Development of Mathematical Models for the Assessment of Fire Risk of Some Indian Coals using Soft Computing Techniques

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By

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(September-2015)

Dedicated to my Parents, wife & my lovely son Pradyun

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CERTIFICATE

This is to certify that the work in the thesis entitled "**Development of Mathematical Models for the Assessment of Fire Risk of Some Indian Coals using Soft Computing Techniques**" being submitted by **Devidas S. Nimaje** in partial fulfillment of the requirement for the degree of Doctor of Philosophy in Engineering to the National Institute of Technology, Rourkela is an authentic record of research work done by him in this department under my guidance and supervision. The data and the results embodied in this thesis have not been, to the best of my knowledge submitted to any other university or Institute for the award of a degree or diploma.

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Place: N.I.T., Rourkela **Devidas S. Nimaje**

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ABSTRACT

Coal is the dominant energy source in India and meets 56% of the country's primary commercial energy supply. In the light of the realization of the supremacy of coal to meet the future energy demands, rapid mechanization of mines is taking place to augment the Indian coal production from 643.75 million tons (MT) per annum in 2014-15 to an expected level of 1086 MT per annum by 2024-25. Most of the coals in India are obtained from low-rank coal seams. Fires have been raging in several coal mines in Indian coalfields. Spontaneous heating of coal is a major problem in the global mining industry. Different researchers have reported that a majority (75%) of these fires owe their origin to spontaneous combustion of coal. Fires, whether surface or underground, pose serious and environmental problems are causing huge loss of coal due to burning and loss of lives, sterilization of coal reserves and environmental pollution on a massive scale.

Over the years, the number of active mine fires in India has increased to an alarming 70 locations covering a cumulative area of 17 km^2. In Indian coalfield, the fire has engulfed more than 50 million tons of prime coking coal, and about 200 million tons of coals are locked up due to fires. The seriousness of the problem has been realized by the Ministry of Coal, the Ministry of Labour, various statutory agencies and mining companies. The recommendations made in the 10th Conference on Safety in Mine held at New Delhi in 2007 as well as in the Indian Chamber of Commerce (ICC)-2006, New Delhi, it was stated that all the coal mining companies should rank their coal mines on a uniform scale according to their fire risk on scientific basis. This will help the mine planners/engineers to adopt precautionary measures/steps in advance against the occurrence and spread of coal mine fire.

Most of the research work carried out in India focused on the assessment of spontaneous combustion liabilities of coals based on limited conventional experimental techniques. The investigators have proposed/established statistical models to establish correlation between various coal parameters, but limited work was done on the development of soft computing techniques to predict the propensity of coal to self-heating that is yet to get due attention. Also, the classifications that have been made earlier are based on limited works which were empirical in nature, without adequate and sound mathematical base.

Keeping this in view, an attempt was made in this research work to study forty-nine coal samples of various ranks covering the majority of the Indian coalfields. The

experimental/analytical methods that were used to assess the tendencies of coals to spontaneous heating were: proximate analysis, ultimate analysis, petrographic analysis, crossing point temperature, Olpinski index, flammability temperature, wet oxidation potential analysis and differential thermal analysis (DTA). The statistical regression analysis was carried out between the parameters of intrinsic properties and the susceptibility indices and the best-correlated parameters were used as inputs to the soft computing models. Further different ANN models such as Multilayer Perceptron Network (MLP), Functional Link Artificial Neural Network (FLANN) and Radial Basis Function (RBF) were applied for the assessment of fire risk potential of Indian coals.

The proposed appropriate ANN fire risk prediction models were designed based on the best-correlated parameters (ultimate analysis) selected as inputs after rigorous statistical analysis. After the successful application of all the proposed ANN models, comparative studies were made based on Mean Magnitude of Relative Error (MMRE) as the performance parameter, model performance curves and Pearson residual boxplots. From the proposed ANN techniques, it was observed that Szb provided better fire risk prediction with RBF model vis-à-vis MLP and FLANN. The results of the proposed RBF network model was closely matching with the field records of the investigated Indian coals and can help the mine management to adopt appropriate strategies and effective action plans in advance to prevent occurrence and spread of fire.

Keywords: Coal; Fire risk; Spontaneous heating; Crossing point temperature; Wet oxidation potential analysis; DTA; Olpinski index; Soft computing; ANN; MLP; RBF; FLANN; MMRE.

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LIST OF ACRONYMS

MT	-	Million Tons
M	-	Moisture
A	-	Ash
VM	-	Volatile matter
FC	-	Fixed carbon
C	-	Carbon
H	-	Hydrogen
N	-	Nitrogen
O	-	Oxygen
S	-	Sulphur
V	-	Vitrinite
L	-	Liptinite
I	-	Inertinite
VMM	-	Visible Mineral Matter
ad	-	Air dried
daf	-	Dry ash free
dmmf	-	Dry mineral matter free
IS	-	Indian Standard
ASTM	-	American Society for Testing and Materials
SPONCOM	-	Spontaneous Combustion
CPT	-	Crossing point temperature
FT	-	Flammability temperature
ΔE	-	Wet oxidation potential difference
Sza	-	Olpinski index
Szb	-	Olpinski index with correction for ash
DTA	-	Differential thermal analysis
IIA	-	Slope at stage IIA
IIB	-	Slope at stage IIB
II	-	Slope at stage II
TP	-	Transition Point
Tr	-	Transition or characteristic temperature
CIL	-	Coal India Limited

SECL	-	South Eastern Coalfields Limited
SCCL	-	Singareni Collieries Company Limited
MCL	-	Mahanadi Coalfields Limited
WCL	-	Western Coalfields Limited
NEC	-	North Eastern Coalfields
NCL	-	Northern Coalfields Limited
IISCO	-	Indian Iron and Steel Company Limited
BCCL	-	Bharat Coking Coal Limited
TISCO	-	Tata Iron and Steel Company Limited
ICC	-	Indian Chamber of Commerce
r	-	Correlation coefficient
μ	-	Mean
σ	-	Variance
SE	-	Standard Error
MISO	-	Multi Input Single Output
ANN	-	Artificial Neural Network
MLP	-	Multi Layer Perceptron
BP	-	Back Propagation
FLANN	-	Functional Link Artificial Neural Network
RBF	-	Radial Basis Function
MSE	-	Mean Square Error
MAE	-	Mean Absolute Error
MRE	-	Magnitude of Relative Error
MMRE	-	Mean Magnitude of Relative Error
RMSE	-	Root Mean Square Error
SEM	-	Standard Error of the Mean

CHAPTER – 1

INTRODUCTION

1.1 Background and Statement of the Problem

Coal is the most wide-spread fossil fuel around the world and more than 75 countries have coal deposits [10]. Due to the limited reserve potentiality of petroleum and natural gas, eco-conservation restriction on hydel projects and geopolitical perception of nuclear power, coal will continue to occupy the center stage of India's energy scenario. The current share of coal in global power generation is over 40% [10]. Hence, in recent years, much attention has been focused on coal production as a source of energy especially in India to meet the power demand [157]. Coal is the predominant energy source in India and meets 56% of the country's primary commercial energy supply [134, 139]. Commercial primary energy consumption in India till date has grown by about 700% since 1970 [7]. India is the third largest coal producing country in the world after China and USA [2].

Coal fires are difficult, persistent in various regions and countries such as China, India, the United States of America, Russia, Australia and Indonesia, with serious environmental, safety and economic consequences [146]. It is well known that 75% of the coal fires occur due to spontaneous combustion (sponcom) of coal [80]. They may be exogenous or endogenous in origin. The auto-oxidation (endogenous fire) of coal at ambient temperature leading to heating and fires has always been long standing problem in coal mines.

Indian coal 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 [6]. Spontaneous combustion of coal generally causes mine fires in Indian coalfields despite various preventive measures have been extensively practiced. Fires, whether surface or underground, pose serious and environmental problems are causing huge loss of coal due to burning and loss of lives, sterilization of coal reserves and environmental pollution [151] and hence attention must paid to take appropriate measures to prevent occurrence and spread of fire. There are large numbers of active fires present in a number of coal mines in India, out of which majority of fires are located in the Jharia coalfield [138]. The first mine fire was reported in Jharia coalfield in 1916. Over the years, the number of such fires has increased to an alarming 70 locations covering a cumulative area of over

17 km^2 [6, 139]. In this coalfield, the fire has engulfed more than 50 million tons (MT) of prime coking coal, and over 200 MT of coal are locked up due to fires [6]. Since the fire in one seam also causes problems to the adjacent seams, it becomes impossible to extract them without extinguishing the existing fires. The seriousness of the problem has been realized by the Ministry of Coal, the Ministry of Labour, various statutory agencies and mining companies The recommendations made in the 10th Conference on Safety in Mines held at New Delhi in 2007 as well as in the Indian Chamber of Commerce (ICC)-2006, New Delhi, it was proposed that all the coal mining companies should rank their coal mines on a uniform scale according to their fire risk on scientific basis [9].

All types of coals do not have the same propensity for spontaneous combustion. Different coals respond differently to self-heating when exposed to similar atmospheric conditions. Therefore, it becomes imperative to categorize coals based on their susceptibility to spontaneous heating for deciding the safety measures. In the past, this differential behaviour of coal has been attributed to the intrinsic as well as the extrinsic properties of coal. A number of approaches have been proposed by different researchers/academicians/scientists for categorizing coals based on their intrinsic properties such as parameters of proximate, ultimate and petrographic analysis of coal as well as the susceptibility indices viz. Crossing point temperature (CPT), Olpinski index (Sza), Wet oxidation potential analysis, Russian U-index method etc. to assess the proneness of coal to spontaneous heating [109]. The propensity to self-heating of coal is decided by the incubation period of the coal seam, which decide the size of the panel to be formed, and it is the most important safety measure in mine planning. It is therefore imperative that mine managers/administrators/planners should determine in advance the spontaneous heating susceptibility of the seam/seams to be mined so that either the coal has been extracted before the incubation period or advance precautionary measures are planned to tackle this menace.

The coal production in India has risen from 643.75 MT per annum in 2014-15 to an expected level of 1086 MT per annum by 2024-25 whereas, the demand for coal has also escalated from 787.03 MT in 2014-15 to 1267 MT by the end of 2024-25 [4, 5]. Presently in India, the coal production scenario is critical. In view of this, the Government of India allotted few mining blocks to private sectors to reduce the gap between demand and supply of coal production. Coal mine fires are considered as one of the hurdles in enhancing the coal production to a certain extent. Hence, preventive measures should be taken ahead of time to arrest/block the occurrence and spread of fire.

Unfortunately, in India no remarkable research work have been made in the application of soft computing techniques for predicting spontaneous heating proneness of Indian coals. Most of the research work carried out in India focused on the evaluation of spontaneous combustion of coal based on limited conventional experimental techniques carried out by academic and research organizations. The investigators have proposed/established statistical models to establish correlation between various coal parameters, but limited work was made on the development of soft computing techniques to predict the propensity of coal to self-heating that is yet to get due attention. In addition, the classifications that have been made earlier are based on limited works which were empirical in nature, without adequate and sound mathematical base.

Keeping this in view, an attempt was made to study the susceptibility of Indian coal seams to spontaneous heating and develop mathematical models using artificial neural network techniques. It will help the mine planners/engineers to know the fire risk of Indian coal mine in advance so that precautionary, as well as preventive measures should be taken to arrest the occurrence and spread of fire. The experimental methods used to assess the tendencies of coals to spontaneous heating in the present study were: proximate analysis, ultimate analysis, petrographic analysis, crossing point temperature, Olpinski index, flammability temperature, wet oxidation potential analysis and differential thermal analysis (DTA). The statistical regression analysis was carried out between the parameters of intrinsic properties and the susceptibility indices and the best-correlated parameters were used as inputs to soft computing models. In this dissertation, different ANN models were applied for the assessment of fire risk potential of Indian coals.

1.2 Objectives and Scope of the Work

The main objectives of the research work can be stated as follows:

- To determine the different intrinsic properties such as Proximate analysis, Ultimate analysis and Petrographic analysis of some Indian coals,
- To study the behavior of coal samples with respect to their susceptibility to spontaneous combustion by using different experimental techniques viz. Crossing point temperature, Flammability temperature, Wet oxidation potential analysis, Olpinski index and Differential thermal analysis,
- To carry out statistical analysis of different intrinsic properties with various susceptibility indices of coal, and

- To develop soft computing based models using ANN viz.: MLP, FLANN and RBF to assess the spontaneous heating susceptibility of coal.

To meet the above objectives, a number of tasks were performed and were enumerated below:

(i) **Literature review**: The relevant works carried out by academicians, scientists, researchers and field engineers globally on mine fires, spontaneous heating of coal, experimental investigations on self-heating of coal, statistical analysis, mathematical models and soft computing techniques were studied to decide the plan of action, specific tasks and targets to be performed.

(ii) **Sample collection and preparation**: Forty-nine coal samples were collected from various coalfields of India such as SECL, SCCL, WCL, NCL, NEC, MCL, IISCO, TISCO and BCCL, and samples were prepared in the laboratory to different sizes as per the standard experimental requirements.

(iii) **Experimentation**: Prepared coal samples were tested in the laboratory as per the Indian Standards to find out the intrinsic properties and susceptibility indices with respect to spontaneous heating risk.

(iv) **Analysis**: Experimental data were statistically analyzed and the best-correlated parameters were chosen as inputs to the soft computing models viz. Artificial neural network (ANN) techniques to know the susceptibility of coal to spontaneous heating. Further**,** the best reliable susceptibility indices along with the most appropriate ANN model was selected and recommended for the assessment of fire risk in Indian coal mines.

1.3 Organization of the Thesis

The thesis comprises of six chapters and the structure of organization of the thesis is depicted in Figure 1.1. A chapter-wise summary of the thesis is given below:

Chapter-1 (Introduction):

This chapter includes the background and statement of the problem, the objectives and scope of the present research work and organization of thesis and the details of the chapters presented in the thesis succinctly.

Chapter-2 (Literature Review):

This chapter presents detailed review of literature focusing on the National and International status on research work being carried out on the spontaneous heating of coal and mine fires, mathematical modeling and soft computing techniques for the assessment of sponcom risk in coal mines.

Chapter-3 (Experimental Methodology):

This chapter describes the various experimental methods carried out on forty-nine Indian coal samples covering the majority of the Indian coalfields. Collection and preparation of coal samples were done with channel sampling method [55]. The procedures of experimental investigations were discussed in detail in two stages:

a) Intrinsic properties such as proximate analysis, ultimate analysis and petrographic study of coal.
b) Susceptibility indices viz. CPT, FT, ΔE, Sza and DTA.

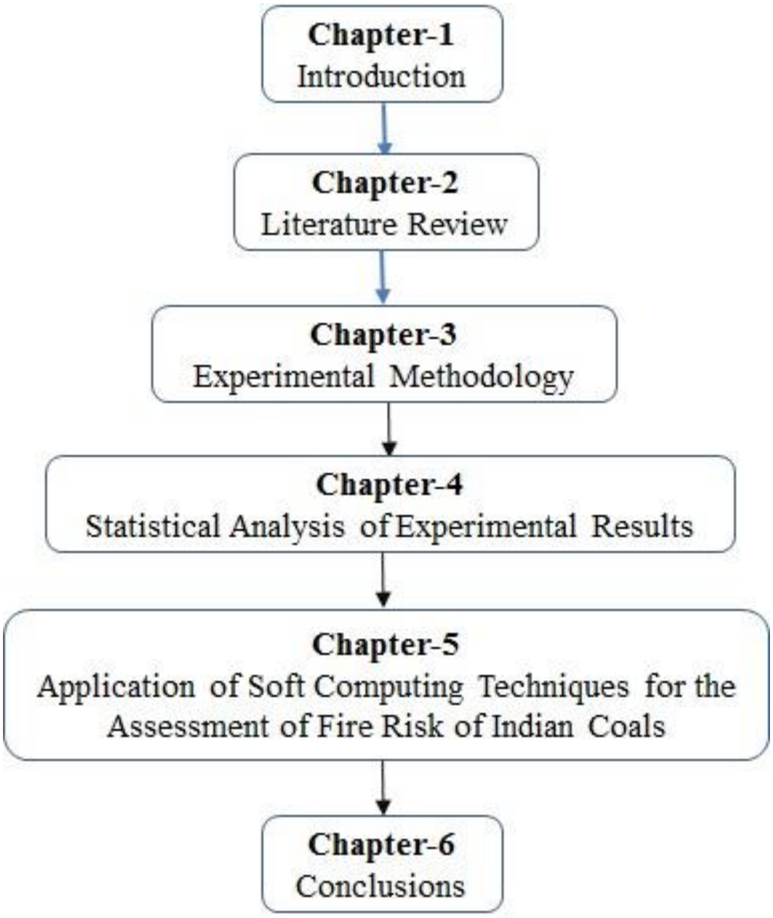


Figure 1.1 Structure of the thesis

Chapter-4 (Statistical Analysis of Experimental Results):

This chapter deals with the results and discussion of the experiments viz. proximate analysis, ultimate analysis, petrographic analysis, CPT, FT, Sza, ΔE and DTA carried out on forty-nine Indian coals. Further, the statistical (univariate and multivariate) analysis was conducted between the parameters of intrinsic properties and susceptibility indices to find out the significantly correlated parameters and used as inputs to the soft computing models.

Chapter-5 (Application of Soft Computing Techniques for the Assessment of Fire Risk of Indian Coals):

In this chapter, different soft computing techniques were discussed. Soft computing techniques viz. ANN models such as MLP, FLANN and RBF network were used for the assessment of fire risk of Indian coals. Implementation of these ANN models was carried out to select the best suitable model to predict the fire risk of Indian coals. MATLAB R2014b was used for the development of neural based models. Five-fold cross-validation [71, 76] was used for designing and comparing the models.

Chapter-6 (Conclusions):

This chapter provides conclusions or findings drawn from the experimental, statistical and ANN models investigations of Indian coals.

The graphical presentation of CPT, ΔE, Sza and DTA curves are incorporated in Appendices 1to 4 respectively.

CHAPTER – 2

LITERATURE REVIEW

This chapter presents detailed review of literature focusing on the global status on research work being carried out by academic, research organizations etc. on spontaneous heating and coal mine fires, mathematical modeling and soft computing techniques for the assessment of sponcom risk in coal mines.

2.1 Spontaneous Combustion

Spontaneous heating means "self-heating of coal resulting eventually in its ignition without the application of external heat". The main cause of spontaneous heating is the auto-oxidation of coal which is accompanied by the absorption of oxygen, the formation of coal complexes. This results in liberation of heat and finally coal catches fire [3, 151].

