Prediction of spontaneous heating susceptibility of Indian coals using fuzzy logic and artificial neural network models

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ABSTRACT

Coal mine fires due to spontaneous heating are a major concern worldwide. Most of these fires could be averted if suitable preventive measures are taken. Since the spontaneous heating potential of all types of coals are not the same, its accurate prediction is essential to plan efficient preventive measures and improve production and storage capabilities of a mine. The current paper presents a comparison of two approaches viz. fuzzy expert system and the commonly used artificial neural networks (ANN) for forecasting the self heating of coals. To apply these techniques, 30 coal samples of varying ranks were collected from different coalfields of the country. The intrinsic properties of the coal seams were determined by proximate, ultimate and petrographic analyses. The spontaneous heating proneness of the samples was studied using crossing point temperature (CPT), which is treated as an important measure for fire susceptibility of coal seams in Indian mines. Correlation studies between the intrinsic properties and CPT was carried out to identify the parameters for prediction purpose. Using moisture, volatile matter, and ash content as input parameters, CPT is predicted using fuzzy logic based on Takagi–Sugeno–Kang (TSK) model and ANN based on back propagation algorithm. Triangular fuzzy membership function is adopted for describing input variables. The results show both the models predict CPT with reasonable accuracy. Fuzzy modelling being a simpler approach, it can be utilized in the field where experimental data on coal properties are not precisely available but human judgement and intuition can be adopted for prediction purpose.

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1. Introduction

Coal mine fires have been a great concern both for the industry and researchers worldwide. Studies carried out by different researchers reveal that in most of the cases, they are caused by spontaneous heating of coal (Feng, Chakravarty, & Cochrane, 1973; Saghafi & Carras, 1997; Sensogut & Cinar, 2000). It is known that all coals, when exposed to air, undergo natural oxidation even at ambient temperatures. Oxygen is adsorbed by a purely physical process, which rapidly converts into a chemical chain reaction resulting in the oxidation of certain constituents of coal with the evolution of small quantity of heat. If this heat is not dissipated either by conduction or convection or radiation or by all three processes, then there occurs further rise in temperature, which accelerates the rate of oxygen sorption and production of heat, culminating in fire. Spontaneous combustion of coal can lead to loss of desirable coal properties and products, creates environmental pollution, agricultural land degradation, and raise concerns about safety and economic aspects of mining especially in coal stockpiles, transportation over long distances, and in underground mining, etc. It is well known that spontaneous heating of coal depends mainly on two types of factors, such as intrinsic and extrinsic. The intrinsic parameters are mainly associated with the nature of the coal, i.e. its physico-chemical characteristics, petrographic distribution and mineral make up. On the other hand, the extrinsic parameters are related to atmospheric, geological and mining conditions prevailing during extraction of coal seams and these are mainly site specific.

