural network:

$$y_{net} = \sum_{i=1}^{k} w_{im}\, v_i(x_i) + w_0 \quad (32)$$

Where, k is the number of hidden layer nodes (RBF function);

y_{net} is the output value of m^{th} node in output layer for the n^{th} incoming pattern;

w_{im} is the weight between i^{th} RBF unit and m^{th} output node;

w_0 is the biasing term at the n^{th} output node.

Step 9: Calculate the error and test for the stopping condition. The stopping condition may be the number of epochs or to a particular extent weight change.

6. Simulation Results and Discussion

To validate the performance of ANN models for prediction of fire risk of Indian coal seams, three ANN models i.e. MLP, FLANN and RBF were used. Best correlated parameters of ultimate analysis (C, H, and O) were chosen as an input for the simulation process. Simulation studies were carried out using MATLAB. The developed models were designed as per the proposed ANN algorithms. The entire system was a MISO (Multi Input and Single Output) model. To develop these models, initially the real-time data was processed experimentally. Cross validation was adopted to validate the samples after divided 49 samples into five folds.

Initially the Input and the output data were normalized and then it was processed in the system. In MLP and RBF, 3-3-1 structure (3 inputs, 3 hidden layers and 1 output) was used, while in FLANN, due to the non-availability of hidden layers, 3 inputs, and 1 output architecture was adopted. The Mean Square Error (MSE) vs. Epochs plot of all the applied ANN models are represented in Figures 4-6. They indicate that MLP, FLANN and RBF network models provide better results with Szb as compared to CPT, FT, and ΔE and require 10.01, 3.13, and 6.24 secs computation time respectively with 2000 epochs.