2.2 Concept of Spontaneous Heating

The interaction of coal-oxygen at ambient temperature liberates heat and the accumulation of such heat would enhance the rate of oxidation and coal catches fire. It is mostly possible, where a large mass of coal is involved, and the ventilation is neither too little to restrict coal-oxygen interaction nor too high to dissipate the generated heat. Under these conditions, ignition of coal mass takes place after the lapse of certain time (known as incubation period). The spontaneous heating is affected by various seam (rank, petrographic composition, particle size, moisture, sulphur etc.), geological (seam thickness, gradient, fault, friability of coal, geothermal gradient, depth, etc.) and mining (mining methods, rate of advance, pillar size, roof condition, ventilation pressure, multi-seam working etc.) factors. The stoichiometric oxidation of coal [151] can be given as:

$$CH_{1.18}N_{0.15}O_{0.35}S_{0.005} + 1.12\ O_2 + 4.15\ N_2 \rightarrow CO_2 + 0.58\ H_2O + 0.005\ SO_2 + 4.15\ N_2 + 138.4\ \text{kcal} \quad (2.1)$$

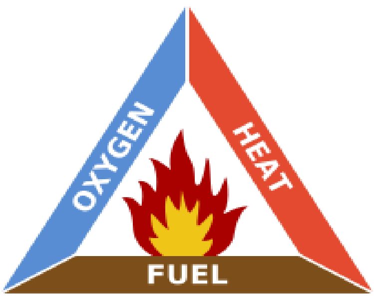


Figure 2.1 Fire triangle [1]

The fire triangle (Figure 2.1) illustrates the three elements: heat, fuel and an oxidizing agent (usually oxygen). A fire naturally occurs when the elements are combined in the right proportion and it can be prevented or extinguished by removing any one of them [1].

The process leading to spontaneous combustion of coal can be summarized as follows:

- The oxidation occurs when oxygen interacts with the coal;
- The oxidation process liberates heat;
- Dissipation of heat will not enhance the temperature of the coal;
- If the dissipation of heat is not dissipated then the temperature of the coal will increase;
- Higher rate of oxidation proceeds at high temperature; and
- Finally, a temperature is reached at which ignition of coal occurs.

2.3 Mechanism of Spontaneous Heating

Absorption of oxygen by coal takes place at all temperatures. The oxidation of coal is heterogeneous in character in which the diffusion of oxygen in the fine pores of the coal and the chemical reactions occurring at the same time influence the rate of reaction. Sevenster (1961**)** found that at low temperature (-80 ^{0}C), the physical adsorption of oxygen in coal was dominant but played a minor role from above 0 ^{0}C [130]. Chemical reactions set in at a temperature of -10 ^{0}C and chemical reactions leading to the evolution of CO, CO_2, H_2O start between 42-55 ^{0}C [130]. This shows that chemisorption process takes place in the very early stages of the sorption process. The oxidation rate decreases from first to hundredth hours at a constant temperature by 1/10th its value and increases ten-fold from a temperature of 30-100 ^{0}C. The oxidation of coal is slow up to a temperature of about 40 ^{0}C and thereafter the rate increases 1.8 times for every 10 ^{0}C rise in temperature. The critical temperature above which the process of oxidation becomes self-sufficient is about 50 ^{0}C for lignite and about 70-80 ^{0}C for bituminous coal [151]. The self-heating temperature of lignite and sub-bituminous coal were found to be as low as 30 ^{0}C and those of bituminous coals were about 60 ^{0}C for U.S. coals and for Indian coals, the value is around 70 ^{0}C [30].

The three stages [154] in the spontaneous combustion of coal (Figure 2.2) are illustrated below sequentially:

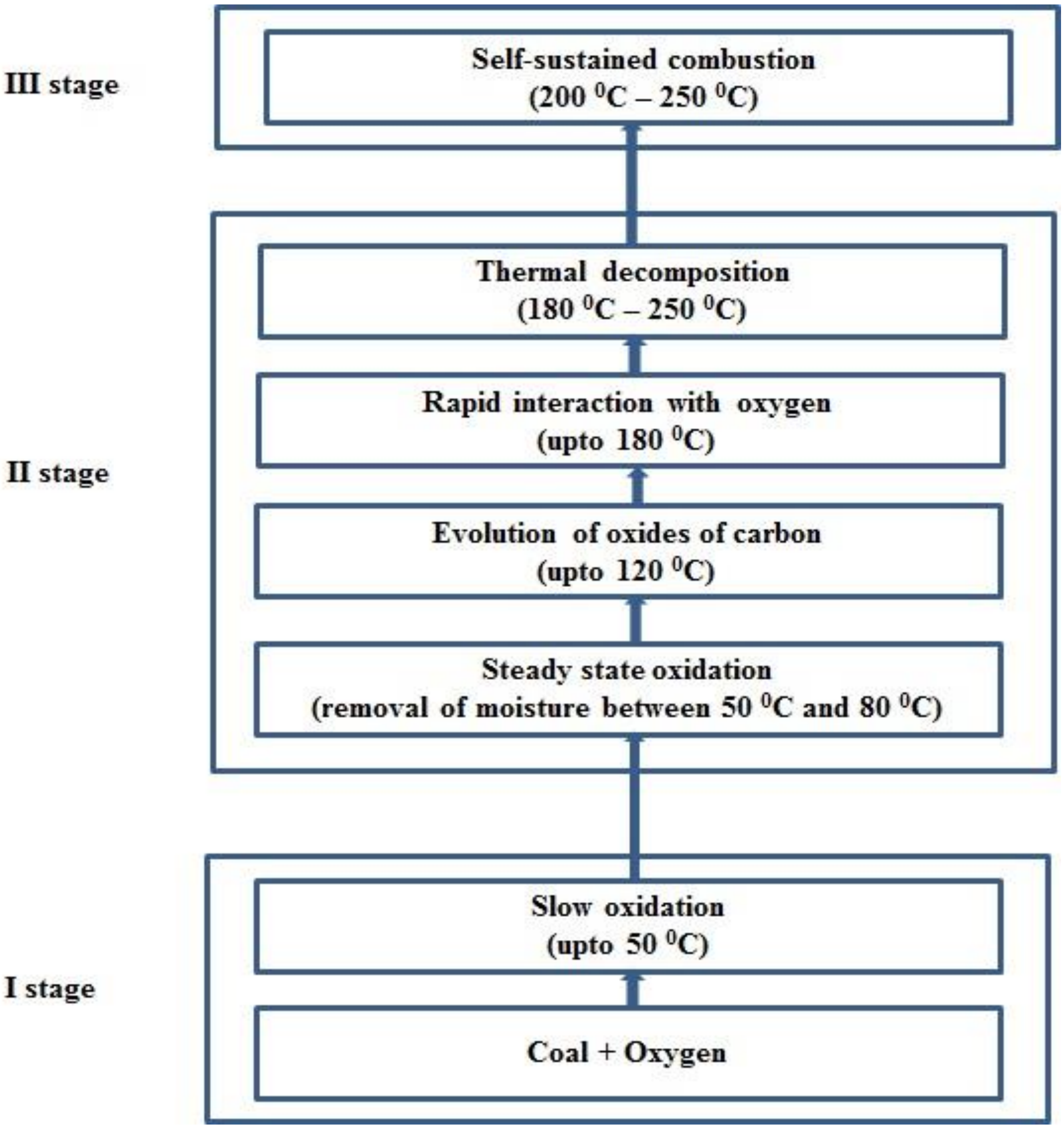


Figure 2.2 Stages in the spontaneous combustion of coal

2.4 Theories of Spontaneous Combustion of Coal

Some of the important theories, which have been put forth to explain the mechanism of oxidation of coal on the basis of pyrite content and coal structure, etc., are discussed in Table 2.1.

Table 2.1. Theories of spontaneous combustion [64, 92,116,151]

Theory	Description
1. Pyrite theory	Plot (1970) suggested that pyrites exposed to moist air cause self-ignition in coal when associated with it. The fact that some coal was containing no pyrites was also susceptible to heating gave doubts to the general acceptability of this theory. Munzner (1972) clarified the effects of pyrites on spontaneous heating

	of coal. He found that in dry samples of coal and pyrites, the heat changes caused by oxidation is the same for both. But in wetted coal to take into account the natural moisture content of the underground coal, the reactivity of coal is doubled, but that of finely dispersed pyrite (0.06 mm) is raised ten times. This means that seams containing finely dispersed pyrites exceeding 5-10% are more susceptible to spontaneous heating and below 5%, it is negligible. At this level of pyrite content, the consumption of oxygen by the oxidation of pyrite reaches a level ten times as that in coal without pyrite.
2. Bacterium theory	Some researchers thought that bacteria promoted self-ignition of coal. Further investigations showed that bacteria exert little influence on self-heating of coal.
3. Phenol theory	It had been demonstrated experimentally that phenolic hydroxyls and polyphenols oxidize faster than many other groups. It offers a method of determining the liability of coals to spontaneous heating.
4. Unsaturated linkage theory	The theory attempts to prove that the proportion of unsaturated compounds in coals determine the intensity of spontaneous combustion for these compounds combine vigorously with oxygen producing heat that ignites the combustion material. It is the most accepted theory but does not adequately explain the phenomenon of self-heating that depends not only on the internal characteristics of coal but also on the physical conditions.
5. Electro-chemical theory	Kamneva and Aleksandrov (1977) suggested this theory that explains auto-oxidation of coals as oxidation-reduction processes in micro-galvanic cells formed by the coal components.

2.5 Characteristics of Spontaneous Combustion of Coal

The characteristics of spontaneous oxidation of coal [2] that can be used to determine the potential for coal fires and framed as guidelines for reducing the probability of a fire are summarized below:

a. Higher inherent (equilibrium) moisture enhances the heating tendency of coal.

b. Lower the ash free Btu and higher the oxygen content increases the heating tendency of coal.

c. Sulphur is considered to be a minor factor in the spontaneous heating of coal. There are many low-sulfur western sub-bituminous and lignite coals that have very high oxidizing characteristics, and there are high sulfur coals that exhibit relatively low oxidizing characteristics.

d. The oxidation of coal is a solid/gas reaction, which happens initially when air (gas) passes over a coal surface (a solid). Oxygen from the air combines with the coal, raising the temperature of the coal. As the reaction proceeds, the moisture in the coal is liberated as a vapor and then some of the volatile matter that normally has a distinct odor is released. The amount of surface area of the coal that is exposed is a direct factor in its heating tendency. The finer the size of the coal, the more surface is exposed per unit of weight (specific area) and the greater the oxidizing potential, all other factors being equal.

e. Many times, segregation of the coal particle sizes is the major cause of heating. The coarser size allows the air to enter the pile at one location and react with fines of high surface area at other location. Coals with a large top size [e.g., 100 mm (≥ 4 in.)], will segregate more in handling than those of smaller size [50 mm (≥ 2 in.)].

f. It is believed that the rate of reaction doubles for every 8 to 11 ^{0}C (15 to 20 ^{0}F) increase in temperature.

g. Freshly mined coal has the greatest oxidizing characteristic, but a hot spot in a pile may not appear before one or two months. As the initial oxidization takes place, the temperature gradually increases and the rate of oxidization accelerates.

h. There is a critical amount of airflow through a portion of a coal pile that maximizes the oxidation or heating tendencies of coal. If there is no airflow through a pile, there is no oxygen from the air to stimulate oxidation. If there is a plentiful supply of air, any heat generated from oxidation will be carried off, and the pile temperature will reach equilibrium with the air temperature; then this is considered a ventilated pile.

i. When there is just sufficient airflow for the coal to absorb most of the oxygen from the air and an insufficient airflow to dissipate the heat generated, the reaction rate increases and the temperatures may eventually exceed desirable limits.

2.6 Factors Affecting Sponcom of Coal

Spontaneous heating is a physicochemical process, which depends on controllable (extrinsic) and uncontrollable (intrinsic) factors [17]. The influence of different factors on the spontaneous risk probability are outlined by Banerjee [17] and listed in Table 2.2.

2.6.1 Intrinsic factors:

These factors are beyond control, which are primarily the properties that are inherent to coal, and geology of the locality. The properties are:

2.6.1.1 *Coal related factors:*

i. Particle size

Finer the size means greater surface area and pores available for oxygen interaction or oxidation process.

ii. Rank of coal

Low-rank coal is low in carbon content and high in the volatile matter, which corresponds to higher oxygen absorption capacity of coal.

iii. Methane content

Coals containing less than 5 cubic meters of methane per ton show high rates of oxygen absorption and are more liable to spontaneous heating because of degasification with respect to time and availability of more surfaces to aerial oxidation.

iv. Ash content

Ash has an inhibiting effect on spontaneous heating of coal except the pyrites, which activates and accelerates the process of oxidation.

v. Moisture content

Moisture content at an optimum value of 20 percent (by USBM) has a maximum rate of oxidation.

vi. Others

High friability, weak caking property, heat capacity of coal, coefficient of absorption of oxygen, proportion of oxygen functional group namely the hydroxyl, carboxyl and carbonyl group and heat effect of oxidation of coal are indicators of higher susceptibility of coal to spontaneous heating.

2.6.1.2 *Geology related factors:*

It does not have a direct bearing on self-heating but only assist in the process.

i. Discontinuities

The fault, fold, dyke and disturbed strata contain bands of inferior coal and cavities for air to percolate through. These conditions are very suitable for the activation of the oxidation process.

ii. Petrology

Liability of self-heating decreases in order of vitrain, clarain, durain, and fusain.

iii. Seam thickness

Thick seam, multi seams in close proximity and seams proneness to rock bumps are the ideal conditions for self-heating.

2.6.2 Extrinsic factors:

These factors are controllable to a certain extent. The parameters are:

2.6.2.1 ***Mining factors***, which vary from mine to mine, are:

i. High loss of coal in worked out area,
ii. Excessive fissuration due to strata movement,
iii. Caving under shallow cover,
iv. Multi-section workings,
v. Partial extraction,
vi. Slow rate of face advance,
vii. Generation of fines in mechanized face operation and
viii. Fractured, crushed or inadequate size of barrier pillars.

2.6.2.2 ***Ventilation factors:*** They are high-pressure differential inside the mine and high water gauge of the surface fan, leakage through stoppings and barrier pillar etc.

Table 2.2. Factors affecting self-heating risk analysis of coals [17]

Sl. No.	Mining parameters /Condition	Set elements	Probability of Sp. heating risk
1	Category of coal (chemical nature)	a. Highly susceptible to self-heating	High
		b. Poorly susceptible to self-heating	Low
2	Friability of coal	a. Highly friable	High
		b. Poor friable	Low
3	Method of working	a. Bord and pillar	High
		b. Longwall type	Low
4	State of stowing	a. Extraction with caving	High
		b. With complete stowing	Low
5	Seam thickness	a. High (> 5m)	High
		b. Low (< 4m)	Low
6	State of extraction	a. Partial extraction	High
		b. Almost complete extraction	Low
7	Nature of extraction	a. Extraction (> one lift)	High
		b. In one lift/slice	Low
8	Geological disturbance	a. Present	High
		b. Absent	Low
9	Rock bumps	a. Present	High
		b. Absent	Low
10	Dykes	a. Present	High

		b. Absent	Low
11	Overburden	a. >300m	High
		b. <300m	Low
12	Parting	a. Shale/fractured structure	High
		b. Rocky and consolidated	Low
13	State of consolidation of barrier/gate road	a Fractured and crushed	High
		b. Well consolidated	Low
14	Scope of accumulation of fines, friability of coal etc.	a. Fine accumulation sustained	High
		b. Fines avoided	Low
15	Method of ventilation	a. Advanced type	High
		b. Retreating type	Low
16	Quantity of ventilation	a. Pressure difference high	High
		b. Pressure difference low	Low
17	Humidity	a. Wet mines	High
		b. Dry mines	Low
18	Sources of hot spots	a. Present	High
		b. Absent	Low
19	Gas emission rate	a. Low	High
		b. High	Low
20	Size of panel	a. Large	High
		b. Small	Low
21	Rate of face advance	a. Slow	High
		b. Fast	Low
22	Chances of blockage / stoppage of face advance.	a. Present	High
		b. Absent	Low

2.7 National and International Status of Research on Spontaneous Combustion of Coals

The global findings of the researchers, academicians, scientists and industries relevant to the current research work are summarized and presented below:

Nubling and Waner (1915) used crossing point temperature method by heating powdered coal sample in an oil bath at a constant heating rate and purging oxygen through the coal bed. The temperature at which the coal coincides with the bath is recorded as the crossing point temperature [102]. Subsequently different authors viz., **Tideswell and Wheeler (1920), Kreulen (1948) and Chauvin (1964)** made few modifications of crossing point temperature technique, allowing oxygen or air to pass through, used the liquid/air bath of different designs and reactor tubes containing coal mass and then determined the crossing point temperature of coal [149,73,34].

Olpinski et al. (1953) found that the exothermicity of the coal pellet at 235^{0}C gives the measure of spontaneous heating susceptibility of the coal and recorded time-temperature curve of the coal bed in the electronic recorder till the temperature crosses 235^{0}C. The rate of rise of temperature at 235^{0}C gives the value of Olpinski index [104].

Maciejasz (1956) utilized H_2O_2 in the exothermicity of coal oxidation in Poland for comparing the spontaneous combustion liability [81].

The oxidation rate **(Munzner and Peters, 1966)** decreases from first to hundredth hours at a constant temperature by $1/10^{th}$ its value and increases tenfold from a temperature of 30-100^0C. The oxidation of coal is slow up to a temperature of about 40^0C and thereafter the rate increases 1.8 times for every 10 ^{0}C rise in temperature [91]. The critical temperature (**Francis and Peters, 1980**) above which the process of oxidation becomes self-sufficient is about 50^0C for lignite and about 70-80^0C for bituminous coal [44].

Banerjee et al. (1972) used CPT, DTA, peroxy complex and rate studies of coal oxidation method to classify some Indian coals with respect to their susceptibility to spontaneous heating. The abovesaid test results were analysed with the parameters of proximate analysis. They recommended that CPT provided better results in low moisture coals. Oxygen avidity studies were better if DTA and CPT provide contradictory results. Therefore, they suggested using all the four methods for coals having moisture content 10% or more [16].

Nandy et al. (1972) investigated 50 Indian coals to classify them with respect to their liability to spontaneous combustion. They observed that CPT normally decreases with increase in the volatile matter, oxygen percentage and moisture content of coal. But beyond 35 % VM, 9% O_2 or 4-6% moisture content, there was not so much change in CPT results. In fact for coals with more than 4-6% moisture content, the CPT values rather show a rising trend. They recommended that 4-6% to be the optimum moisture having a higher susceptibility to spontaneous combustion [98].