Most mine fires start very small and gradually expand in size. Most of these fires could be averted if suitable preventive measures are taken. Accurate prediction of self heating potential of coal seams is therefore essential to plan efficient preventive measures. In the past, a number of researchers have attempted to assess the spontaneous heating tendency of coal by carrying out different experiments in the laboratory and different countries of the world follow different methods for this purpose, for example crossing point temperature (CPT) in India, Russian U-index in Russia,
Olpinski index in Poland, adiabatic calorimetry in USA, etc. These simple indices have traditionally been considered for prediction of self heating liability. In addition to this, some researchers have tried to predict the spontaneous heating susceptibility of coal by developing risk indices based on the results obtained from CPT and differential thermal analysis (DTA) experiments (Didari, 1988; Feng et al., 1973; Gouws & Wade, 1989; Mahadevan & Ramlu, 1985). Schmal, Duyzer, and Van Heuven (1985) developed a one-dimensional mathematical model called dry coal model describing the spontaneous heating process for dry coal at relatively low temperatures of less than 100 °C. They observed that the most important parameters that affect spontaneous heating, particularly for the time between stacking and spontaneous ignition were the porosity of the pile, the initial temperature of coal, and the evaporation and condensation of coal moisture. Saghafi and Carras (1997) developed a mathematical model of spontaneous combustion applied to longwall mining by using the conservation laws of mass, energy and momentum. The model simulated the processes of heat generation and heat transport within a goaf. They solved the coupled partial differential equations on a 2D space grid using finite difference scheme. Cygankiewicz (2003) developed a mathematical model to forecast the self heating process of coal based on adiabatic calorimetric data. Grekov, Koshovsky, and Cygankiewicz (2001) studied the compensation effect in the interrelationship of the activation energy with the pre-exponential factor in the Arrhenius reaction of coal oxidation, and developed a mathematical model of kinetics of non-isothermal heterogeneous oxidation of coal and formulated the initial and boundary problem of description of the spontaneous heating process of the coal particle. Brooks and Glasser (1986) developed a one-dimensional model, which consisted of three differential equations describing temperature, oxygen concentration and pressure variations in a coal stockpile. On solving the model for steady state, they classified the coal dumps as safe, unsafe or conditionally safe. Krishnaswamy, Agarwal, and Gunn (1996) developed a two-dimensional mathematical model of self heating of coal in open stockpiles neglecting the effect of moisture migration. Panigrahi and Saxena (2001) and Singh and Demirbilek (1987) have attempted the statistical appraisal of intrinsic factors to predict the liability of coal to spontaneous combustion. Mukherjee and Sarkar (1997) attempted to revaluate the relationship between elementary analysis data of bituminous coals and their crossing point temperature values and found the relationship to be highly sensitive to variations in petrographic compositions, air-dried moisture and ash level of the coal samples. A few researchers have developed computerized approaches for data acquisition and evaluation of spontaneous heating potential of coal seams (Ren & Richards, 1994; Smith, Moron, & Lazzara, 1991; Zaharijev, Chrstov, Krougly, & Batchvarov, 2001). However, the relationship between the intrinsic properties and the spontaneous heating potential of coal seams is complex and difficult to describe through a mathematical model. Instead of using mathematical model, this relationship can also be constructed using fuzzy logic (FL) and artificial neural networks (ANN), which have been used by many researchers for a variety of engineering applications. As a qualitative approach, fuzzy logic provides a methodology to mimic human expert and allow the use of data and information from expert knowledge. Fuzzy logic also provides an easier and simpler mechanism in developing the model due to its nature that allow decision-making process that involves a vague, imprecise, incomplete and ambiguous information. Fuzzy model has been successfully applied for prediction of compressive and bond strength of concrete (Ozcan, Atis, Karahan, Uncuoglu, & Tanyildizi, 2009; Tanyildizi, 2005), palm oil production (Amelia, Wahab, & Hassan, 2009), zinc ions separation from waste water (Sadrzadeh, Ghadimi, & Mohammadi, 2009), and structural design (Erdik, 2009). If the inputs and outputs of a system behave in a non-linear way and interrelationship is difficult to establish, ANN can be adopted for prediction purpose. ANNs are basically a family of massively parallel architectures that solve difficult problems via the cooperation of highly interconnected but simple computing elements (or artificial neurons). The processing elements of a neural network are similar to the neurons in the brain, which consist of many simple computational elements arranged in layers (Bhadeshia, 1999; Dong, Longtu, Cewen, Juntao, & Zhiulu, 2003; Kai, Juntao, Longtu, & Zhiulu, 2005).

Fuzzy control theory can be applied on linear and non-linear systems. It does not need to handle the tedious mathematical models of controlled body. It needs only to set a simple controlling method based on engineering experience. Thus, it can be useful in complicated processes such as spontaneous heating susceptibility of coals. A fuzzy system (FS) is a non-linear mapping of an input data vector into a scalar output using fuzzy logic. This mapping is performed using the fuzzification, fuzzy inference, and defuzzification. The function of fuzzifier is to determine the degree of membership of a crisp input in a fuzzy set. The fuzzy rule-base is used to represent the fuzzy relationship between input and output fuzzy variables. The output of the fuzzy rule-base is determined based on the degree of membership specified by the fuzzifier. The inference engine calculates the rule’s conclusion based on its membership degree. Optionally, if needed, a defuzzifier is used to convert outputs of the fuzzy rule-base into crisp values. Fuzzy inference engine uses “IF–THEN” rules to map input variables to desired output. Generally, the rule is extracted from expert opinion, engineering knowledge and experience with a view to effectively handle uncertainty and ambiguity in the system. The most important types of fuzzy inference systems are Mamdani’s fuzzy inference system and Takagi–Sugeno–Kang method (TSK) of fuzzy inference process. The main difference between the two methods lies in the consequent of fuzzy rules. Mamdani fuzzy systems use fuzzy sets as rule consequent whereas TSK fuzzy systems employ linear functions of input variables as rule consequent.