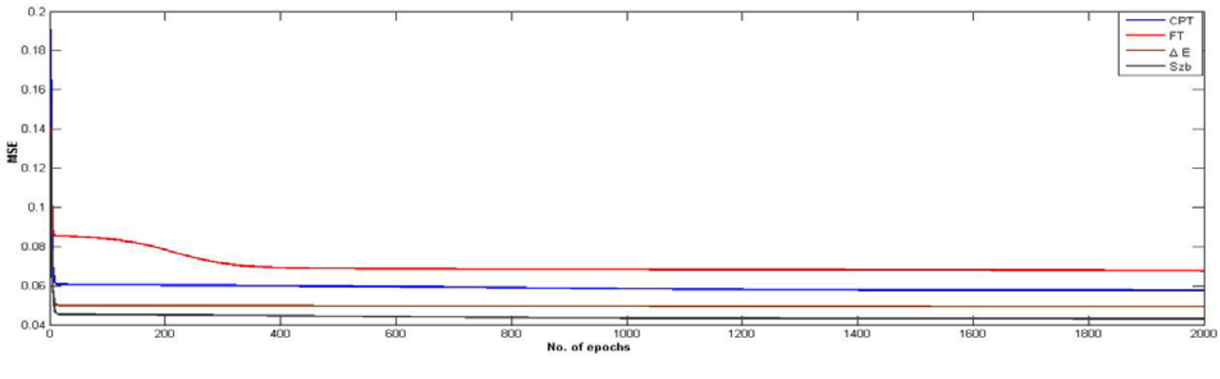

Figure 4. Performance curve of MLP

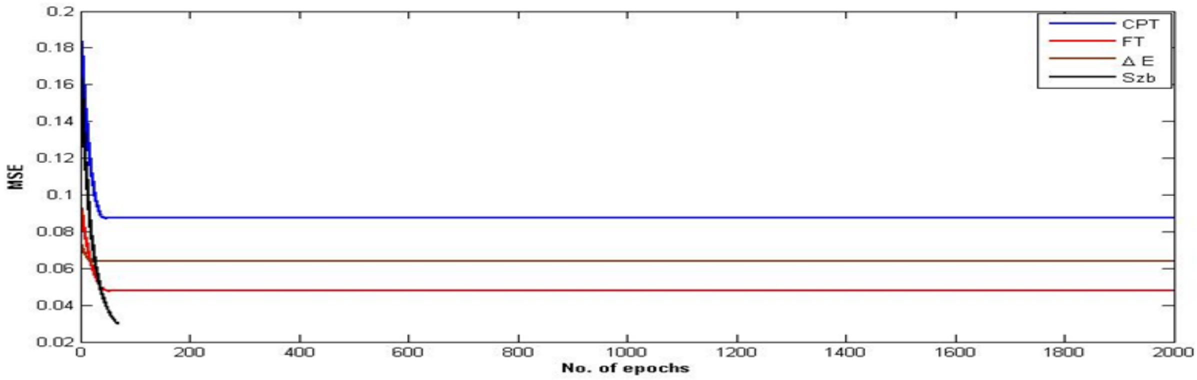

Figure 5. Performance curve of FLANN

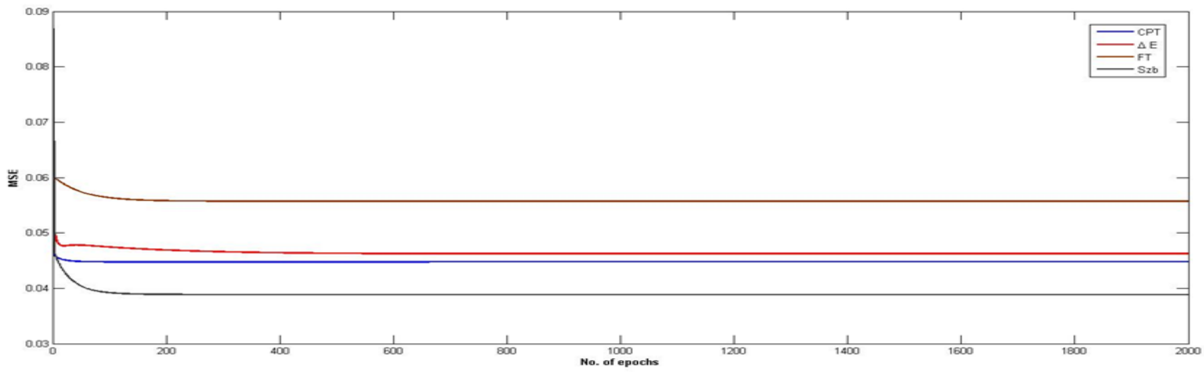

Figure 6. Performance curve of RBF network

7. Results and Discussion

The results of the investigated intrinsic properties viz., parameters of proximate analysis, elements of ultimate analysis and the macerals of petrographic analysis are summarized in Table 2. Proximate analysis results show that for three non-coking coal samples (SECL-9, MCL-8 and WCL-8), the moisture content was very high i.e. ≥ 11% and it matches with the field investigation; whereas coking coals showed very less (0.82%-1.44%) moisture content. Ash content and volatile matter in the collected non-coking coals varied in the range of 11.04% - 37.84% and 20.77% - 40.92% but in North-Eastern Coalfield (NEC-1 – NEC-6), it ranges from 6.2% - 13.5% and 43.26% - 56.30% . For the coking coals, these values were between 15.05% - 31.57% and 14.24% - 18.48% respectively. High inherent moisture and volatile matter coals have a higher tendency to spontaneous heating [1]. Therefore, only three parameters of proximate analysis viz., Moisture (M), Ash (A), and Volatile matter (VM) have been considered to ascertain the tendency of coal to spontaneous heating.

In the ultimate analysis, the carbon content is an indicator of the rank of coal. Coals containing higher oxygen are more prone to spontaneous combustion [34]. Indian coals have low sulphur content except in North-Eastern Coalfield. The result shows that NEC coals have sulphur content less than 3%, which should not reflect on spontaneous combustion of coal. Additionally, nitrogen content in the collected coal (~ 4%) does not relate to the rank of coal, and therefore it would not have any effect on spontaneous combustion. The classification of the coal was done following the percentage of carbon, hydrogen and oxygen in coal [2]. Hence, only carbon (C), hydrogen (H) and oxygen (O) have been considered and they play a vital role as compared to other elements Nitrogen (N) and Sulphur (S) of ultimate analysis. The results of the petrographic analysis are summarized in Table 2. The degree of proneness to spontaneous combustion increases with the increase of vitrinite and liptinite, but decreases with the increase of inertinite content [23,31].