Bhattacharyya (1972) investigated the influence of humidity on the initial stage of the spontaneous heating of coal and studied the effect of desorption of moisture from the coal. Experiments were carried out on different coals where desorption of water from the coals by air was certain to take place. The results inferred that desorption of moisture acts as an inhibitor to the spontaneous combustion of coal. For a particular coal, the heat loss increases with the rise in the humidity deficiency of the air. The effects of rank, particle size and weathering on spontaneous heating of coals were also discussed [24].

Marinov (1977) determined the changes in weight, elementary composition, oxygen functional groups and in spin concentration of different coal samples heated in humid air at the rate of 1^0C/min to various temperatures. The mixtures of low-molecular-weight hydrocarbons had evolved before self-ignition were measured by gas chromatography, and the temperatures of self-ignition were determined in an oxygen medium using a Leitz microscope. The aromatic part of coal was acting as an oxidizing agent in the region where hydrogen was less affected by molecular oxygen [83].

Elder and Harris (1984) investigated six Kentucky bituminous coals undergoing pyrolysis at three different heating rates in an inert atmosphere. Differential scanning calorimetry was used to measure thermal degradation. Thermogravimetry was employed to measure the changes in weight and was used to normalize the heat flow data along with the thermal behaviour of the several coals. The specific heats of the dry coals lie in the range 1.21-l.47 J gK^{-1}, 100-300 ^{0}C. The exothermic heat flow from 300 to 550 ^{0}C, where the major weight loss occurs, has been associated with the primary carbonization process, the development of the plastic state and the onset of secondary gasification, which is responsible for coke formation. In coals of high pyritic sulphur, the endothermic pyrite/pyrrhotite transformation at ≈580^{0}C was clearly distinguished. Modified Kissinger equation was used for global kinetic analysis of the thermogravimetric data at the maximum rate of weight loss. Activation energy and pre-exponential factor values of the order of 198-220 kJ mol^{-1} and 2-85 x 10^{12} s^{-1} were obtained [43].

Mahadevan and Ramlu (1985) correlated the experimental results of different Indian coals through the liability and mine environment index (including geological and mining factors) in determining the liability of coals to spontaneous heating. An attempt was made to represent mine environment index and risk index based on Indian conditions. The risk classification seems to agree reasonably well with the field experience. This approach could, therefore, be adopted in evaluating the danger due to spontaneous heating [82].

Uribe and Perez (1985) inferred that the principal drawback of ‘International Classification of Hard Coals’ was not applicable to coals of variable macerals, especially those have high inertinite content. Additionally, the parameters viz., volatile matter and calorific value used in the International Classification and other national systems for the degree of coalification were dependent on variable maceral composition. The proposed classification scheme was based on two parameters determined with microscopic techniques: (i) mean maximum reflectance of vitrinite; and (ii) petrographic composition (vitrinite and exinite). A third parameter was chosen to qualify the different classes of coal: the volatile matter for anthracitic coals; dilatation for semi-anthracitic and bituminous coals; and calorific value for sub-bituminous coals and lignites. The scheme was expressed by mean of a code number of four digits, which referred to the rank (first digit), type (second and third digits) and qualification (fourth digit) of coal [153].

Singh and Demirbilek (1986) suggested the use of potassium permanganate solution and designated permanganate values as a measure of the degree of oxidation of coals. Wet oxidation potential analysis is an indirect method of measuring the oxidation tendency of coals, by the interaction of coal with oxidants like H_2O_2, $KMnO_4$, Br_2 etc. [136].

Sinha (1986) reported a loss of scarce prime coking coal resources due to the fires in the Jharia coalfield. Fires in coal mine endanger safety, stability and cause environmental pollution. Prior to nationalization, fire control measures were constrained due to the lack of resources. In the post-nationalization period, preventive measures have been taken to control and liquidate coal-mine fires. Hence, there was a need to frame the government policy on speedy implementation of fire control projects [140].

Ghosh (1986) made an attempt to evolve a technique to identify coal's proneness to spontaneous heating. Few suggestions have also been made to control such fires. If pyrite is present in finely divided form, the liability of coals towards spontaneous combustion increases; and the temperature of a coal bed increases if water was added to it, which tends to indicate that water spraying cannot be considered as an effective measure to control spontaneous combustion. Moreover, it was also suggested that if a coal body was chilled (to -193°C) because of the contraction of micro pores and micro cracks in the coal. Atmospheric O_2 was less likely to enter the coal through micro pores and micro cracks, and hence chances of spontaneous combustion due to auto-oxidation were diminished [46].

Brooks and Glasser (1986) developed a model of three differential equations expressing the temperature, oxygen concentration and pressure variations in a coal bed. In this model, the mechanism for oxygen transports was taken into account. This model was solved for the steady-state; these solutions provided valuable insight into the nature of self-heating. The influence of coal particle size, void age, coal reactivity and bed length were discussed and it was concluded that the particle size and void age played a vital role in determining the safety of a coal dump [28].

Stott et al. (1987) measured the tendency of as-mined sub bituminous coal towards spontaneous heating in a 2 m length apparatus, with a moisture content of 18 % (by wt.), without any external source of heat. A successful preliminary result has been achieved with this apparatus. The experiment closely duplicated the full process of one-dimensional spontaneous heating of coal containing its as-mined moisture content [145].

Smith and Lazzara (1987) showed that the liability of bituminous coals to spontaneous heating was directly related to the dry ash free oxygen percentage. In fact, they could derive an empirical relationship between oxygen percentage (d.a.f.) and the propensity of spontaneous heating of coal as determined using an adiabatic oven [142].

Singh and Demirbilek (1987) carried out the statistical analysis for the assessment of coal to spontaneous combustion. An adiabatic oxidation test was conducted on 47 different coals, along with the intrinsic properties. The measure of liability of coal to spontaneous heating was based on the initial rate of heating and total temperature rise in an adiabatic oxidation experiment. A multiple regression statistical analysis between initial rate of heating and total temperature rise and thirteen independent variables generated a set of empirical equations to predict the proneness of coal to spontaneous heating. The equations derived by subdividing the data set according to rank classification can permit accurate prediction of temperature rise, thus evaluating the liability of coal to self-heating. The contribution made by various intrinsic factors to the self-heating potential of coal was estimated by using isolated factor analysis techniques [137].

Wang et al. (1988) used mathematical modeling to investigate the effect of pressure on low-temperature oxidation of coal and it indicated that high partial pressure of oxygen significantly accelerated the physical and chemical interaction between coal and oxygen. Based on these findings, developed a new test method for ranking the susceptibility of coal to spontaneous heating, using a high-pressure technique to shorten the testing period. They observed that, when the facility was operated at 5MPa oxygen pressure, the time needed to carry out an experiment will be shortened by 75% in comparison to atmospheric pressure [155].

Chandra and Chakrabarti (1989) studied the coalification trends covering a wide range of geological age of Indian coals (Permian, Eocene to Pleistocene). The relation between the maximum huminite/vitrinite reflectance in oil and the volatile matter was found to be similar to that of the British carboniferous coals. The similarity was also been found in measuring elemental carbon and hydrogen following Seyler's band and was similar to the British Carboniferous coals. The petrographic composition of coal has been controlled by the nature of the peat, paleodepth, paleotemperature and paleo heating in the coal basins [32].

Karmakar and Banerjee (1989) determined the susceptibility of coal to spontaneous combustion using three methods namely: CPT, Olpinski index (Sz), and U-index. Experimental data obtained by these methods for sixteen coal samples were presented. This study revealed that a linear relationship exists between CPT, Sz and Russian U indices. Coals with low moisture and high VM content exhibit high susceptibility to spontaneous combustion. S_Z index being a convenient and faster method and can be used as an alternative to commonly adopted CPT method in India [65].

Tarafdar and Guha (1989) reported the results of wet oxidation of coal by alkaline permanganate solution involving measurements of differential temperature at different base temperatures, and potential changes between a saturated calomel electrode and a carbon electrode immersed in the coal oxidant mixture at a constant temperature within a definite reaction time. These measurements were made on seven coal samples of known crossing point temperatures (CPT) out of which four samples, were considered to be highly susceptible to spontaneous heating and three were found to be poorly susceptible to spontaneous heating. They suggested that differential temperature and potential difference measurements during wet oxidation of coal might be used as alternative technique for the assessment of liability of coal to spontaneous heating [148].

Navale and Saxena (1989) reported that coals of the Karharbari formation were characterized by high inertinite content although several local seams were richer in vitrinite content. In contrast, Barakar and Raniganj coal seams were characterized by high vitrinite content, although some coal seams were richer in inertinite content. The four main petrographic coal facies found in Permian strata were: (i) fusic, rich in inertinite group macerals over vitrinite; (ii) trimaceric, rich in vitrinite group macerals over inertinite macerals ('vitro-fusic'); (iii) trimaceric, rich in inertinite-group macerals over vitrinite and liptinite ('fuso-vitric'); and (iv) vitric, rich in vitrinite-group macerals. The succession of these four facies with time was governed mainly by changes in climate and peat-forming floras and paleoenvironmental conditions [100].

Miron et al. (1990) using adiabatic oven, experimented with 100 g of coal samples of size fractions -74+150 µm and determined self-heating temperature (SHT min ^{0}C) from a series of tests in 5 ^{0}C increments. He derived an empirical relationship to predict SHT min ^{0}C, from pressure drop measurements. In USA, Australia, New Zealand and other countries, investigators used adiabatic calorimeter for categorization of coal [85].

Clemens et al. (1990) used DTA at varying temperatures to analyze the reactions between dried low-rank coals and oxygen that provided an immediate and sharp exothermic response. The exotherm increased with increasing temperature and was mostly found in highly susceptible coals to spontaneous combustion. A second exotherm was seen below 120 °C temperature after 15-20 min [38].

Clemens et al. (1991) studied the chemical and thermal responses of six dried coals purging oxygen or air using isothermal differential thermal analysis (DTA) and diffuse reflectance infrared Fourier transform spectroscopy (DRIFTS). Reaction temperatures from 30 to 180°C were used for samples varying from lignites to bituminous coals. The exothermicity of coal may be used as an indicator to spontaneous combustion. The first product signal detected by DRIFTS was assignable to the carbonyl stretch frequency of carboxylic acid/aldehyde functionality. At higher temperatures the rate of increase of this signal detected by DRIFTS correlated closely with the thermal response profiles and suggesting that, regardless of coal rank, the reactions responsible for coal heating across the 30-180°C range involve the formation and breakdown of the peroxy-precursors of these carbonyl-containing products. Oxidations were also carried out under a static blanket of O_2/Argon at each temperature and the gas mixture was analysed after five hours. At the lower temperatures, no changes were seen. At 90°C, oxides of carbon were first detected and their yields increased with temperature [39].

Chandra et al. (1991) carried out CPT and Olpinski index method to ascertain the sponcom of IB valley coals of Orissa, India. Results of the experimental investigation showed that the IB valley coals were moderate to highly susceptible to sponcom. They reported that there was a linear relationship between Olpinski index and CPT and further suggested that Olpinski index provides quicker results as compared to CPT [31].

Sen (1992) used petrography for evaluating and assessing the properties of Indian coals which are conspicuously heterogeneous in nature. The importance of an International Petrographic classification was focused on a comparative study of classification and codification of coal using petrographic parameters. An attempt was made to categorize the Indian coals using vitrinite and exinite contents and vitrinite reflectance as parameters [129].

Beamish (1994) developed a technique at the University of Auckland for proximate analysis of coals by thermogravimetry using sample weights of less than 20 mg. Samples were collected from three New Zealand coalfields and the Bowen Basin of Queensland, Australia and were analysed in the laboratory. Coals tested were sub bituminous to semi anthracite type, and ash contents varied from 3.1 to 21.4% on dry basis. Results obtained were within the acceptable limits following the standard procedure. Volatile matter of the coal showed a logarithmic increase with the decrease in sample weight. Sample weights of 15.5 ± 0.5 mg should be used to minimise the effect on repeatability and optimization of the equipment. The technique was ideally suited for (i) analysing samples where the insufficient material was available for standard proximate analysis and (ii) correlation with micro studies of coal [20].

Carras and Young (1994) reviewed the status of some numerical models developed to predict the spontaneous heating and also understand the phenomenon of self-heating of coal and coal mine waste dumps. The commonly used industrial tests to predict the self-heating propensity of coal were assessed and their limitations were identified. They required further necessary work to be carried out to ascertain the role of water on the oxidation rate of coal and other carbonaceous materials, as well as validation of numerical models on commercial size coal stockpiles [29].

Huai et al. (1994) inferred that the maturity of coal can be related to the geothermal gradient that the coal have been subjected to and was accompanied by the increase in aromaticity and also by an increase in protonation of the aromatic structures [53].

Gouws and Knoetzef (1995) discussed elements of two South African research programmes. One programme investigated the explosibility of coal dust while the second studied the relative tendency of coal to spontaneous heating. Both applications examined the use of indices, based on routine coal analyses, to predict the results of laboratory experiments. They compared the prediction of self-heating liability indices and discussed the results obtained by testing samples from collieries where incidents of spontaneous combustion or coal-dust explosions occurred [47].

Mishra and Ghosh (1996) reported that the Tertiary sediments of the North-Eastern region of India range in age from Palaeocene to Oligocene. The coal deposits of Meghalaya and the Mikir and North Cachar Hills of Assam contain thin seams of Eocene age. The coal deposits of Oligocene age occurred in a narrow, linear belt of overthrusts referred to as the 'belt of Schuppen', that extends from Nagaland through Assam to Arunachal Pradesh; they were deposited in near-shore, deltaic, wet forest swamps to marshy environments, close to a geosynclinal trough. The coal seams attained considerable thickness in the Makum and Namchik-Namphuk coalfields. The coals were vitrinite-rich (> 70 vol%, mineral-matter-free, mmf), with moderate amounts of liptinite (> 8 vol%, mmf) and inertinite (> 5 vol%, mmf). The coals were high in the volatile matter (38-57 %, dry, mineral-matter-free basis, dmmf), sulphur (1-10 %) and hydrogen contents (4-9% dmmf). The carbon content of the coals ranged from 68% to 85% (dmmf). The coals had caking properties in restricted zones. The vitrinite reflectance of the Oligocene coals (%Rmax = 0.53-0.74) was slightly higher than that of the Eocene coals (%Rmax = 0.37-0.67). As per ASTM Standard, the Eocene coals can be classified as sub-bituminous C to high volatile bituminous C and the Oligocene coals as sub-bituminous A to high volatile bituminous B. Most of the Eocene and Oligocene coals were suitable for combustion and conversion (e.g., liquefaction) processes. The coals with caking properties were used up to 5-10% in blends for metallurgical coke provided their sulphur and ash contents were < 3% and <10% respectively [86].

Krishnaswamy et al. (1996) developed a two-dimensional model for spontaneous combustion of coal stockpiles neglecting the influence of moisture. Wind-driven forced convection was found to be the dominant mechanism for the flow of air within the open stockpile. The effects of bed porosity, side slope, wind velocity, coal reactivity and bed particle size were examined. A correlation was also developed for safe long-term storage of coal stockpiles [74].

Pis et al. (1996) studied the self-heating behaviour of fresh and oxidized coals using differential thermal analysis (DTA). Six coal samples of various ranks were used, and oxidation was performed in air at 200 ^{0}C for periods of up to 72 hours. As the rank of the coal increases, the self-heating, the end of combustion temperatures and the total heat loss (area under the DTA curve) also increase. An increase in the self-heating temperature, a decrease in the temperature of the end of combustion and a reduction in total heat flow were observed. A relationship between the calorific value and the total heat loss was determined using the ASTM standard method [115].

Ren and Edwards (1997) studied the problem of spontaneous combustion of coal at the Department of Mineral Resources Engineering of Nottingham University. Standardized adiabatic oxidation tests have been traditionally used to identify coals prone to spontaneous combustion. Intrinsic coal properties, geological settings and mining techniques were used to evaluate the potential of self-heating of coal with the computerized apparatus coupled with an expert system. This approach was explored for airflow behaviour and nitrogen inertization processes simulation within the goaf. Such a model would be used in locating the areas most susceptible to spontaneous combustion and improving the utilization of nitrogen [123].

Nugroho et al. (1998) investigated low-rank Indonesian coal, with low in sulfur and ash content and high moisture content (5–18%). Consequently, it had a higher tendency to self-heating and assess the hazard for three typical coals that were used for both domestic and export purposes. Crossing point temperature method was used to determine the activation energy and reactivity of the low-temperature slow oxidation reaction. This used the transient temperature profiles to reduce the activation energy and reactivity of the sample. It was found that crossing point temperature method was valid as long as the coal experiment was not highly supercritical. The Frank-Kamanetskii comparable approach of determining the critical temperature for different sample sizes showed good agreement for estimating activation energy [103].

Xiulin et al. (1999) reviewed the spontaneous combustion of coal in China and other countries to study the prediction and forecasting techniques of self-heating of coal. The safety of Miners played a significant role while extracting coal from mines. They pointed out the progress in the prediction and forecasting techniques of coal self-heating and also analyzed its merits and demerits [160].

Jones (2000) reported that the oven-heating test for the propensity of coals and carbon to spontaneous heating showed fundamentally flawed. Hence, he proposed a new soundly based test with the same experimental set-up that provided more reliable predictions [63].

Rosema et al. (2001) developed a numerical model "COALTEMP" to study the oxidation and possible spontaneous combustion of coal exposed to the atmosphere and the daily cycle of solar irradiation. The differential equations describing heat flow, oxygen flow and oxidation in the coal matrix and also presented the exchange of heat, radiation and oxygen with the atmosphere. The model was then used to study the spontaneous combustion of Rujigou Coal Basin in particular. The role of spontaneous combustion and mining activities in the development of coal fires was analysed and conclusions were drawn with respect to coal fire prevention [125].

Blazak et al. (2001) assessed core samples from two pits at Callide using the R_{70} (self-heating rate index) test. The highest R_{70} value recorded to date is 16.22°C/h in Pit 1, which was consistent with the sub bituminous rank of the coal. Pit 2 had a lower maximum R_{70} value of 11.79°C/h for similar ash content. It was due to an increase in the rank of coal in Pit 2. There was a strong negative correlation between ash content and self-heating rate in Pit 1 that was related to the presence of kaolinite in the coal acting as a heat sink. This relationship could be used to model the self-heating hazard of the pit. In Pit 2, quartz and siderite were present in the coal but were less effective heat sinks for lowering the self-heating rate of the coal [25].