This paper presents the prediction of spontaneous heating susceptibility of coals based on laboratory tests with the help of fuzzy expert system and compared with commonly used prediction tool like artificial neural networks. To apply these techniques, a number of coal samples both from fiery and non-fiery seams of different coal fields were collected and their intrinsic properties were determined by carrying out proximate, ultimate and petrographic analyses. Crossing point temperature (CPT) experiment was carried out to determine the spontaneous heating susceptibility potential of coal seams. Statistical analysis has been carried out to determine the appropriate intrinsic properties required for prediction purposes. The statistically significant parameters have been used to predict the crossing point temperature of coals.

2. Collection of coal samples for the study

In order to study the intrinsic properties of coal governing spontaneous heating, 30 coal samples were collected from different Indian coalfields belonging to varying ranks and spreading over seven different mining companies. The coals belonging to Gondwana formation and age of coal seams vary from lower Permian to Jurassic times. The coal samples were collected from different seams following channel sampling procedure (JS-436, 1964; Peters, 1978) and brought to the laboratory in sealed condition for analysis. The details of samples collected, i.e. name of the seam, colliery/mines and the subsidiary company is presented in Table 1. The intrinsic properties of these samples were determined by proximate, ultimate and petrographic analyses.

The moisture (M), volatile matter (VM) and ash content (A) of coal samples were determined by proximate analysis following
3. Determination of crossing point temperature

The crossing point temperature (CPT) of the coal samples were determined at the Mine Environment laboratory of Indian School of Mines University, Dhanbad following the procedure and experimental set up described by Panigrahi, Udaybhanu, and Ojha (1971, 1994; IS 9127 (Parts – I and II), 1979; Stach et al., 1982). The results of proximate, ultimate and petrographic analyses have been presented in Table 2.
4. Determining the parameters for prediction of spontaneous heating susceptibility

In order to determine suitable parameters for prediction of spontaneous heating susceptibility, extensive correlation studies were carried out between CPT and the coal characteristics as obtained from proximate, ultimate and petrographic analyses. CPT is taken as dependent variable and each constituent obtained from the proximate, ultimate and petrographic analyses as an independent variable. It was observed from the correlation study that the constituents of proximate analysis show better correlation with CPT than that of the ultimate and petrographic analyses (Panigrahi & Sahu, 2004). Therefore, three parameters, viz. moisture, volatile matter and ash content obtained from proximate analysis have been considered for prediction of CPT. Correlation between the constituents of proximate analysis and CPT is as presented in Table 3.

Table 3

<table>
<thead>
<tr>
<th>Serial no.</th>
<th>Dependent variable</th>
<th>Empirical relation</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CPT</td>
<td>$179.59 + 67.35M$</td>
<td>0.68</td>
</tr>
<tr>
<td>2</td>
<td>CPT</td>
<td>$1.478 + 1.499\ln VM + 41$</td>
<td>0.78</td>
</tr>
<tr>
<td>3</td>
<td>CPT</td>
<td>$149.317 + 4.425 \cos(1.534A + 1.353)$</td>
<td>0.39</td>
</tr>
</tbody>
</table>

5. Fuzzy expert system

Detailed analysis on fuzzy system can be found in numerous literatures (Cox, 1992; Mendel, 1995; Zadeh, 1965, 1976). Block diagram of a typical fuzzy logic system is presented in Fig. 1. As outlined in Fig. 1, a fuzzy rule-based system consists of four parts: fuzzifier, knowledge base, inference engine and defuzzifier. These four parts are described below:

- **Fuzzifier**: The real world input to the fuzzy system is applied to the fuzzifier. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. The fuzzifier converts this precise quantity to the form of imprecise quantity like ‘large’, ‘medium’, ‘high’, etc. with a degree of belongingness to it. Typically, the value ranges from 0 to 1.

- **Knowledge base**: The main part of the fuzzy system is the knowledge base in which both rule-base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules while as the rule-base contains a number of fuzzy if-then rules.

![Fig. 1. Structure of fuzzy rule-based system.](image1)

![Fig. 2. TSK model in MATLAB platform.](image2)
Inference engine: The inference system or the decision-making unit performs the inference operations on the rules. It handles the way in which the rules are combined.

Defuzzifier: The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block.