The results of the susceptibility indices i.e. CPT, Szb, ΔE, and FT are summarized in Table 3. Usually, CPT decreases with increase in percentages of volatile matter, oxygen, and moisture but more than 35% Volatile Matter; 4-6% Moisture, and 9% Oxygen do not have much effect on CPT [26]. If Szb increases, it implies increases in the susceptibility of coal to spontaneous heating and the fire risk rating can be ascertained using Table 1. The tendency of coal to spontaneous combustion increases with higher wet oxidation potential difference [1]. In FT, coal that is more susceptible towards aerial oxidation burns at low temperature as compared to less susceptible coals.

From the multivariate analysis shown in Table 5, it can be inferred that CPT and Szb show significant correlation results at 5% level of significance with the combined parameters of proximate (M, VM, and A) and ultimate (C, H, and O) analysis based on correlation coefficient, (r= 0.98 and 0.95), standard error, (SE = 0.28 and 0.27), and variance (σ = 0.01 and 0.06) as compared to the other parameters. So these parameters can be used to predict the susceptibility of coal to spontaneous combustion. Macerals of the petrographic analysis and other susceptibility indices show no significant correlation due to less r, high SE and high σ. But the univariate statistical analysis shows that parameters of ultimate (C, H, and O) analysis shows significant correlation with all investigated susceptibility indices (CPT, FT, Szb, and ΔE) and hence can be used as input parameters to ANN models.

The performance analysis of ANN models reveals that Szb provides better results as compared to CPT, ΔE, and FT and can be used for the prediction of fire risk of Indian coals (Figure 4-Figure 6). Further, Figure 7 shows that average MMRE is less in Szb after cross validation viz., MLP (0.56), FLANN (0.72), and RBF (0.49). It implies that RBF network model shows less average MMRE as compared to MLP and FLANN and can provide better prediction of fire risk of Indian coals with Szb.

The collected coals are categorized into three categories based on fire risk rating of Olpinski index (Table 1). Table 6 shows that NCL-1 and -2 are classified into high fire risk, whereas SECL-3,5,9, SCCL-3,8, MCL-1,2,3,4,5,7, WCL-1,2,3,4,5,6,8,9,10, and NEC-1,2,3,4,5 are categorized into medium fire risk, and the rest of the coal samples are low fire risk category. The results of the experimental studies were observed to match closely with the field observations for coal categorization based on the Olpinski index.