Kaymakci and Didari (2002) evaluated the results of linear and multiple regression analyses to detect the relation between spontaneous combustion parameters (derived from time-temperature curves obtained from laboratory tests) and coal parameters (obtained from proximate, ultimate and petrographic analyses). The linear regression analyses had shown that ash (A), volatile matter (VM), carbon (C), hydrogen (H), exinite (E), inertinite (I) and mineral matter (MM) were the major factors affecting spontaneous combustion. According to the multiple regression analyses, the major factors were volatile matter, carbon, hydrogen, nitrogen (N), oxygen (O), sulfur (S) and inertinite. Based on the results, some empirical equations were derived using statistical models [67].

Kucuk et al. (2003) evaluated the spontaneous combustion characteristics of Askale lignite of Turkey. Crossing point temperature was adopted to examine the effect of gas flow rate, the moisture of coal piles, the humidity of the air and particle size on the spontaneous combustion characteristics of coal samples in laboratory condition. The amounts of three predominant oxygen functional groups (carboxyl, hydroxyl and carbonyl) in untreated and moist coal samples were also used to determine with wet chemical methods. The amounts of oxygen functional groups in moist coal samples did not differ significantly from that of untreated coal. The liability of lignite to spontaneous combustion increased with decreasing particle size, the humidity of the air and increasing the moisture content of the coal [75].

Pietrzak and Wachowska (2003) used five different rank coals with different content of sulphur subjected to oxidation by peroxyacetic acid (PAA), 5% nitric acid, with oxygen in 0.5N Na_2CO_3 aqueous solution and the aerial oxidation for 7 days at 125 ^{0}C. Radmacher method was used to demineralize the coal samples by oxidation process and additionally for the pyrite-free coal samples. Proximate, elemental and spectral analyses were carried out. Results showed that the most effective oxidising agents were 5% HNO_3 and PAA. Depending on the oxidising agent, the loss of sulphur in the solid oxidation products was different [114].

Krajciova et al. (2004) developed a mathematical model including a detailed radiation balance of the coal stockpile surface. The periodic boundary condition differs from that applied to the horizontal surface. The energy from the sun has a strong influence on the temperature profile in a coal stockpile. Four types of coal were studied with different reactivity. They observed the influence of several factors (coal reactivity, coal matrix porosity, meteorological conditions, coal reactivity (two-dimensional model), coal matrix porosity (two-dimensional model)) on the temperature profile in two types of coal stockpiles. A one-dimensional model was applied in a situation where coal was stored in underground. In this case, only the topside was exposed to the ambient conditions. A two-dimensional model was necessary when describing a commonly used heap-like stockpile. The changing boundary conditions must be applied on the top side as well as on both slopes. Finally, a long-term simulation for average weather at a particular place was studied [72].

Michalski (2004) investigated the coal mine fires located in the Jharia Coalfield in the state of Jharkhand, India thoroughly by team of consultants from the United States and Canada, representing the best expertise and available technology. The recommendations resulting from the investigation have mostly gone unheeded. Recognition of the magnitude of the problem with all its manifestations placed a daunting burden on both the Indian government and coal industry resulting in a policy to do little or nothing. Alternative mitigation efforts were also identified that could ameliorate the effects of the fires and benefit the region, its inhabitants, and the mining industry [84].

Demirbas and Demirbas (2004) reported mathematical models based on ultimate analysis with Dulong's equation to calculate the calorific value of coal. The higher heating value (HHV) at constant pressure measured the enthalpy change of combustion with water condensed. The HHVs (MJ/kg) of the lignocellulosic fuels as a function of carbon (C) or carbon + hydrogen (C + H) contents (wt. %) were calculated using the following equations:

$$HHV = 0.3699\ (C) + 1.3178 \qquad (2.2)$$

$$HHV = 0.3856\ (C + H) - 1.6938 \qquad (2.3)$$

For the equations (2.2 and 2.3), the correlation coefficients were 0.9734 and 0.9814 respectively. There was a significant correlation between the HHV of the lignocellulosic fuels and their carbon or (carbon + hydrogen) contents [42].

Singh and Shukla (2004) made an attempt to characterize the coals of Pench, Kanhan, and Tawa (Pathakhera) Valley coalfields of Satpura Gondwana basin. This westernmost Gondwana basin of Peninsular India was graben/half-graben type and was ranging in age from Permian to Cretaceous. The Barakar Formation (Permian) was exclusively coal-bearing with a total coal reserve of nearly 2000 million tons. The results showed that the coals of this basin were rich in inertinite (22.8-58.7%, 24.5-62.0% mmf basis) and vitrinite (24.4-52.4%, 24.4-56.0% mmf basis). The concentration of liptinite ranges from 8.8% to 23.2% (9.0-26.0%

mmf basis). The dominant micro lithotypes of these coals were inertite and vitrite with comparatively low concentrations of vitrinertite and clarite. The vitrinite reflectance (Rmax% values) suggested that the Pench Valley (0.30-0.58%) coals were sub bituminous C to high volatile C bituminous in rank, while the Kanhan and Tawa Valley coals (0.52-0.92%) were sub bituminous A to high volatile A bituminous in rank [135].

Stracher and Taylor (2004) discussed coal fires burning around the world were characterized by the emission of noxious gases, particulate matter, and condensation by-products. Underground mine fires and burning plants/trees ignited by natural causes or human error were responsible for atmospheric pollution, acid rain, perilous land subsidence, the destruction of floral and faunal habitats, human fatalities and increased coronary and respiratory diseases. Some of the oldest and largest coal fires in the world occurred in China, the United States of America and India. The techniques used to arrest coal fires include slurry and ash injection, surface and tunnel sealing, aqueous foam technology, remote sensing and computer software. Elusive, unpredictable, or cost prohibitive coal fires might burn indefinitely, choking the life out of a community and its environment [146].

Smith and Glasser (2005) investigated a range of coal properties such as the heat capacity, the heat of reaction with oxygen and the activation energy of varying rank and geological origin that were considered to be most critical in terms of heat generation in a bulk medium of coal [143].

Ren and Balusu (2005) presented computational fluid dynamics (CFD) modeling capability developed by CSIRO for improving the knowledge of flow migration dynamics in longwall goaf areas. CFD can be used to study the ingress of oxygen into the goaf in different ventilation scenarios and goaf drainage arrangements. It helped to design the strategies of effective gas control and spontaneous combustion risk management in the goaf. Innovative goaf inertisation strategies were developed and implemented during longwall sealing operations. They were also working on framing of general guidelines for proactive goaf inertisation strategies to prevent the development of spontaneous heating behind active longwall faces [122].

Liu et al. (2005) worked on the characterization of coal from the Jining coalfield. The 31 and 32 seams of the Permian Shanxi formation and seams 6, 10, 15, 16 and 17 of the Carboniferous Taiyuan formation were analyzed for coal petrography, mineralogy, and geochemical parameters. It was found that the analyzed coal had high vitrinite, low to medium inertinite and liptinite contents, lower ash yield, and higher sulfur content [79].

Ozdeniz and Sensogut (2006) did a computer controlled measurement of spontaneous combustion in coal stockpiles of the Western Lignite Corporation, Turkey. The objective of a computerized measurement system was to measure temperature changes existing in a coal stockpile. Twenty temperature sensors were placed at certain points inside the coal stockpile to sense the electrical signal conversion of temperatures and the transfer of these electrical signals into computer media by using analogue-digital conversion unit after applying filterization and upgrading processes and the record of this information into a database at particular time intervals were provided. Further, the graphs of these time-temperature data were plotted. These graphs were used to examine the behavior of coal stockpiles in terms of spontaneous combustion and take necessary precautions against self-combustion in advance [105].

Yildirim et al. (2006) stated that there were several developments in determining the spontaneous combustion susceptibility of coal. Most of the methods of concern were purely been based on the internal properties of the coal itself. The relation between the crossing-point method and the electrical resistance of coal was examined to outline the spontaneous combustion tendency of coal. The electrical resistance property could be used as a parameter to assess the spontaneous combustion tendency of coal [161].

Singh (2006) reported that coal, the most dominant fossil fuel in India is vital to its energy security. It is India's economical source of primary energy and meets around two-thirds of the country's energy needs. The power sector is the largest consumer, followed by the industrial sector such as steel, cement, and brick manufacturing units. While coal was poised for significant growth, it faces many social and environmental challenges. Environmental concerns will be the key to the coal industry’s future. Relative to other fossil fuels, coal is less energy efficient and pollutes more. The primary concerns at the regional levels have to do with the environmental impacts on air, water, land, forest, biodiversity, climate and the costs of mitigating these. Even with its major hurdles, coal will remain a future mainstay, a foundation and a fundament of our economy. Coal has a crucial role in meeting current needs and is a resource bridge to meet future goals with the application of new technology. He suggested that applying the right technology in the most efficient and environmentally friendly manner to control the spontaneous heating of coal to improve the production of coal mines [134].

Arisoy et al. (2006) developed a computer model to simulate a bulk-scale, one-dimensional test column. Model predictions were verified by using the experimental results from a 2 m test column at the University of Queensland. It was used to conduct a practical test capable of providing reliable data on coal self-heating. In particular, the hot spot development in test runs closely matched model predictions. Features of moisture transfer and hot spot migration were clearly visible, both in the model and in tests in the column. Under the specific conditions considered in this study, it showed that a sub bituminous coal can reach thermal runaway in 4.5 days. The results obtained in this study indicated that there was a definite need to consider the influence of coal moisture on spontaneous combustion [12].

Behera (2007) measured the difference between calculated and experimental volatile matter of coals which may be related to petrological or chemical parameters. The volatile displacement (δv) values of Meghalaya coals were calculated from their chemical analyses. Correlations of volatile displacement (δv) with parameters such as carbon, hydrogen, moisture, oxygen, oxygen plus sulphate sulphur, oxygen plus pyritic sulphur, oxygen plus organic sulphur and total sulphur were studied. An approximately linear relationship exists only between δv and moisture, and δv and total sulphur and not between other parameters. The linear relationship with total sulphur indicated that the coals may become abnormal mainly due to the marine environment of deposition and weathering of that region [23].

Chatterjee et al. (2007) made an attempt to study the coal fire dynamics of Jharia Coalfield during the 1990s from medium resolution satellite thermal IR data such as Landsat-5 TM and Landsat-7 ETM+ data (acquired in 10.4–12.5 mm spectral region). The dynamics of coal fire was addressed on the two aspects: (i) changes in the spatial extent of fire-affected areas and (ii) propagation of coal fire during the 1990s. A marked decrease in the spatial extent of fire-affected areas during the 1990s was observed in this study [33].

Patel et al. (2007) reported the estimation of GCV (Gross Calorific Value) of a coal sample based upon its proximate and ultimate analyses. These correlations between them were mainly linear in character although there were indications that the relationship between the GCV and a few constituents of the proximate and ultimate analyses could be nonlinear. Accordingly, seven nonlinear models were developed using the artificial neural networks (ANN) for the estimation of GCV with a special focus on Indian coals. The comprehensive

ANN model developed used all the major constituents of the proximate and ultimate analyses as inputs. It was found that the GCV prediction accuracy of all the models was excellent. Also, the performance of the ANN models was found to be consistently better than that of their linear counterparts. Additionally, a sensitivity analysis of the comprehensive ANN model was performed to identify the important model inputs, which significantly affect the GCV. The ANN based modeling approach can be gainfully extended for estimating the GCV of a wide spectrum of solid, liquid and gaseous fuels [111].

Choudhury et al. (2007) reported that macerals and mean reflectance (R_{max}) of coal were influencing the characteristics of coal combustion. Vitrinite and liptinite were considered to be reactive components towards combustion. Numerous studies on Gondwana coals suggested that some inertinites with, low in reflectance having mean reflectance up to 1.30%, showed good burning behaviour and they could be even more reactive than vitrinite. The thermogravimetric analysis (TGA) technique was used to assess combustion characteristics of the coal samples. The traditional parameters such as fuel ratio and rank, as reflected by the vitrinite reflectance, did not correlate well with the TGA parameters. Rather, TGA parameters were found to have good correlation with the petro factor, which combines the effect of the rank and the total reactive macerals (vitrinite, semi vitrinite, liptinite) and low reflecting reactive inertinites. The study indicated the necessity of considering the role of low-rank inertinites while assessing the combustion behavior of inertinite rich non-coking/non-caking coals [37].

Zong-Xiang et al. (2007) carried out numerical simulation study on methane drainage from goaf and spontaneous combustion of coal. The results showed that deep and large flux methane drainage increases the air leakage from working faces to the goaf and formed new spontaneous combustion zones induced by drainage near vents. This increases the risk of self-ignition of coal which ultimately reducing the self-ignition period and enhances the scale of self-ignition [165].

Adamus (2008) did investigations of 62 coal samples of Ostrava-Karvina coalfield in the Upper Silesian Basin of Czech Republic for hydrocarbon. 150 g coal sample of size 0.2 to 2 mm was placed in gas chromatograph and was heated gradually at an interval of 20 ^{0}C with 20 ml/min of air purging into it and found that in each coal sample CO_2, CO, CH_4, H_2, ethane (C_2H_6), propane (C_3H_8), butane (C_4H_{10}), ethylene (C_2H_4) and propylene (C_3H_6) and measured them at different temperatures. It was concluded that in an early stage of spontaneous combustion, it was suitable to use binary indicator CO_2/CO. This binary indicator in case of increasing temperature of the spontaneous combustion focussed on center at relatively low temperature because of releasing gases from the focus edge with lower temperature. For evaluation of relatively high temperature of spontaneous combustion focus then shifted to the non-saturated hydrocarbons serve, i.e. binary indicator C_2H_4/C_3H_6. Further, the research work was focused on improvement of assessment of self-heating temperature using indicator gases [11].

Yuan and Smith (2008) conducted computational fluid dynamics (CFD) modelling to study the properties of coal on the potential for spontaneous combustion in longwall gob areas. A two longwall panel district using a bleeder ventilation system was simulated. The permeability and porosity were used as inputs for the three-dimensional CFD modeling. The spontaneous heating was modeled as the low-temperature oxidation of coal in the gob using kinetic data obtained from previous laboratory-scale spontaneous combustion studies. Heat generated from coal oxidation was dissipated by convection and conduction, while oxygen and oxidation products were transported by convection and diffusion. Unsteady state simulations were conducted for three different US coals, and simulation results were compared with the test results. Further, the effects of coal surface area and heat of reaction on the spontaneous heating process were also examined [162].

Tripathi (2008) reported that underground coal in the panel can be extracted within incubation period without any symptoms of spontaneous heating. Nevertheless, incompatible geo-mining conditions, spontaneous combustion occurs frequently within the proclaimed incubation period of the mine panel; resulting massive quantities of coal being left un-extracted due to premature sealing. He focused on developing and testing methods or technologies for uprising the incubation period of spontaneous combustion of coal in an underground mine panel. The methods comprised of the development of objective models (equations) for the assessment and evaluation of causative factors playing significant roles in abrupt change of incubation period; the rise of temperature due to, increased rate of oxidation, fragmentation, impact and friction after commencing of the roof fall; and propagation of fire into the interconnected workings. The technologies comprised of the development and application of water fog, chemical fog, gel fog and inert gel fog and other methods at various Indian mines [150].

Beamish and Arisoy (2008(a)) conducted adiabatic self-heating tests on sub bituminous coal cores collected from the Callide Basin, Queensland, which covered a mineral matter content range of 11.2–71.1%. In all the cases, the heat release rate did not confirm to an Arrhenius kinetic model, but can best be described by a third order polynomial. Assessment of the theoretical heat sink effect of the mineral matter revealed that the coal was less reactive than predicted using a simple energy conservation equation. The disseminated mineral matter in the coal was, therefore, inhibiting the oxidation reaction due to physicochemical effects [19].

Beamish and Arisoy (2008(b)) stated that a large database of coal self-heating rates under adiabatic conditions was developed at The University of Queensland. Coals were tested from Australia (Queensland and the New South Wales), New Zealand (North and South Island), Indonesia and the United States of America. From the investigations, definitive relationships and trends were established for the effects of various intrinsic coal properties on self-heating rates. Past views on the effects of coal rank, type and inorganic constituents were examined. Many of the published relationships didn't hold true in terms of coal self-heating rates. A propensity rating scheme was developed which was routinely used in Australia for assessing coals and identifying appropriate mining strategies for spontaneous combustion management planning [18].

Zubíček (2008) reported that **s**pontaneous combustion of coal mass represents a major concern about the health hazard of workers and also endangering mining operations, which is associated with a failure of coal mining and costs for suppression of endogenous fire. Spontaneous combustion plays a significant role in deep working coal seams liable to spontaneous combustion. The susceptibility of coal to spontaneous heating was considered as a feature of coal mass specified by a laboratory test. Since the seventies in OKR (Ostrava-Karvina Coalfield), Olpinski index and the coal oxidation method under adiabatic conditions were used to verify the tendency of coal to spontaneous combustion. Later the method of pulse calorimetry and the CPT (Crossing Point Temperature) methods were included for the OKR coal and experimentally verified [166].

Chelgani et al. (2008) analysed the effects of proximate and ultimate analysis, macerals, and coal rank (R_{max}) of Kentucky coal samples from calorific value of 4320 to 14960 (BTU/lb) (10.05 to 34.80 MJ/kg) on Hardgrove Grindability Index (HGI) using multivariable regression and artificial neural network methods (ANN). The stepwise least square mathematical method showed that the relationship between (i) moisture, ash, volatile matter, and total sulfur; (ii) ln (total sulfur), hydrogen, ash, ln ((oxygen + nitrogen)/carbon) and moisture; (iii) ln (exinite), semifusinite, micrinite, macrinite, resinite, and R_{max} input sets with HGI in linear condition and obtained correlation coefficients of 0.77, 0.75, and 0.81, respectively. The ANN can predict HGI with correlation coefficients of 0.89, 0.89 and 0.95

respectively in the testing process. It was determined that ln (exinite), semifusinite, micrinite, macrinite, resinite, and R_{max} can be used as the best predictors for the estimation of HGI on multivariable regression (R^2 = 0.81) and also by artificial neural network methods (R^2 = 0.95) in testing process. Hence, the ANN can be employed as a reliable and accurate method, in the HGI prediction [35].