In general two popular fuzzy inference systems are available: Mamdani fuzzy model and TSK fuzzy model. The selection depends on the fuzzy reasoning and formulation of fuzzy IF-THEN rules. Mamdani fuzzy model (Mamdani & Assilia, 1975) is based on the collections of IF-THEN rules with both fuzzy antecedent and consequent predicts. The benefit of this model is that the rule-base is generally provided by an expert and hence to a certain degree it is translucent to explanation and study. Because of its easiness, Mamdani model is still most commonly used technique for solving many real world problems. The TSK fuzzy model was proposed by Takagi and Sugeno (1985) in an effort to formalize a system approach to generating fuzzy rules from an input–output data set. Antecedent is set of inputs inter divided into fuzzy membership function and consequent is a crisp function usually a polynomial. The TSK system formalizes a system approach to generate fuzzy rules from an input–output data set. The model consists of IF-THEN rules with fuzzy antecedents fuzzy and mathematical functions in the consequent part. The antecedent fuzzy sets partition the input space into number of fuzzy regions while the consequents function describes the system’s behavior in these regions. The construction of TSK model is done in four steps: (1) determination of fuzzy sets in the rule antecedents, (2) determination of output mathematical functions, (3) determination of rule-base for the inference engine and (4) aggregation of output to produce defuzzified result. The TSK model in MATLAB platform is depicted in Fig. 2.

### 5.1. Selection of variables

The first step in system modelling is the identification of input and output variables called the system variables. Only those inputs that affect the output to a large extent are selected. It has already been mentioned in Section 4 that moisture, volatile matter and ash influence CPT significantly; hence, these parameters are chosen as input variables and CPT as output variable. Fuzziness in a fuzzy set is characterized by its membership functions. It classifies the element in the set whether it is discrete or continuous. The membership function are introduced in the inputs, i.e. percentage of moisture contents, volatile matter contents and ash contents in order to represent various levels of fuzzy sets in the input functions. In general, triangular and trapezoidal membership functions are

<table>
<thead>
<tr>
<th>Variables</th>
<th>Names</th>
<th>Range</th>
<th>Membership functions</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>INPUTS</td>
<td>M%</td>
<td>[0–14.5]</td>
<td>Low [0 0 5.5]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Medium [1 7.25 12.75]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>High [9 14.3 14.5]</td>
<td></td>
</tr>
<tr>
<td>VM%</td>
<td>[17–37]</td>
<td>Low [17 17 24]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium [20 27 34]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>High [30 37 37]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A%</td>
<td>[7–43]</td>
<td>Low [7 7 20]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium [12 25 38]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>High [30 43 43]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OUTPUTS</td>
<td>CPT (°C)</td>
<td>[138–180]</td>
<td>Lowest [144]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Lower [148]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Low [150]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Medium [152]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>High [155]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Higher [168]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Highest [180]</td>
<td></td>
</tr>
</tbody>
</table>

![Fig. 3. Fuzzy representation of %M.](image-url)
used to normalize the crisp inputs because of their simplicity and computational efficiency. The triangular membership function as described in Eq. (1) is used to convert the linguistic values in the range of 0–1.

**Fig. 4.** Fuzzy representation of %VM.

**Fig. 5.** Fuzzy representation of %A.
where \( a, b, c \) are the parameters of the linguistic value and \( x \) is the range of the input parameters. In this proposed model, each input have three triangular membership functions, where the output of the proposed model has five triangular membership functions. In the selection procedure, the above mentioned inputs and the output

\[
\text{triangle}(x; a, b, c) = \begin{cases} 
0, & x \leq a, \\
\frac{x-a}{b-a}, & a < x \leq b, \\
\frac{c-x}{c-b}, & b < x \leq c, \\
0, & c > x.
\end{cases}
\] (1)

Fig. 6. Fuzzy representation of output.

Fig. 7. Representation of linguistic rule-base in MATLAB platform.
The relationship between input and the output were represented in the form of IF-THEN rules. As per the fuzzy systems, the inputs ‘M%’, ‘VM%’, ‘A%’ and ‘CPT (°C)’ have three membership functions each. Taking non-repetitive rules 21 rules have been generated. The rules of the TSK fuzzy system are generated in the following ways:

<table>
<thead>
<tr>
<th>Rule number</th>
<th>Inputs</th>
<th>Output (CPT °C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>High Medium Low</td>
<td>Low</td>
</tr>
<tr>
<td>2</td>
<td>High Medium Low</td>
<td>Low</td>
</tr>
<tr>
<td>3</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>High Medium Low</td>
<td>Low</td>
</tr>
<tr>
<td>7</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Medium Medium Low</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Low Low Low Medium</td>
<td>Medium Low</td>
</tr>
<tr>
<td>16</td>
<td>Low Low Low Medium</td>
<td>Medium Low</td>
</tr>
<tr>
<td>17</td>
<td>Low Low Low Medium</td>
<td>Medium Low</td>
</tr>
<tr>
<td>18</td>
<td>Medium Medium Low</td>
<td>Low</td>
</tr>
<tr>
<td>19</td>
<td>Low Medium Low Low</td>
<td>Medium Low</td>
</tr>
<tr>
<td>20</td>
<td>Medium Medium Low</td>
<td>Low</td>
</tr>
<tr>
<td>21</td>
<td>High Medium Low</td>
<td>Low</td>
</tr>
</tbody>
</table>