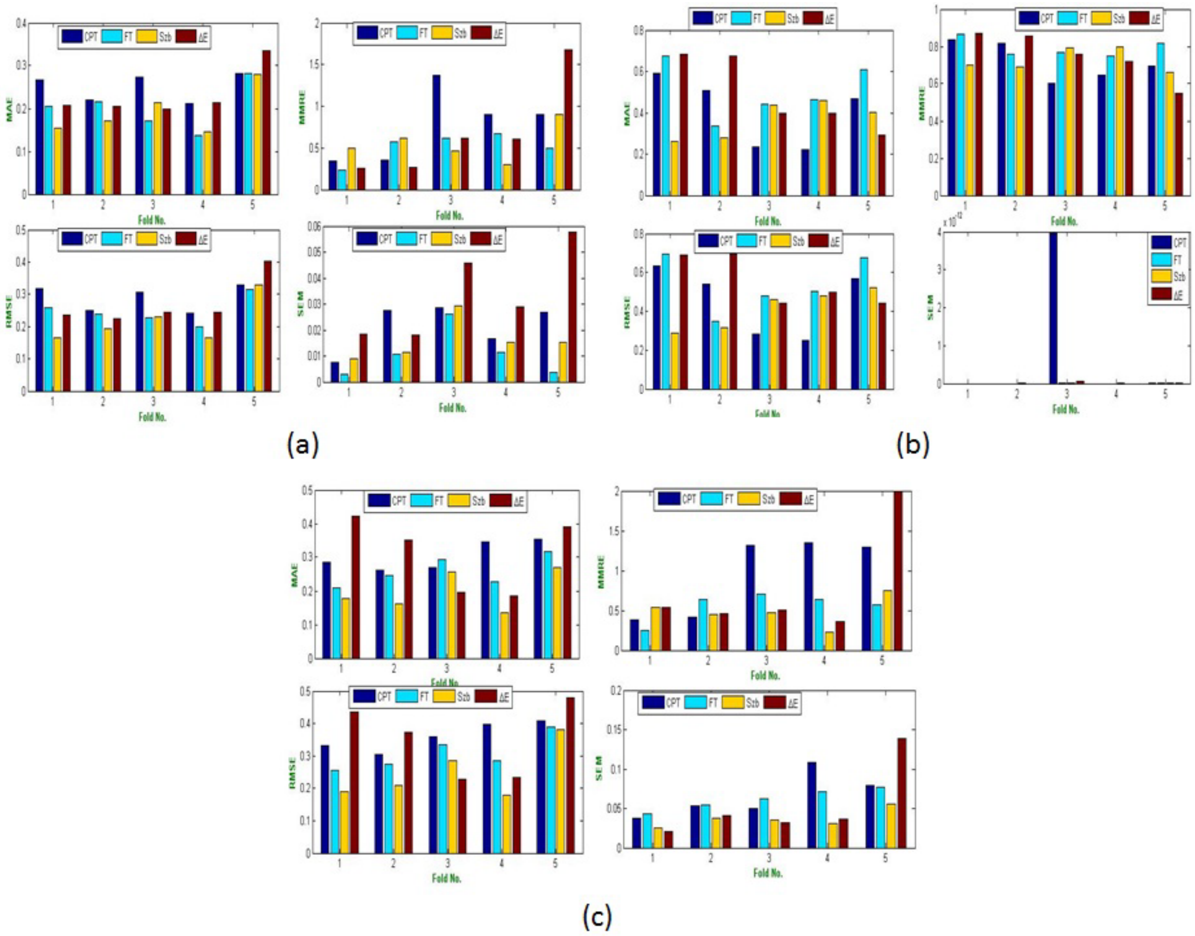

Figure 7. Graphical representation of performance of evaluation parameters in (a) MLP (b) FLANN (c) RBF network models

Table 6. Results of categorization of coals

Susceptibility Index	**Fire risk rating**		
	Poorly susceptible	**Moderately susceptible**	**Highly susceptible**
Szb (^{0}C/min)	SECL-1,2,4,6,7,8,10, SCCL-1,2,4,5,6,7,9, MCL-6,8, WCL-7, NEC-6, IISCO-1,2, BCCL-1 and TISCO-1	SECL-3,5,9, SCCL-3,8, MCL-1,2,3,4,5,7, WCL-1,2,3,4,5,6,8,9,10 and NEC-1,2,3,4,5	NCL-1,2

8. Conclusions

The following conclusions are drawn from the present investigations:

1. From the statistical analysis (univariate and multivariate), it could be interpreted that parameters of ultimate (C, H, and O) analysis shows better significant correlation with Szb as compared to other susceptibility indices (CPT, ΔE, and FT) and can be used as input parameters to ANN models.
2. The performance analysis of ANN models (MLP, FLANN, and RBF network) revealed that Szb provides better results as compared to CPT, ΔE, and FT and can be used for the prediction of fire risk of Indian coals.
3. The performance evaluation of cross validation implies that RBF network model can provide better prediction of fire risk of Indian coals with Szb than MLP and FLANN based on least MMRE.
4. The simulation study showed that RBF provides appropriate fire risk prediction with Szb as compared

to MLP and FLANN, and, hence can be implemented in hardware.

5. The results of the experimental investigations were matched closely with the field observations based on Olpinski index. NCL-1 and -2 are categorized into high fire risk, whereas rest of the samples were classified into medium and low fire risk category Hence, Olpinski index can be used as a reliable index to predict proneness of Indian coals to spontaneous combustion.

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