Cliff (2009) reviewed the laboratory testing and modelling carried out by different researchers and inferred that there was no reliable method to predict the proneness for a coal seam to spontaneous combustion. The complexities of the spontaneous combustion process were explored by delving into the chemistry of the oxidation process. Demonstration of laboratory testing and modelling of spontaneous combustion could be of limited accuracy. Laboratory tests and simulations were carried out under conditions could not reflect the full complexity of the underground environment. But still the experimental work is meaningful, and the results need to be included for proper risk assessment that includes the contributions and influences of other parameters not able to be adequately modelled or simulated in the laboratory. Additionally, laboratory testing can influence of such things as water content, ash content and particle size. It was recommended that the Trigger Action Response Plans (TARP) in underground coal mines go beyond detection of spontaneous combustion and can be used as a better indicator to identify the increased likelihood of spontaneous combustion and controlling measures should be taken in time to prevent spontaneous combustion from occurring [40].

Behera and Mohanty (2009) measured crossing point temperature and peroxy complex to assess the spontaneous heating character of Talcher coals. Coal samples collected from the two horizons i.e. Karharbari formation and Barakar formation were separately studied, and the values measured for the parameters mentioned above were recorded. It was found that the coals of this coalfield were highly susceptible to spontaneous combustion, but the coals of the Karharbari formation showed less susceptibility as compared to Barakar formation [22].

Rai et al. (2009) applied the artificial neural network (ANN) technique to reduce the number of blast design parameters affecting the shape and powder factor of blasted muck piles. A scientific approach was used to minimize the number of input parameters for an ANN model. The input features were selected based on the least mean squared error value of the data set after proper training. Optimum numbers of blast design parameters were selected after the elimination of some input parameters. The results were tested and validated with actual data set at acceptable correlation levels [118].

Mohalik and Singh (2009) carried out extensive literature study on thermal analyses of coal and concluded that the quantifying of self-heating characteristics of coal from differential thermal analysis (DTA) and thermogravimetry analysis (TGA) curves were tedious work as compared to differential scanning calorimetry (DSC) curves. So, DSC curves were more quantitative than others, because it can provide transition temperature and amount of heat evolved during the process. The repeatability of the experiment under identical conditions was producing the same results as compared to DTA and TGA. The DSC study can be used as one of the indicators to determine the susceptibility of coal to spontaneous heating. The acceptability of this method for determining spontaneous heating characteristics of coal mainly depends on how closely it predicts the spontaneous heating in the field conditions [87].

Table 2.3 Experimental parameters used by different researchers in DTA studies for the assessment of spontaneous heating of coal [87]

Sl. No.	Name of the author	Parameters							
		Particle size/mesh	Heating Rate (°C/min)	Atmosphere	Sample Amount (mg)	Flow rate (ml/ min)	No. of sample studied	Reference material	Temp. range (°C)
1	Whitehead and Breger (1950)	-	10, 20	Air/ Vacuum	-	-	-	-	Ambient to 550
2	Glass (1955)	-100	10, 20	-	-	-	7	-	Ambient to 1000
3	Berkowitz (1957)	-65	6	Nitrogen	100	2.5	6	Dry quartz	Ambient to 500
4	Banerjee and Chakraborty (1967)	-72, -200, -10 +60	1, 3, 5, 10, 15	Atmospheric Air	600	-	6	Calcined alumina	Ambient to 400
5	Banerjee et al. (1972)	-72	5	Atmospheric Air	600	-	6	Calcined alumina	Ambient to 400
6	Haykiri-Acma et al. (1993)	-	15	Nitrogen	-	-	-	-	Ambient to 1000
7	Podder et al. (1995)	-100	10	Argon	10	100	5	-	30 - 900
8	Iordanidis et al. (2001)	-16	10	Nitrogen	-	150	7	Alumina	Ambient to 1000
9	Kok (2002)	-60	10	Air	10	167	4	Alumina	20 - 900
10	Elbeyli and Piskin (2006)	-65	10	Air/ Nitrogen	10	100	1	-	Ambient to 1000

11	Haykiri-Acma et al. (2006)	-65	20	Atmosphere	20	-	7	Alumina	Ambient to 1000
12	Sis (2007)	-8+10 to -400	10	Air	10	50	1	Alpha Alumina	Ambient to 900
13	Ozbas (2008)	-	10	Nitrogen	10	50	15	Alpha Alumina	Ambient to 900

Khandelwal and Singh (2010) studied various intrinsic properties of coal, such as proximate analysis, ultimate analysis, and macerals. These properties can manage the rank and calorific value of different coal varieties. Macerals in coal required sophisticated microscopic instrumentation and expertise. They made an attempt to predict the concentration of macerals of Indian coals using the artificial neural network (ANN) by incorporating the proximate and ultimate analysis of coal. To investigate the appropriateness of this approach, the predictions by ANN were compared with multivariate regression analysis (MVRA). For the prediction of macerals, data sets were taken from different coalfields of India for training and testing of the network. The network was trained by 149 datasets with 700 epochs and tested and validated by 18 datasets. It was found that coefficient of determination between measured and predicted macerals by ANN was significant as well as mean absolute percentage error was very marginal as compared to MVRA prediction [69].

Chelgani et al. (2010) analysed the results obtained from ultimate analysis, proximate and petrographic analyses of Kentucky coals to predict coal rank parameters (vitrinite maximum reflectance (R_{max}) and gross calorific value (GCV)) using multivariable regression and artificial neural network (ANN) methods. Volatile matter, carbon, total sulfur, hydrogen and oxygen were used to predict both R_{max} and GCV by regression and ANN. Multivariable regression equations to predict R_{max} and GCV showed $R^2 = 0.77$ and 0.69, respectively. Results from the ANN method with a 2–5–4–2 arrangement that simultaneously predicted GCV and R_{max} showed R^2 values of 0.84 and 0.90, respectively. They suggested that the artificial neural network method could be used to predict R_{max} and GCV when regression results do not have high accuracy [36].

Ruilin and Lowndes (2010) proposed the use of a coupled artificial neural network (ANN) and fault tree analysis (FTA) model to predict the potential risk of coal and gas outburst during the underground mining of thick and deep Chinese coal seams. The model developed has been used to investigate the gas emission characteristics and the geological conditions in the Huaibei coal mining region, Anhui province, China. An analysis of the results obtained from FTA model identified eight model parameters related to the gas content or geological conditions of the coal seams, which characterize the potential risk of in situ coal and gas outbursts. These parameters were used as input variables to an ANN model and developed a qualitative risk index to characterize the potential risk level of occurrence of coal and gas outburst events. Four different potential risk alarm levels were classified as: SAFE, POTENTIAL, HIGH and STRONG. Solutions to the prediction model were obtained using a combination of quantitative and qualitative data including the gas content or gas pressure and the geological and geotechnical conditions of coal seams. The application of this combined method can be identified as more explicit and accurate model. An analysis of the model concluded that the coupled FTA and ANN model may offer a reliable alternative method to assess the potential risk of coal and gas outbursts [126].

Xiao and Tian (2011) reported that prediction of spontaneous combustion of coal mine plays an important role in mine production safety. There was a complicated nonlinear relation between the danger of coal layer spontaneous combustion and its influencing factors. The neural network can indeed show the nonlinear relationship. For predicting the coal mine layer correctly, a method combining the advantages of genetic algorithm (GA) and BP neural network was introduced. At first, the notion of using multilayered BP as the representation method of genetic and the searching technique was introduced, and a novel method of using GA to train connection weights of BP neural network was designed. According to the characteristics of mine coal layer spontaneous combustion danger, three key influencing factors were selected as the judging indexes. Then the model for predicting the danger of mine coal layer spontaneous combustion was built. The practical application indicated that the capability of the new method was fast learning of ANN and escaping local optima. The results showed that the designed model was very efficient for predicting the danger of mine coal layer spontaneous combustion [158].

Xin-hai et al. (2011) stated that forecast is impoprtant for preventing and controlling the disaster of spontaneous combustion (sponcom). Gaseous products of coal, such as carbon monoxide, ethylene, propane and hydrogen, were commonly used as indicators to reflect its status of sponcom in coal mines. Nevertheless, since the corresponding relationship between the temperature and the indicators was non-linear and could not be depicted with simple mathematical formula, it was very difficult to diagnose and forecast coal sponcom by monitoring indicator gases' distribution. A forward feeding 3-layer artificial neural network (ANN) model was employed to express the corresponding relation between temperature and index gases of coal sponcom more accurately. A large amount of data from programmed temperature oxidation experiments was employed to train the network. It was proved that the ANN model can forecast coal sponcom accurately [159].

Pattanaik et al. (2011) collected coal samples from different coal seams of the Chirimiri coalfield that covered the entire stratigraphic sequence. These samples were tested for chemical analysis, crossing point temperature (CPT), petrography, infrared studies (IR) and differential thermal analysis (DTA). All the test results vindicated that the parameters mentioned above had a definite relationship with the stratigraphic disposition or the ranks of coal. The low-rank coals found as younger seams in the stratigraphic sequence were more prone to spontaneous combustion whereas the higher rank coals found at the bottom of stratigraphic sequence were less prone to spontaneous combustion. From the combustibility characterization by different tests, it was found that the upper Duman and Kaperti seams placed as younger seams in the stratigraphic sequence were highly prone to spontaneous combustion whereas the lower Karakoh and Sonawani seams seemed to be least prone to spontaneous combustion [113].

Khorami et al. (2011) analyzed the results of proximate, ultimate, and petrographic analysis of Kentucky coals to predict Free Swelling Index (FSI) using multivariable regression and Adaptive Neuro Fuzzy Inference System (ANFIS). Three different input sets: (i) moisture, ash and volatile matter; (ii) carbon, hydrogen, nitrogen, oxygen, sulfur and mineral matter; and (iii) group-maceral analysis, mineral matter, moisture, sulfur and vitrinite maximum reflectance (R_{max}) were applied for both methods. Non-linear regression achieved the correlation coefficients of 0.38, 0.49 and 0.70 respectively. By using the same input sets, ANFIS predicted FSI with higher correlation coefficients of 0.46, 0.82 and 0.95 respectively. Results showed that input set (iii) can provide the best predictor of FSI in both prediction methods and adaptive neuro fuzzy interface system (ANFIS) can be used to predict FSI, when regression does not have appropriate accuracy in results [70].

Rafezi et al. (2011) assessed the properties of 4540 U.S. coal samples collected from 25 states such as gross calorific value (GCV) and the parameters of proximate and ultimate analysis. Multivariate regression analysis and ANFIS were used to predict GCV based on the significant correlations between the parameters of proximate and ultimate analysis [117].

Muthreja et al. (2012) emphasized that on the land acquisition along with stringent environmental law will compel the coal companies to have waste dumps of more height. This problem will arise due to the increase in demand for coal production in India and mechanization of surface method of mining. Numerical and physical models were developed to study the role of geo-grids in waste dump stability. Here, they also discussed the comparative results of dump stability analysis of numerical and physical modeling [93].

Sharma et al. (2012) determined the petrographic composition of some high sulphur tertiary Indian coal samples and predicted their reactivity. Multi-variable regression analysis investigated the relationship between macerals and Gross Calorific Value (GCV) of these coal samples. The maceral analysis indicated that the North-East (NE) Indian coal samples had high vitrinite content (80.07% average), moderate to low liptinite (10.23% average) and low inertinite (9.3% average). The liptinite and inertinite contents were found to have a strong linear relationship (R^2=0.9283 and R^2= 0.9223). From this study, GCVs can be easily interpreted [131].

Jain and Paul (2012) reported that Lodna coke plant, an industrial unit of Bharat Coking Coal Limited (BCCL)-a subsidiary of Coal India Limited (CIL) in Jharia coalfields was shut down due to approaching underneath coal seam fire. A scientific study was conducted by Centre of Mining Environment, Indian School of Mines, Dhanbad, India to assess the status of fire vis-à-vis stability of the industrial structure. It was found that few of the underneath seams were virgin, and some were unapproachable below the coke plant. They threw light on the method of investigation for the approaching mine/coal seam fire in a safe and scientific manner. The basic aim of this study was to provide status of fire in and around coke plant without prediction of any time frame for propagation of fire in near future, as the control of mine fire depends on the technicalities required for the fire control and the action taken by the BCCL mine authorities. The study included measurements of surface temperature, underground temperature with available bore holes, analysis of coal and gases present in various coal seams. Based on various observations and calculations, findings were elaborated [60].

Danko and Bahrami (2012) developed a numerical mine ventilation, heat, moisture, and contaminant transport model – MULTIFLUX. This model was made free of both numerical dispersion and the systematic error in concentration travel time even if relatively large grid size was used. In this mathematical model, there was no need to make incredibly small grids in the mine ventilation network [41].

Morla et al. (2013) reported that **s**pontaneous combustion was one of the causes of fire in underground coal mines especially in thick coal seams and caused loss of working personnel, production, valuable reserves and damage or loss of expensive mining equipment. The blasting gallery method in an 11 m thick seam in Indian geological conditions was considered to model prediction and control of spontaneous combustion (sponcom) in thick coal seams. To find sponcom properties of the coal, gas evolution test, sponcom propensity test, differential scanning calorimetry, and crossing point temperature tests were conducted for the specified thick seam. The knowledge of goaf gas behaviour in the blasting gallery extraction method during sponcom can be useful for controlling and minimizing the effects of fire. They discussed the application of computational fluid dynamics (CFD) simulations to investigate the goaf gas behavior at the time of sponcom in the blasting gallery panels. CFD simulations studies were also conducted with ascentional and descentional ventilation systems with inert gas injection at a single injection point, multiple injection points and various inert gas flow rates. The results indicated that the descentional ventilation system was useful for goaf inertisation, and multiple inert gas injection points were more effective than the single point injection [89].

Nimaje et al. (2013) used some experimental techniques based on petrological, thermal and oxygen avidity studies for assessing the spontaneous heating liability of coals in the world (Australia, USA, Czech Republic, China, India etc.). Crossing point temperature (CPT) is one of the most common methods in India to evaluate the fire risk of coal so that appropriate strategies and effective action plans can be made in advance to prevent occurrence and spread of fire and hence minimize coal loss. The spontaneous heating risks of some of the Indian coals covering few major coalfields were assessed using CPT apparatus. Statistical analysis was carried out between CPT and the proximate analysis parameters and it was found that the Mixture Surface Regression (MSR) model was more useful and gave excellent residual values as compared to the polynomial and simple multiple regression models. The performance of Anderson-Darling testing was done on the prediction results of MSR model and measured value of CPT showed that the residual follows normal distribution; hence justified the suitability of model for the prediction of spontaneous heating liability of coal [101].

Singh (2013) reported that the majority of fires in different coalfields were mainly due to spontaneous combustion of coal. The auto oxidation of coal ultimately leads to spontaneous combustion that is considered as the major cause for the disastrous of coal mine coal producing countries like USA, China, Australia, India, and Germany. There were various technologies available in different parts of the world to prevent and control spontaneous heating. Out of these technologies, chemical inhibitors play an important role in controlling and combating fires. He elaborated the causes, mechanism of spontaneous heating and technological advancements mainly in the development of chemical inhibitors for controlling and combating fire in coal mines [139].

Beamish et al. (2013) carried out investigations on few reactive coals of Australia and U.S. to enumerate the effect of adding the anti-oxidant agent by conducting moist coal adiabatic oven test. For the particular amount of inhibitor applied to the coal sample, there was a substantial reduction in the self-oxidation of the coal. For bituminous coal, there was an extension by a factor, while it was double for the highly volatile bituminous coal. The result made out of the experimentation was similar to the site experience on the application of the anti-oxidant on the spontaneous coal [21].

Ozdeniz et al. (2014) reported that, in underground coal mine besides exothermic reactions, hazardous, explosive and flammable gases were released into the surrounding air. This situation causes interruptions in production, economic losses and environmental problems. To avoid these issues, coal production at the longwall face should be stopped, and the contact of the coal with air should be prevented. The temperatures changes throughout the longwall in the spontaneous combustion condition were measured by a temperature sensor placed inside the longwall. Also, the temperature of the exhaust air and concentration of some mine gases (CO, CH_4, O_2 and CO_2) were also measured. Graham's ratio was calculated and used to determine spontaneous combustion. The temperature of the longwall increased with time and the coal production of longwall was stopped. After eliminating the air contact of coal, the temperature recording was continued, and the temperature changes in the inner part of the longwall were observed continuously [106].

Avila et al. (2014) used thermogravimetric analysis (TGA) to study the reactive properties of coals in low-temperature oxidation. Coal samples were pulverized into a size fraction of <106 μm and were analyzed. The "adsorption of oxygen" test was conducted with two heating rates (3 and 5 ^{0}C /min) consisted of exposing coal samples to slow heating rates in air, and recorded the net mass increases from 20 to 250 ^{0}C with the weight gain ranges from 0.0 to 4.4%. The highest level of adsorption was achieved with the lowest heating rate. A second thermogravimetric test for spontaneous ignition potential (TG_{spi}) was developed under the linear segment of the weight derivative curve between 150 and 350 ^{0}C at different heating rates in air medium (3, 5, 7, 10, and 20 ^{0}C/min). From these results, a relationship between the mass loss rate and the temperature was obtained (TG_{spi} index), where highly reactive coals produced high values. The "oxygen adsorption" test precedes "spontaneous combustion". The "TG_{spi}" test was more related to the combustion process, post-ignition. These results indicated that the "oxygen adsorption" test could be useful to identify coals prone to self-oxidation [14].

Panigrahi and Ray (2014) used wet oxidation potential technique for determining the proneness of coal to spontaneous combustion. 78 coal samples were collected from thirteen different mining companies covering most of the Indian Coalfields and used for the experimental investigations. 936 experiments were carried out by varying experimental conditions to standardize this method for wider application. The results of the wet oxidation potential (WOP) method were correlated with the intrinsic properties of coal by carrying out proximate, ultimate and petrographic analyses of the coal samples. The correlation studies were performed with Design Expert 7.0.0 software. Further, the artificial neural network (ANN) analysis was performed to ensure the best combination of experimental conditions to be used for obtaining optimum results. They concluded that the experimental conditions should be 0.2-N $KMnO_4$ solution with 1-N KOH at 45°C to achieve optimum results for finding out the liability of coal to spontaneous combustion. The results were validated with Crossing Point Temperature (CPT) data which is widely used in Indian mining scenario [107].

Wang et al. (2015) simulated the effectiveness of grouting to prevent the coal spontaneous combustion at a goaf in Haizi Colliery, China. The colliery had been operated over 27 years and had an elaborate ventilation network including air flow leakages that could lead to the spontaneous combustion of coal at goaves. Firstly, the mine ventilation simulator MIVENA was used to analyze the mine ventilation network airflows to control airflows in and out of working faces and goaf. In the second approach, numerical simulations were carried by the simulator FLUENT to predict spontaneous combustion of residual coal with leakage flow in the 3205 goaves. The goaf was divided into three zones based on oxygen concentration in the goaf area. Finally, the numerical simulation results showed that the slurry grouting method could be used as an efficient and economical method by reducing porosity in the goaf area to prevent spontaneous combustion of residual coal [156].