5.2. Determination of linguistic rule-base

The relationship between input and the output were represented in the form of IF-THEN rules. As per the fuzzy systems, the inputs ‘M%’, ‘VM%’, ‘A%’ and ‘CPT (°C)’ have three membership functions each. Taking non-repetitive rules 21 rules have been generated. The rules of the TSK fuzzy system are generated in the following ways:

5.3. Defuzzification

The TSK output membership functions are either linear or constant. The TSK approach has fuzzy sets in the premise part only and IF-THEN control rules are given as follows:

\[ R_r : \text{IF } X_1 \text{ is } S_1^{(1)}, X_2 \text{ is } S_2^{(2)}, \ldots, X_n \text{ is } S_n^{(n)} \]

\[ \text{THEN } Y_r = f_r(X_1, X_2, \ldots, X_n) \]

where \( S_r^{(i)} \) is a fuzzy set corresponding to a partition domain of the input variable \( X_i \), \( r \) is the number of input variables, \( f_r \) is a function of the input variables, and finally \( Y_r \) is the output of the \( r \)th IF-THEN inference rule \( R_r \).

The general algorithm of the TSK inference system is expressed as follows. It is assumed that there are \( R_r (r = 1, 2, 3, \ldots, k) \) rules in the above-mentioned form.

1. For each implication \( R_r, Y_r \) is calculated by the function \( f_i \) in the consequent part:

\[ Y_r = f_i(X_1, X_2, \ldots, X_n) \]

\[ = c_r(0) + c_r(1)X_1 + c_r(2)X_2 + \cdots + c_r(n)X_n \]

For zero order TSK model, the output level, \( Y_i \), is constant, i.e. \( c_r(1) = c_r(2) = \cdots = c_r(n) = 0 \) for every output \( Y_r \).

2. The weights are calculated as follows:

\[ r_r = (m_1^r \land m_2^r \land \cdots \land m_n^r)P^r \]

where, \( m_1^r, m_2^r, \ldots, m_n^r \) denotes the \( x \) cuts of MFs according to input values for the \( r \)th rule. An \( x \) cut of the fuzzy set \( A(A_x) \) is a crisp set, which contains all the elements in \( U \) that have membership values greater than or equal to \( A_x \). The universe of discourse \( U \) is the \( n \)-dimensional Euclidean space \( R^n \). The occurrence probability is shown by \( P \) and \( \land \) stands for min or production operation. For the sake of simplicity, \( P \) is taken as equal to 1.

Table 6

<table>
<thead>
<tr>
<th>Input parameters for training</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error tolerance</td>
<td>0.01</td>
</tr>
<tr>
<td>Learning rate (( \beta ))</td>
<td>0.025</td>
</tr>
<tr>
<td>Momentum parameter (( \alpha ))</td>
<td>0.02</td>
</tr>
<tr>
<td>Noise factor (( NF ))</td>
<td>0.01</td>
</tr>
<tr>
<td>Number of epochs</td>
<td>300,000</td>
</tr>
<tr>
<td>Number of hidden layer</td>
<td>4</td>
</tr>
<tr>
<td>Number of input layer neuron (I)</td>
<td>3</td>
</tr>
<tr>
<td>Number of output layer neuron (O)</td>
<td>1</td>
</tr>
</tbody>
</table>

Fig. 8. The three layer neural network.
3. The final output $Y$ inferred from $k$ implications is given as the weighted average of all $Y_r$ with the weights $r$, as:

$$Y = \frac{\sum_{r=1}^{n} r_r Y_r}{\sum_{r=1}^{n} r_r}$$

6. Neural computation

Spontaneous heating of coal is a complex process and there exists a non-linear relationship between CPT and the intrinsic parameters. Earlier researchers have found that CPT is influenced...
by a number of intrinsic parameters. Therefore a robust methodology is needed to study this relationship. In this work, a statistical method, responding to the constraints, is implemented to correlate the operating parameters. This methodology is based on artificial neural networks (ANN), which is a technique that involves database training to predict input–output evolutions. The details of this methodology are described by Rajasekaran and Vijayalakshmi Pai (2003). In the present analysis the moisture, volatile matter and ash content obtained from proximate analysis are taken as the input parameters for training. Each of these parameters is characterized by one neuron and consequently the input layer in the ANN structure has three neurons. The database is built considering experiments at the limit ranges of each parameter. Experimental result sets are used to train the ANN in order to understand the input–output correlations. The database is then divided into three categories, namely: (i) a validation category, which is required to