Ray and Panigrahi (2015) described wet oxidation potential method for determining the susceptibility of coal to spontaneous heating. Experiments were carried out on 78 coal samples of the Indian coalfields for proximate and ultimate analyses of coal. Correlation analysis was performed between wet oxidation potential and parameters of intrinsic properties of coal. It was found that the wet oxidation potential difference showed a good correlation with moisture content, volatile matter, oxygen, hydrogen and carbon content of coal [121].

National and international status of research on sponcom of coal reveals that the studies carried out by the academicians, scientists, researchers and industry personnel were based on characterization, statistical analysis and mathematical modelling. Some of the researchers worked on intrinsic properties viz. proximate analysis, ultimate analysis, calorific value and maceral studies as well as the susceptibility indices such as crossing point temperature, wet oxidation potential analysis, differential thermal analysis, Olpinski index, Russian U-index, differential scanning calorimetry etc. but there is no reliable method to evaluate the fire risk of Indian coals.

In this dissertation, experimental investigations such as intrinsic properties and the susceptibility indices of some Indian coals covering the majority of the Indian coalfields have been carried out. Literature survey indicated that limited work was carried out on fire risk assessment of Indian coals using soft computing techniques. Therefore, an attempt has been made to develop mathematical models using soft computing techniques which can help the mine management to predict in advance the fire risk of Indian coals and thereby adopt appropriate strategies and effective action plans to prevent occurrence and spread of fire.

CHAPTER – 3

EXPERIMENTAL METHODOLOGY

To assess the liability of coals to spontaneous combustion, it is important to investigate the Indian coals by various experimental techniques following standard testing procedures. This chapter discusses the techniques used for collection and preparation of coal samples, as well as experimental methods for estimation of intrinsic properties as well as susceptibility indices of coals in detail.

3.1 Sample Collection and Preparation

3.1.1 Sample collection

Sample collection sites were selected with practically no dirt bands in order to maintain uniformity, covering more or less the same area. Channel sampling method was used to collect forty-nine non-coking and coking in-situ coal samples from various sites covering major coalfields of India, viz. South Eastern Coalfields Limited (SECL), Singareni Collieries Company Limited (SCCL), Mahanadi Coalfields Limited (MCL),Western Coalfields Limited (WCL), North Eastern Coalfields (NEC), Northern Coalfields Limited (NCL), Indian Iron and Steel Company (IISCO), Bharat Coking Coal Limited (BCCL) and Tata Iron and Steel Company Limited (TISCO) as per Indian standard IS: 436(Part-I/Section I)–1964 [55] and were coded accordingly. Location map of the collected coal samples are marked on India map (Figure 3.2). Section wise channel (30 cm x 10 cm) samples were collected from the seams with the help of chisel and hammer, after dressing down the coal face, to avoid contamination and the method (channel sampling) is shown in Figure 3.1. The in-situ coal samples collected on a rexin cloth from individual sections of seams, were further broken down to a convenient size, coned and quartered at sampling sites in the mine itself or in the laboratory to get representative samples and were then quickly transferred into an airtight containers or packed in polythene bags so that they were not oxidized.

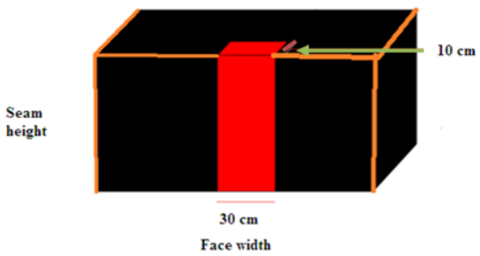
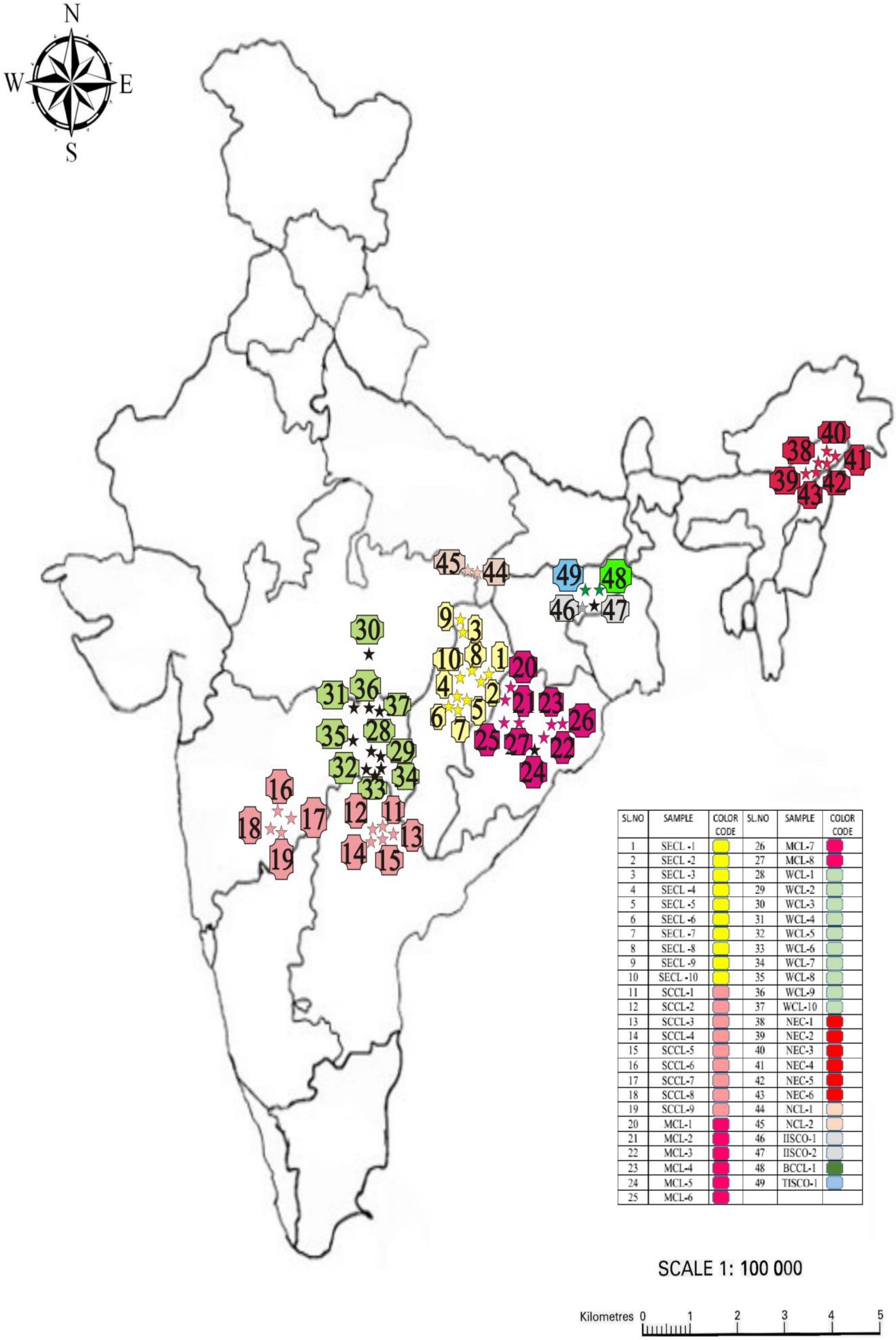


Figure 3.1 Channel sampling method



SL.NO	SAMPLE	COLOR CODE	SL.NO	SAMPLE	COLOR CODE
1	SECL -1		26	MCL-7	
2	SECL -2		27	MCL-8	
3	SECL -3		28	WCL-1	
4	SECL -4		29	WCL-2	
5	SECL -5		30	WCL-3	
6	SECL -6		31	WCL-4	
7	SECL -7		32	WCL-5	
8	SECL -8		33	WCL-6	
9	SECL -9		34	WCL-7	
10	SECL -10		35	WCL-8	
11	SCCL-1		36	WCL-9	
12	SCCL-2		37	WCL-10	
13	SCCL-3		38	NEC-1	
14	SCCL-4		39	NEC-2	
15	SCCL-5		40	NEC-3	
16	SCCL-6		41	NEC-4	
17	SCCL-7		42	NEC-5	
18	SCCL-8		43	NEC-6	
19	SCCL-9		44	NCL-1	
20	MCL-1		45	NCL-2	
21	MCL-2		46	IISCO-1	
22	MCL-3		47	IISCO-2	
23	MCL-4		48	BCCL-1	
24	MCL-5		49	TISCO-1	
25	MCL-6				

Figure 3.2 Location map of sampling sites

3.1.2 Sample preparation

The collected coal samples were crushed and sieved as per the experimental requirements following IS: 436(Part-I/Section I)–1964 [55].

3.2 Experimental Techniques to Assess:

To achieve the objectives of the research framework, the experimental work was divided into two categories, namely:

1. Intrinsic properties such as proximate analysis, ultimate analysis, and petrographic analysis, and
2. Susceptibility indices such as crossing point temperature method, Olpinski index method, wet oxidation potential analysis, flammability temperature method, and differential thermal analysis.

3.2.1 Intrinsic properties

3.2.1.1 Proximate analysis

Proximate analysis involves the determination of parameters namely, moisture (M), volatile matter (VM), ash (A), and fixed carbon (FC) for the collected coal samples on as received basis in a laboratory following Indian Standard IS: 1350 (Part-I)–1984[54]. **Procedure:**

a) Moisture (M)

1 g of coal sample of -72 mesh was kept in a petri dish. Petri dish with coal sample was placed it in the oven at a temperature of 105 ^{0}C for 1.5 hours. After 1.5 hours, allowed the sample to cool to room temperature by placing it in a desiccator and weigh the sample. The loss of weight was the moisture content in a coal sample.

The moisture was calculated using the formula:

$$M\ \% = \frac{(W_1 - W_2)}{W_1} \tag{3.1}$$

Where, W_1 – initial weight of the coal sample; and

W_2 – the final weight of the sample after 1.5 hours.

b) Volatile matter (VM)

1 g of coal sample of -72 mesh size was kept in a crucible and placed in a muffle furnace at a temperature of 925 ^{0}C for 7 minutes. After 7 minutes, allowed the sample to cool to room temperature by placing it in a desiccator and weigh the sample.

The volatile matter was calculated using the formula:

$$VM\ \% = \frac{(W_1 - W_2)}{W_1} - Moisture\ \% \tag{3.2}$$

Where, W_1 - weight of the coal sample; and

W_2 - the final weight of the sample after 7 minutes.

c) Ash (A)

1g of coal sample of -72 mesh size was kept in a silica crucible and placed it in a muffle furnace at a temperature of 450 ^{0}C for 30 minutes and then the temperature of the furnace was raised to 850 ^{0}C and kept it for 1 hour. Placed the sample in a desiccator to cool to room temperature and weigh the sample.

The ash was calculated using the formula:

$$A\ \% = \frac{(W_1 - W_2)}{W_3} \tag{3.3}$$

Where, W_1 – weight of the silica crucible and ash;

W_2 – weight of the silica crucible; and

W_3 - weight of the coal sample.

d) Fixed carbon (FC)

It was obtained by subtracting the percentage of moisture, volatile matter and ash from 100.

FC % = 100 – (M + VM + A)

The following relations [13] were used to convert the as received results of proximate analysis to % dry, % dry ash free (daf) and % dry mineral matter free (dmmf) bases.

<u>Dry basis</u>

$$\text{Ash} = \frac{\text{Ash \% on air dried basis}}{100 - \text{moisture \%}} \text{ x } 100 \tag{3.4}$$

$$\text{VM} = \frac{\text{Volatile matter \% on air dried basis}}{100 - \text{moisture \%}} \text{ x } 100 \tag{3.5}$$

$$\text{FC} = 100 - (\text{ash + volatile matter}) \text{ on \% dry basis} \tag{3.6}$$

<u>Dry ash free basis</u>

$$\text{VM} = \frac{\text{Volatile matter \% on air dried basis}}{100 - (\text{moisture+ash})\%} \text{ x } 100 \tag{3.7}$$

$$\text{FC} = 100 - \text{volatile matter on \% daf basis} \tag{3.8}$$

<u>Dry mineral matter free basis</u>

$$\text{VM} = \frac{\text{Volatile matter \% on air dried basis} - 0.1 \text{ ash on air dried basis}}{100 - (\text{moisture} + 1.1 \text{ ash}) \text{on \% air dried basis}} \text{ x } 100 \tag{3.9}$$

FC = 100 – volatile matter on % dmmf basis (3.10)

3.2.1.2 Ultimate analysis

It involves the determination of the elemental composition of coal, viz. carbon, hydrogen, nitrogen, and sulphur. CHNS elemental analyzer (Vario EL, Germany) with thermal conductivity detector (Plate 3.1) was used for the purpose. The elemental analyzer works on the principle of catalytic combustión of coal in an oxygen atmosphere and high temperature. The combustión gases were free from foreign volatile halogen gases and component oxides of the elements C, H, N and S were separated from each other with the help of specific adsorption columns and determined in succession with thermal conductivity detector using helium as a carrier gas [120].

Procedure

Before starting the analysis and in between sample-to-sample, one or two blank runs are performed to eliminate the memory effects from the previous samples analysis. Approximately 4 mg of coal sample and 2-3 mg of Wolfram catalyst (WO_3) were taken in the sample boat and packed tightly. This packet was placed in the carousel as per the serial order given. The system came to a standby mode after furnaces reached programmed temperature (Furnace 1: 1200 ^{0}C, Furnace 2: 850 ^{0}C) then the samples were fed into the combustion tube successively by automatic turning of the carousel. Due to combustion of the sample, these elements (CHNS) were converted into their oxides and they were adsorbed onto the respective adsorption tubes. After certain time these adsorbed gases were desorbed one by one through heating and finally quantified from the response of thermal conductivity detector, a universal detector for all gases. From a number of gases formed, the instrument automatically calculates the percentages of elements (CHNS) present in the sample. Oxygen in coal samples was calculated by subtracting the sum of the percentage of C, H, N, S, ash and moisture from 100. Oxygen desorption of absorbed gases can be attained at the following temperatures: CO_2 Column 100 ^{0}C, SO_2 Column 210 ^{0}C and H_2O Column 150 ^{0}C [120].

Plate 3.1 CHNS analyzer (Vario EL, Germany)

The following relations [13] were used to convert the as received results of the ultimate analysis to % dry, and % dry ash free (daf) bases

Dry basis

$$C = \frac{\text{C \% on air dried basis}}{100 - \text{moisture \%}} \text{ x } 100 \quad (3.11)$$

$$H = \frac{\text{H \% on air dried basis}}{100 - \text{moisture \%}} \text{ x } 100 \quad (3.12)$$

$$N = \frac{\text{N \% on air dried basis}}{100 - \text{moisture \%}} \text{ x } 100 \quad (3.13)$$

$$S = \frac{\text{S \% on air dried basis}}{100 - \text{moisture \%}} \text{ x } 100 \quad (3.14)$$

$$O = 100 - (C + H + N + S + ash) \text{ on \% dry basis} \quad (3.15)$$

Dry ash free basis

$$C = \frac{\text{C \% on air dried basis}}{100 - (\text{moisture+ash})\%} \text{ x } 100 \quad (3.16)$$

$$H = \frac{\text{H \% on air dried basis}}{100 - (\text{moisture+ash})\%} \text{ x } 100 \quad (3.17)$$

$$N = \frac{\text{N \% on air dried basis}}{100 - (\text{moisture+ash})\%} \text{ x } 100 \quad (3.18)$$

$$S = \frac{\text{S \% on air dried basis}}{100 - (\text{moisture+ash})\%} \text{ x } 100 \quad (3.19)$$

$$O = 100 - (C + H + N + S) \text{ on \% daf basis} \quad (3.20)$$

3.2.1.3 Petrographic analysis

Coal is a sedimentary rock composed of a number of distinct organic entities called macerals and lesser known amounts of an inorganic substances called as minerals. Each maceral has a different set of property and it influences the behavior of coal. Coal surface can be analyzed at the macroscopic level and microscopic level. At the macroscopic level, coal appears as banded or non-banded rock. The bands are divided into four major lithotypes – vitrain, clarain, durain and fusain. At the microscopic level, coal has three basic groups of macerals and mineral matter. The macerals are of four types – vitrinite, liptinite, inertinite and visible mineral matter. Petrographic analyses of some coal samples were carried, as per the procedure laid down by the International Committee on Coal and Organic Petrography [58, 59] and IS: 9127(Part- I & II)–1979 Indian Standard [56, 57] under oil, using reflected light microscope.

Preparation of polished particulate mounts

The coal samples were prepared for the maceral analysis using the following steps:

a) Embedding

About 10 g of carnauba wax was heated in a porcelain bowl till it was melted and effervescence ceased. Then about 0.5 g of nigrocene powder was added with a constant stirring by glass rod and subsequently about 8 g of coal powder (+/-18 mesh size) was added to the molten carnauba wax. Throughout the process, a constant stirring was required. This mixture was carefully poured into a one-inch square metallic mould placed on a clean glass plate. It was then allowed to cool down and finally taken out carefully from the mould.

b) Grinding

The coal pellet was grounded on a glass plate using 400 mesh size carborundum powder for about 30 minutes and after that by 600 mesh size powder for about 20 minutes. Then the surface was washed under a jet of water and then allowed to dry. This was followed by fine grinding using 1000 mesh size carborundum powder for 10 to 15 minutes.

c) Polishing

The first polishing was done on an emery paper 4/0 type using a drop of water until the surface of the pellet starts shining. This was followed by polishing on a rotating lap having a speed of 120 r.p.m. The disc of the lap was covered with a blazer cloth and a solution of light Magnesium Carbonate was poured over the cloth. Now, the polished surface was washed with water. For the final polishing, a glass plate covered with a selvyt cloth and a solution, prepared from alumina powder-grade III, was used. The polishing was done for about 10 minutes and then the pellet was washed under a jet of water.

Procedure

The maceral analysis was carried out on polished particulate mounts (Plate 3.3) in white incident light using a ‘Leitz Orthoplan- Pol Microscope’ (Plate 3.2) equipped with 50-X oil immersion objective and a 10-X ocular. The modal analysis was performed with the help of a mechanical stage and point counters, and the spacing between the counts was maintained at 0.4 mm. Six hundred (600) counts were taken on each sample and a number of macerals, viz. vitrinite, liptinite, and inertinite were found out using a microscope. From the previous research investigations on Indian coals, it was observed that petrographically, coking coals contains vitrinite reflectance (Rmax) values ranged from 0.80% to 1.40% [32] while non-coking coals have Rmax values 0.4% to 0.79%. In view of this, for Indian coals having low vitrinite content, it may not be effectively used as a rank indicator for the collected (forty-five non-coking and four coking) Indian coals.

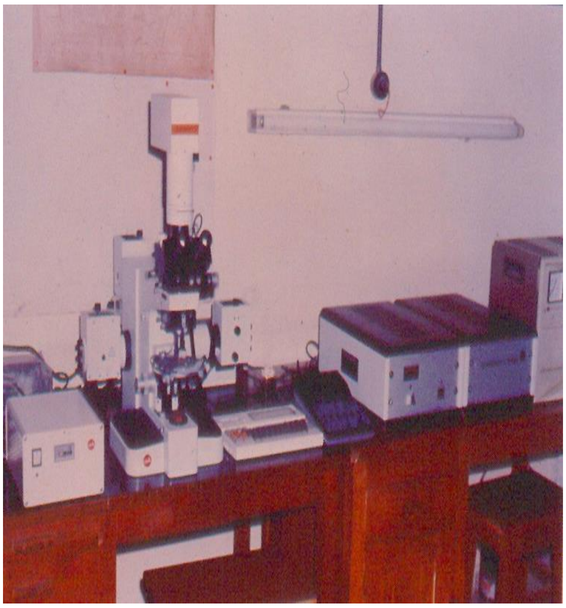


Plate 3.2 Leitz orthoplan-pol microscope

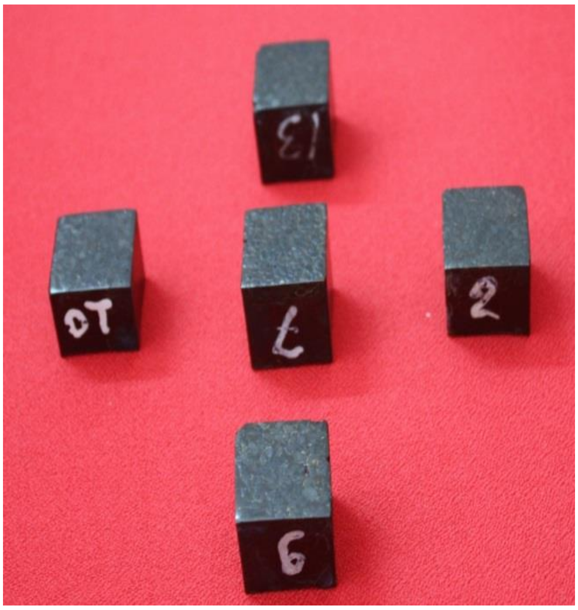


Plate 3.3 Polished particulate mounts

3.2.2 Susceptibility indices

3.2.2.1 Crossing point temperature method

Crossing point temperature (CPT) is the lowest temperature at which the temperature of coal coincides with that of the furnace/bath (Figure 3.3). The heating rate, the air flow and particle size must be optimized. The commonly used air bath CPT apparatus [17, 82] is shown in Plate 3.4 and it requires the following:

- Amount of coal: 4 g of coal
- Size of coal: - 100 + 200 mesh
- Heating rate: 1°C/min.
- Oxygen/air flow rate: 80 ml/min.

The air bath crossing point temperature apparatus was used to determine the CPT of the collected coal samples with few modifications [101] in the original apparatus:

- Rotameter was used instead of U-tube flowmeter.
- The drying tower was used to absorb moisture instead of a chemical circuit used in air flow circuit.
- Furnace/bath temperature controller was used instead of dimmerstat to maintain a constant heating rate of 1 ^{0}C/min.

Procedure

In this method, the coal (4 g) of -100 +200 mesh was heated in a reaction tube in the tubular furnace at constant 1 ^{0}C/min heating rate; with oxygen purging at 80 ml/min until the coal temperature crossed the furnace or bath temperature. The heating rate was controlled by furnace/bath controller, and the readings were noted [101]. The curve between bath and coal temperature with respect to time and the CPT was found to indicate the liability of coal to spontaneous heating. The fire risk of the coal samples can be ascertained using Table 3.1.

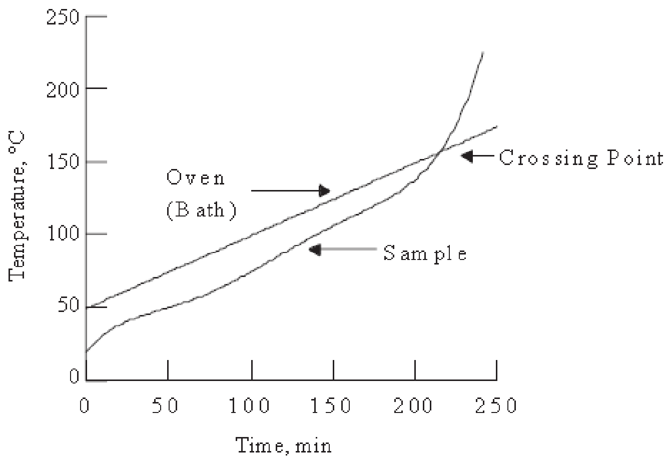


Figure 3.3 Time vs Temperature curve for CPT [67]

Table 3.1 Fire risk evaluation of coals based on CPT [82]

CPT(^{0}C)	Risk Rating
120 to 140	Highly susceptible
140 to 160	Moderately susceptible
>160	Poorly susceptible

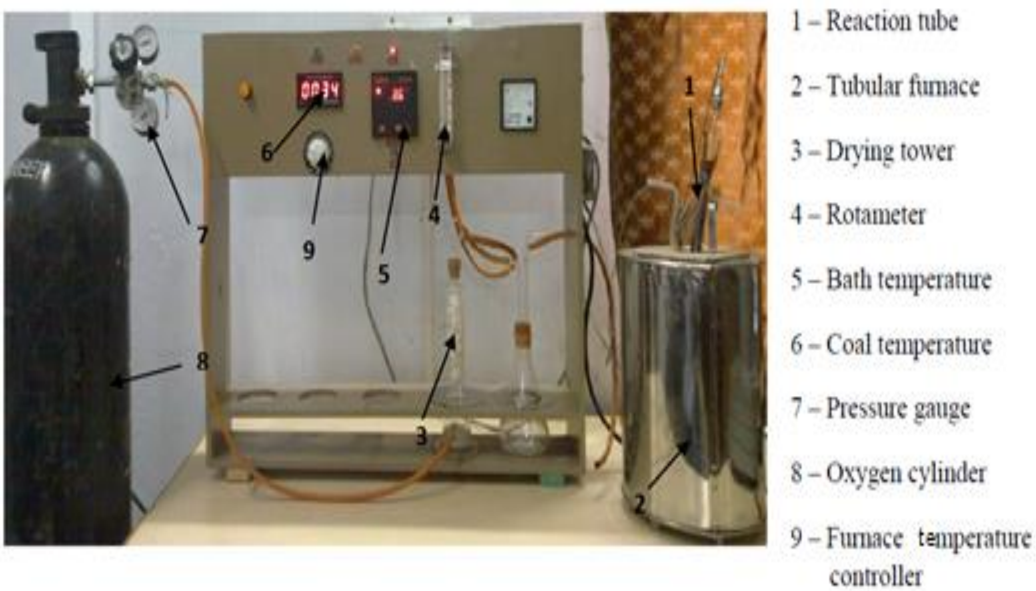


Plate 3.4 Crossing point temperature apparatus

3.2.2.2 Olpinski index method

In this method, liquid quinoline was heated in an electric oven to boil gently at a temperature of 230^{0}C producing quinoline vapour. The coal sample was grounded and small pellet of 1g of -72 mesh was prepared using the pressing unit. This pellet was heated indirectly by quinoline vapour in an atmosphere of oxygen at a predetermined rate. While heating the coal pellet, a thermocouple is inserted into it, and output of the thermocouple was recorded. The graph was plotted between the coal pellet temperature and time. The rate of rise of temperature at the moment of equalization of purging oxygen and coal pellet temperature was graphically determined by drawing tangent to the curve at the point corresponding to the quinoline vapour temperature at 230 ^{0}C (Figure 3.4). The rate of rise of temperature determined is an indication of the spontaneous heating susceptibility of the coal known as the Olpinski index (Sza). The fire risk of Indian coals can be ascertained using Table 3.2. In this method, the Sza index was corrected for ash content of the coal [65, 104] and was expressed as Szb using the equation 3.21:

$$\text{Szb} = \frac{\text{Sza}}{100-\text{A}} \text{ x } 100 \tag{3.21}$$

Where, Szb – Spontaneous heating index free of ash; and

A – Ash content of coal (%).

The increase of Szb index indicates that the sample is more susceptible to spontaneous combustion. The advantage of this method is that it takes less time and providing reasonable results as compared to crossing point temperature method.

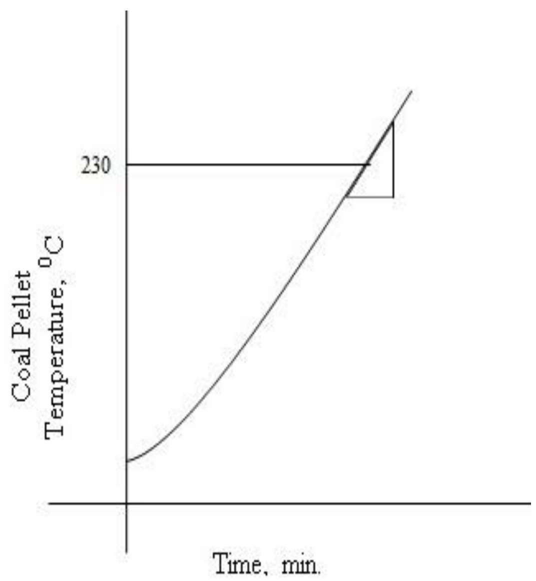
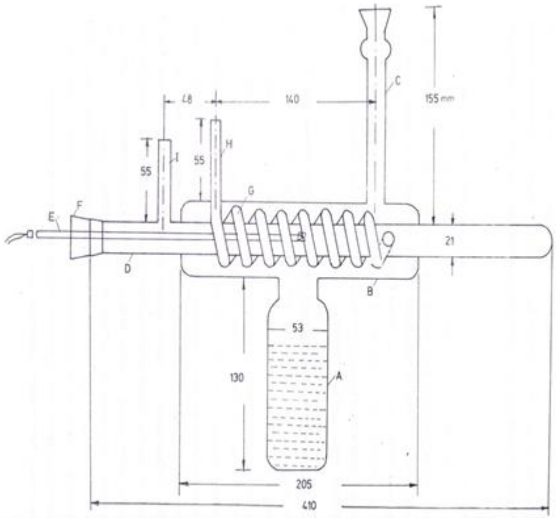


Figure 3.4 Olpinski index curve at 230 ^{0}C [65]

Plate 3.5 Olpinski index apparatus



A - Cylindrical glass vessel containing quinoline

B - Cylindrical glass enclosure perpendicular to A

C - Funnel-cum-condenser

D - Reaction tube

E - Thermocouple

F - Rubber cork

G - Spiral glass tube to preheat oxygen

H - Air inlet

I - Air outlet

Figure 3.5 Quinoline bath of Olpinski index apparatus [65]

Construction

The quinoline bath was made of glass and the schematic view is presented in Figure 3.5. It may be observed that it is having cylindrical glass vessel A of volume about 280 cc, which is connected to another cylinder B perpendicular to it. A funnel C is attached to cylinder B for pouring quinoline into the vessel and it also acts as a condenser. The reaction tube D passes axially through B so that this tube can be heated by the quinoline vapour. One end of the reaction tube is closed and the other end is open. A thermocouple E is introduced through the open end to reach upto the central line of the quinoline vessel and it is secured in that position by rubber cork F that closes the open end of the reaction tube. A glass tube G passes spirally over the reaction tube D and is connected to it towards its closed end. The other end of the spiral tube is connected to an oxygen cylinder through a flow meter to maintain the desired level of oxygen flow. The oxygen flowing through the spiral tube is preheated by the quinoline vapour and is released towards the closed end of reaction tube D. this preheated oxygen passes over the coal pellet mounted on the head of the thermocouple and finally went out through the outlet I. The quinoline bath is placed in an electric oven to heat the liquid quinoline. The temperature of the oven is controlled by a regulator and is maintained at such a level that the quinoline boils gently. The condensation of the quinoline vapour mainly takes place in the condenser C. if there is excess rise of temperature there may be unnecessary loss of quinoline vapour, because the quinoline vapour may not be effectively condensed in the condenser. The electric oven containing a quinoline bath should be placed in fume chamber with an exhaust fan to clear the quinoline vapour out of the laboratory [109]. Olpinski index apparatus is shown in Plate 3.5.

Procedure

It consists of the following steps [65, 109]

a) Preparation of pellets
b) Determination of Sza index

a) Preparation of pellets

Coal pellet was prepared with the help of pressing unit of 1g coal sample of – 72 mesh size.

b) Determination of Sza index

Olpinski index was determined using the following steps:

1. The quinoline vessel was filled up with quinoline upto its neck. It was placed in an electric oven. The oven was put on, and a controller regulated its current. Initially the current was maintained at a low level and gradually it was increased.
2. The thermocouple connected to the temperature recorder was introduced into the reaction tube.
3. Within an hour or so, quinoline starts boiling and the recorder displayed the vapour temperature. As soon as the temperature reaches 230 ^{0}C the knob of the oven was adjusted to maintain the temperature at the same level.
4. The thermocouple, which was inside the reaction tube, was taken out and allowed to cool down to room temperature.
5. The oxygen was purging at 80 cc/min and was maintained using the rotameter.
6. The thermocouple was inserted and touches the bottom surface of the coal pellet, and the thermocouple along with the coal pellet was carefully introduced into the reaction tube. The pellet should lie just above the quinoline bath so that it can be directly heated with quinoline vapour and was fixed in that position by the rubber stop cork.
7. The coal pellet temperature was noted down at an interval of 30 seconds.
8. The temperature of the pellet rises and finally it burns. As soon as the smoke was visible from the gas outlet, the thermocouple was taken out.
9. While taking out the thermocouple if the burnt pellet does not come out, then it was pushed to the closed end of the reaction tube by a glass rod. The reaction tube was cleaned off any coal powder lying in it.
10. When the thermocouple attains the room temperature the steps 6 to 9 were repeated with other pellets.
11. It yields time versus temperature graph for all the samples.

The rate of rise of coal pellet temperature was graphically determined by drawing a tangent to the curve at the point corresponding to the quinoline vapour temperature at 230^{0}C. Olpinski index was calculated from the graph (Figure 3.4) and the fire risk was obtained using Table 3.2.

Table 3.2 Classification of liability of Indian coals to spontaneous combustion based on Olpinski index [151, 17]

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

3.2.2.3 Wet oxidation potential analysis

Coal oxidation leading to (i) an immediate formation of surface oxides, followed by (ii) the formation of colloidal humic acids and finally to (iii) small aromatic and aliphatic acids in an alkaline medium is a stepwise process. It has been found that alkaline permanganate oxidation of different coals produces carbonic, acetic, oxalic, and many benzene carboxylic acids [110, 148]. It is a quick method of categorization using wet oxidation potential apparatus (Figure 3.6).

Procedure

0.5 g of coal of -72 mesh was mixed with a mixture of 50 ml of 0.1-N of potassium permanganate ($KMnO_4$) and 50 ml of 1-N potassium hydroxide (KOH) solution and the coal oxidant suspension was continuously stirred by using a magnetic stirrer. The millivolt meter records the EMF (wet oxidation potential difference, ΔE) between saturated calomel and carbon electrodes at an interval of 1 min until potential difference attains a constant value (Plate 3.6). The potential difference was recorded up to 30 min. (usually attained a steady value between 3 and 30 min, depending on the type of coal) was found out and then a graph between time and the potential difference was plotted [110, 148].

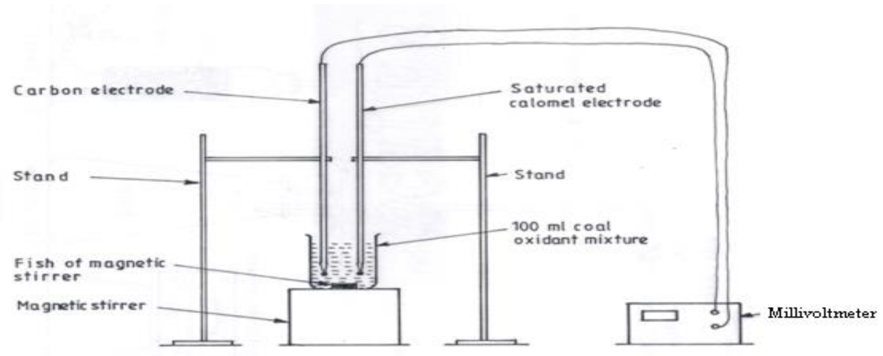


Figure 3.6 Schematic diagram of wet oxidation potential apparatus

Plate 3.6 Wet oxidation potential apparatus

3.2.2.4 Flammability temperature method

The ignition temperature of a coal decreases with increasing oxidation of coal and the difference between the ignition temperature of coal before and after oxidation can be used as a measure of the susceptibility of the coal to spontaneous combustion. The flammability temperature is the minimum temperature at which the coal begins to ignite [17, 119]. It depends on the rank of coal, nature and intensity of ignition source, particle size, moisture, ash content and oxygen concentration [17].

Procedure

The apparatus (Figure 3.7) consists of a tube furnace that can be heated to the desired temperature. The coal sample of about 0.2 g of -200 mesh size was kept in a vessel and the pressurized air is circulated in the furnace using solenoid valve. The pressurized air will form an intimate coal dust-air mixture before entering the furnace. When the furnace temperature was equal to the ignition temperature of coal, the coal catches fire, and the temperature was noted. The circulated air was pre-dried to eliminate any errors due to humidity [119].