![Fig. 11. Surface plot of CPT with A% and VM%.](image1)

![Fig. 12. Surface plot of CPT with M% and VM%.](image2)
define the ANN architecture and adjust the number of neurons for each layer; (ii) a training category, which is exclusively used to adjust the network weights and (iii) a test category, which corresponds to the set that validates the results of the training protocol. The input variables are normalized so as to lie in the same range group of 0–1. Different ANN structures (I–H–O) with varying number of neurons in the hidden layer are tested at constant cycles, learning rate, error tolerance, momentum parameter, noise factor and slope parameter. Based on least error criterion, one structure, shown in Fig. 8, is selected for training of the input–output data. The learning rate is varied in the range of 0.001–0.100 during the training of the input–output data. Number of neurons in the hidden layer is varied and in the optimized structure of the network, this number is 4. The number of cycles selected during training is high enough so that the ANN models could be rigorously trained. Seventy five percent of data is used for training whereas 25% data is used for testing. The parameters used for network training is given in Table 6.

7. Results and discussions

In this study, prediction of spontaneous heat susceptibility of Indian coal seams has been done using ANN and TSK models. Correlation study of inputs variables and CPT, which is treated as an indicator for assessment of coal susceptibility in India coal mines, indicate that constituents of proximate analysis show better correlation with CPT than that of other analyses. Therefore, three parameters, viz. moisture, volatile matter and ash content obtained from proximate analysis have been considered for prediction of CPT. Comparisons of the measured and predicted CPT values by TSK and ANN models with $R^2$ coefficients are shown in Figs. 9 and 10 respectively. The response plots for CPT with different input parameters for TSK model have been presented in Figs. 11–13.

It can be seen from Fig. 9 that TSK model predict the CPT values of coal seams with $R^2$ of 0.82. Fig. 10 shows that ANN model predict the CPT values of coal seams with $R^2$ of 0.91, which is superior to TSK model. It is found that percentage relative error in TSK model is 8.1250% whereas in ANN model it is 9.4203%. Both ANN and TSK models can be used to predict the heat susceptibility of coal seams using the same parameters of coal ingredients obtained from proximate analysis, comparison between two models in terms of $R^2$ shows that ANN provides better results than the TSK results. The major advantage with TSK model lies in the fact that human judgment and intuition can be effectively used for prediction of CPT values, which helps in field applications. It can be observed from Figs. 11–13 that the proposed rule-base is capable of predicting CPT values in the experimental domain quite efficiently as the rule covers a larger decision surface.

8. Conclusions

The spontaneous heating susceptibility of coal seams is determined by CPT method. However, it is not always possible to carry out the experiment in the field, since it requires sophisticated and costly experimental set up. Moreover, it is time consuming and failure of power supply for a few minutes during experiments, especially when the temperature approaches the crossing point, gives erroneous value of CPT and the whole experiment has to be repeated. Therefore, prediction of spontaneous heating susceptibility with fuzzy logic and ANN models could be a viable option than experimentation in the field. In this study, two approaches viz. fuzzy logic based on TSK model and ANN based on back propagation algorithm were used to predict the spontaneous heating of coals. Both the models consider the intrinsic properties determined by proximate analysis as input parameters. Determination of these parameters is a routine task in the field as these are required to determine the grade of coals and hardly demand any costly experimental setup. It is observed that there is a close relationship between the experimentally determined CPT and those predicted by both the models. ANN models generally require a large database for training purpose in order to improve the prediction accuracy. Once a database is generated with sufficiently large number of coal samples, it would be easier to predict the spontaneous heating susceptibility of coal accurately without
determining the spontaneous heating of coals by experimental means. As compared to ANN, implementation of TSK for prediction purpose does not require a large dataset and computational time can be saved since it does not require training. However, a larger database is desirable for creating the rule-base so that prediction accuracy can be improved. It is expected that the results of this study will benefit the practicing mining engineers and researchers to a great extent in predicting the spontaneous heating susceptibility of the seams and accordingly plan the mining activities and precautionary measures to deal with fire problems in mines.

References