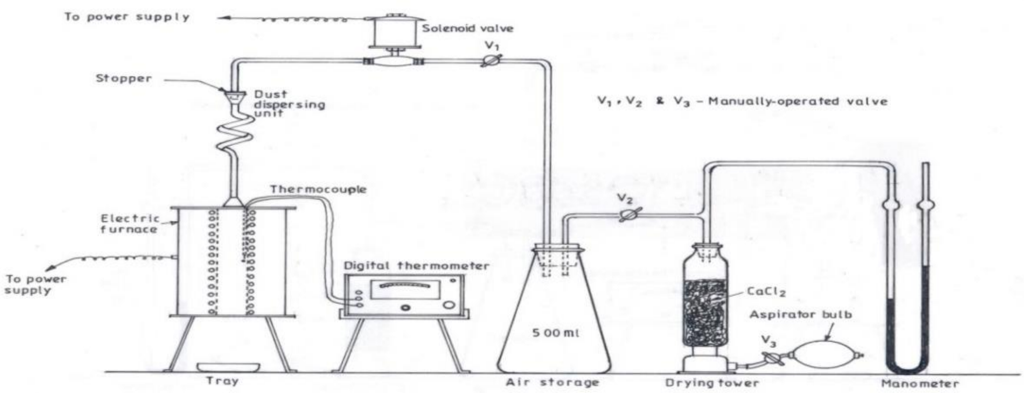


Figure 3.7 Schematic diagram of flammability temperature apparatus

3.2.2.5 Differential thermal analysis

The differential thermal analysis (DTA) (Plate 3.7) is a useful tool to measure qualitative and quantitative heat changes of any physico-chemical transitions [15]. The three stages of transitions in the thermograms (Figure 3.8) i.e., (i) endothermic reaction that predominates mainly from the release of moisture from coal in the initial stage of heating followed by (ii) the exothermic reaction, which covers a number of concurrent reactions in the second stage of heating which ultimately leads to (iii) reactions of very high exothermicity in third stage [15]. The rate rise of heat evolution in the second stage is observed to be much lower for coals with lower susceptibility to spontaneous heating and, thus, delays the initiation of the third stage. However, once initiated, the exothermicity in the third stage for even the poorly susceptible coals may be as high as that of highly susceptible ones [17, 88, 108]. The criteria thus set for categorizing coals from DTA studies are (i) the sharpness of the slope of thermograms in the second stage and (ii) the temperature of initiation of the third stage.

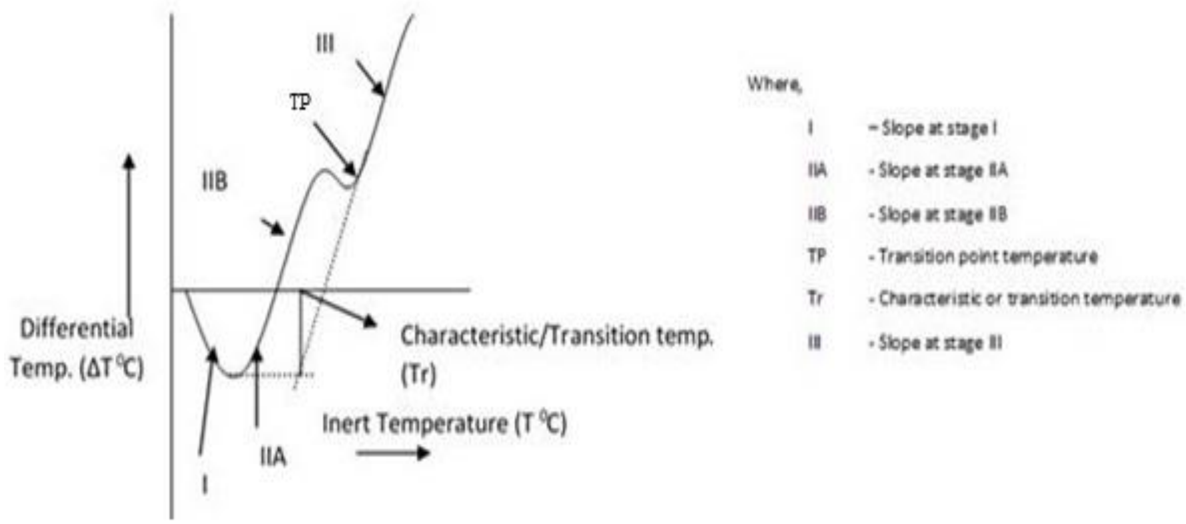


Figure 3.8 DTA thermogram

Procedure

1. About 0.6 mg of coal (more or less same as reference alumina) of -72 mesh was kept in a sample holder.
2. Maintained the rate of heating as 5 ^{0}C/min with an air medium.
3. Switched on the instrument and the software was set according to required conditions, viz. the heating rate was maintained at 5^{0} C/minute and the final temperature was taken as 450^{0}C.
4. The thermogram obtained was then analyzed for the slopes of various stages and transition temperature to know the proneness of coal to spontaneous heating.

Plate 3.7 DTG (60/60H, Shimadzu, Japan)

CHAPTER – 4

STATISTICAL ANALYSIS OF EXPERIMENTAL RESULTS

In this chapter, the experimental results of intrinsic properties, viz. proximate analysis, ultimate analysis and the macerals of petrographic analysis; as well as susceptibility indices such as crossing point temperature, flammability temperature, wet oxidation potential analysis, Olpinski index, and differential thermal analysis are summarized in tabular format. Further, the statistical analysis (univariate and multivariate) was carried out between intrinsic properties and the susceptibility indices to select the best-correlated parameters.

4.1 Experimental Results

The results of the experiments carried out on forty-nine in-situ coal samples covering selected coalfields of India are summarized in the following sections:

4.1.1 Intrinsic properties

The results of intrinsic properties such as parameters of proximate analysis, elemental composition of ultimate analysis, and maceral composition of petrographic analysis are presented in Table 4.1, 4.2, and 4.3 respectively.

Table 4.1 Results of proximate analysis

Sl. No.	Coal sample	Basis	M %	A %	VM %	FC %
1	SECL -1	ad	7.63	14.10	32.42	45.85
		dry	---	15.26	35.10	49.64
		daf	---	---	41.42	58.58
		dmmf	---	---	40.35	59.65
2	SECL -2	ad	3.16	25.60	35.21	36.03
		dry	---	26.43	36.36	37.21
		daf	---	---	49.42	50.58
		dmmf	---	---	47.54	52.46
3	SECL -3	ad	6.41	16.45	24.59	52.55
		dry	---	17.58	26.27	56.15
		daf	---	---	31.88	68.12
		dmmf	---	---	30.39	69.61
4	SECL - 4	ad	5.95	16.24	39.79	38.02
		dry	---	17.27	42.31	40.42
		daf	---	---	51.14	48.86
		dmmf	---	---	50.10	49.90
5	SECL -5	ad	8.25	12.10	39.54	40.11
		dry	---	13.19	43.10	43.71
		daf	---	---	49.64	50.36

		dmmf	---	---	48.87	51.13
6	SECL -6	ad	7.62	22.55	20.77	49.06
		dry	---	24.41	22.48	53.11
		daf	---	---	31.49	68.51
		dmmf	---	---	29.44	70.56
7	SECL -7	ad	8.15	14.99	30.91	45.95
		dry	---	16.32	33.65	50.03
		daf	---	---	40.22	59.78
		dmmf	---	---	39.03	60.97
8	SECL -8	ad	8.86	11.16	30.52	49.46
		dry	---	12.24	33.49	54.27
		daf	---	---	38.16	61.84
		dmmf	---	---	37.28	62.72
9	SECL -9	ad	12.57	17.11	33.66	36.66
		dry	---	19.57	38.50	41.93
		daf	---	---	47.87	52.13
		dmmf	---	---	46.57	53.43
10	SECL -10	ad	8.21	19.30	28.14	44.35
		dry	---	21.03	30.65	48.32
		daf	---	---	61.18	38.82
		dmmf	---	---	37.15	62.85
11	SCCL-1	ad	2.43	33.07	27.96	36.54
		dry	---	33.89	28.66	37.45
		daf	---	---	43.35	56.65
		dmmf	---	---	40.29	59.71
12	SCCL-2	ad	2.13	25.94	33.42	38.51
		dry	---	26.5	34.15	39.35
		daf	---	---	46.46	53.54
		dmmf	---	---	44.46	55.54
13	SCCL-3	ad	2.73	14.46	35.83	46.98
		dry	---	14.87	36.84	48.29
		daf	---	---	43.27	56.73
		dmmf	---	---	42.26	57.74
14	SCCL-4	ad	3.76	25.68	34.13	36.43
		dry	---	26.68	35.46	37.86
		daf	---	---	48.37	51.63
		dmmf	---	---	46.42	53.58
15	SCCL-5	ad	3.17	15.28	35.99	45.56
		dry	---	15.78	37.17	47.05
		daf	---	---	44.13	55.87
		dmmf	---	---	43.06	56.94
16	SCCL-6	ad	3.66	37.84	25.88	32.62
		dry	---	39.28	26.86	33.86
		daf	---	---	44.24	55.76
		dmmf	---	---	40.38	59.62
17	SCCL-7	ad	3.77	27.15	32.84	36.24
		dry	---	28.21	34.13	37.66
		daf	---	---	47.54	52.46

		dmmf	---	---	45.39	54.61
18	SCCL-8	ad	3.69	17.41	40.40	38.5
		dry	---	18.08	41.95	39.97
		daf	---	---	51.21	48.79
		dmmf	---	---	50.10	49.90
19	SCCL-9	ad	2.86	11.04	38.91	47.19
		dry	---	11.37	40.06	48.57
		daf	---	---	45.19	54.81
		dmmf	---	---	44.48	55.52
20	MCL-1	ad	7.13	37.48	23.17	32.22
		dry	---	40.36	24.95	34.69
		daf	---	---	41.83	58.17
		dmmf	---	---	37.61	62.39
21	MCL-2	ad	6.42	35.25	25.76	32.59
		dry	---	37.66	27.52	34.82
		daf	---	---	44.15	55.85
		dmmf	---	---	40.55	59.45
22	MCL-3	ad	2.81	13.46	30.19	53.54
		dry	---	13.85	31.06	55.09
		daf	---	---	36.05	63.95
		dmmf	---	---	35.01	64.99
23	MCL-4	ad	6.63	11.20	40.92	41.25
		dry	---	12.00	43.83	44.18
		daf	---	---	49.80	50.20
		dmmf	---	---	49.11	50.89
24	MCL-5	ad	3.89	16.20	35.55	44.36
		dry	---	16.86	36.99	46.15
		daf	---	---	44.49	55.51
		dmmf	---	---	43.34	56.66
25	MCL-6	ad	6.13	37.12	26.78	29.97
		dry	---	39.54	28.53	31.93
		daf	---	---	47.19	52.81
		dmmf	---	---	43.49	56.51
26	MCL-7	ad	7.77	14.01	26.46	51.76
		dry	---	15.19	28.69	56.12
		daf	---	---	33.83	66.17
		dmmf	---	---	32.62	67.38
27	MCL-8	ad	11.71	22.74	22.48	43.07
		dry	---	25.76	25.46	48.78
		daf	---	---	34.29	65.71
		dmmf	---	---	31.93	68.07
28	WCL-1	ad	6.03	14.50	39.97	39.50
		dry	---	15.43	42.53	42.04
		daf	---	---	50.30	49.70
		dmmf	---	---	49.37	50.63
29	WCL-2	ad	4.00	22.00	37.00	37.00
		dry	---	22.92	38.54	38.54
		daf	---	---	50.00	50.00

		dmmf	---	---	48.47	51.53
30	WCL-3	ad	6.50	16.00	35.50	42.00
		dry	---	17.11	37.97	44.92
		daf	---	---	45.81	54.19
		dmmf	---	---	44.66	55.34
31	WCL-4	ad	3.50	23.10	32.50	40.90
		dry	---	23.94	33.68	42.38
		daf	---	---	42.28	55.72
		dmmf	---	---	42.47	57.53
32	WCL-5	ad	5.50	16.00	34.50	44.00
		dry	---	16.93	36.51	46.56
		daf	---	---	43.95	56.05
		dmmf	---	---	42.78	57.22
33	WCL-6	ad	6.00	17.50	33.50	43.00
		dry	---	18.61	35.64	45.75
		daf	---	---	43.79	56.21
		dmmf	---	---	42.47	57.53
34	WCL-7	ad	7.30	16.00	31.50	45.20
		dry	---	17.26	33.98	48.76
		daf	---	---	41.07	58.93
		dmmf	---	---	39.81	60.19
35	WCL-8	ad	11.00	13.50	30.00	45.50
		dry	---	15.17	33.71	51.12
		daf	---	---	39.74	60.26
		dmmf	---	---	38.64	61.36
36	WCL-9	ad	4.13	19.50	28.97	47.40
		dry	---	20.34	30.22	49.44
		daf	---	---	37.93	62.07
		dmmf	---	---	36.31	63.69
37	WCL-10	ad	4.00	16.09	30.18	49.73
		dry	---	16.76	31.44	51.80
		daf	---	---	37.77	62.23
		dmmf	---	---	36.49	63.51
38	NEC-1	ad	1.32	6.20	43.26	49.22
		dry	---	6.28	43.84	49.88
		daf	---	---	46.78	53.22
		dmmf	---	---	46.42	53.58
39	NEC-2	ad	1.90	6.90	44.12	47.08
		dry	---	7.04	44.97	47.99
		daf	---	---	48.38	51.62
		dmmf	---	---	47.98	52.02
40	NEC-3	ad	4.06	11.63	54.12	30.19
		dry	---	12.12	56.41	31.47
		daf	---	---	64.19	35.81
		dmmf	---	---	63.69	36.31
41	NEC-4	ad	2.36	11.21	55.45	30.98
		dry	---	11.48	56.79	31.73
		daf	---	---	64.16	35.84

		dmmf	---	---	63.68	36.32
42	NEC-5	ad	2.15	13.50	54.44	29.91
		dry	---	13.80	55.64	30.56
		daf	---	---	64.54	35.46
		dmmf	---	---	63.96	36.04
43	NEC-6	ad	2.53	8.31	56.30	32.86
		dry	---	8.53	57.76	33.71
		daf	---	---	63.14	36.86
		dmmf	---	---	62.80	37.20
44	NCL-1	ad	7.94	19.40	28.40	44.26
		dry	---	21.07	30.85	48.08
		daf	---	---	39.09	60.91
		dmmf	---	---	37.42	62.58
45	NCL-2	ad	8.03	19.06	31.21	41.70
		dry	---	20.72	33.94	45.34
		daf	---	---	42.81	57.19
		dmmf	---	---	41.27	58.73
46	IISCO-1	ad	0.82	31.57	14.24	53.37
		dry	---	31.83	14.36	53.81
		daf	---	---	21.06	78.94
		dmmf	---	---	17.20	82.80
47	IISCO-2	ad	0.97	27.96	16.58	54.49
		dry	---	28.23	16.74	55.03
		daf	---	---	23.33	76.67
		dmmf	---	---	20.19	79.81
48	BCCL-1	ad	1.39	16.30	18.48	63.83
		dry	---	16.53	18.74	64.73
		daf	---	---	22.45	77.55
		dmmf	---	---	20.88	79.12
49	TISCO-1	ad	1.44	15.05	17.86	65.65
		dry	---	15.27	18.12	66.61
		daf	---	---	21.39	78.61
		dmmf	---	---	19.94	80.06

NB: *Where, M - Moisture, A - Ash, VM - Volatile matter, FC - Fixed carbon, ad - air dried, daf - dry ash free, dmmf - dry mineral matter free, IISCO-1,2, BCCL-1, and TISCO-1 are coking coals, whereas rest of the samples are non-coking coals.*

Table 4.2 Results of ultimate analysis

Sl. No.	Coal sample	Basis	M %	A %	C %	H %	N %	S %	O %
1	SECL -1	ad	7.63	14.10	65.55	3.71	1.16	0.3	7.55
		dry	---	15.26	70.97	4.02	1.25	0.32	8.17
		daf	---	---	83.75	4.74	1.48	0.38	9.64
2	SECL -2	ad	3.16	25.60	58.08	3.67	1.11	0.3	8.08
		dry	---	26.43	59.97	3.79	1.15	0.31	8.34
		daf	---	---	81.53	5.15	1.56	0.42	11.34

3	SECL -3	ad	6.41	16.45	62.32	3.54	1.12	0.25	9.90
		dry	---	17.58	66.59	3.78	1.20	0.27	10.58
		daf	---	---	80.79	4.59	1.46	0.32	12.84
4	SECL - 4	ad	5.95	16.24	62.25	3.83	1.36	0.31	10.07
		dry	---	17.27	66.18	4.07	1.44	0.33	10.70
		daf	---	---	80.00	4.92	1.74	0.40	12.94
5	SECL -5	ad	8.25	12.10	65.20	4.97	1.29	0.81	7.38
		dry	---	13.19	71.07	5.42	1.40	0.88	8.04
		daf	---	---	81.86	6.24	1.62	1.02	9.27
6	SECL -6	ad	7.62	22.55	55.33	4.12	1.53	0.89	9.74
		dry	---	24.41	59.89	4.46	1.66	0.96	10.55
		daf	---	---	77.26	5.75	2.14	1.24	13.60
7	SECL -7	ad	8.15	14.99	60.25	4.03	1.57	0.61	10.41
		dry	---	16.32	65.59	4.39	1.70	0.66	11.33
		daf	---	---	78.38	5.24	2.04	0.79	13.54
8	SECL -8	ad	8.86	11.16	62.24	4.92	1.20	0.43	11.19
		dry	---	12.24	68.29	5.40	1.32	0.47	12.28
		daf	---	---	77.81	6.15	1.50	0.54	13.99
9	SECL -9	ad	12.57	17.11	56.22	3.15	0.25	0.73	9.97
		dry	---	19.57	64.30	3.60	0.29	0.83	11.40
		daf	---	---	79.94	4.48	0.36	1.04	14.18
10	SECL -10	ad	8.21	19.30	56.92	4.22	1.35	0.38	9.62
		dry	---	21.03	62.01	4.60	1.47	0.41	10.48
		daf	---	---	78.52	5.82	1.87	0.52	13.27
11	SCCL-1	ad	2.43	33.07	48.83	4.12	3.21	0.46	7.87
		dry	---	33.89	50.05	4.22	3.29	0.47	8.07
		daf	---	---	75.71	6.39	4.98	0.71	12.21
12	SCCL-2	ad	2.13	25.94	59.21	3.99	1.03	0.55	7.15
		dry	---	26.5	60.50	4.08	1.05	0.56	7.31
		daf	---	---	82.32	5.55	1.43	0.76	9.94
13	SCCL-3	ad	2.73	14.46	67.25	3.16	1.65	0.21	10.54
		dry	---	14.87	69.14	3.25	1.69	0.22	10.84
		daf	---	---	81.22	3.82	1.99	0.25	12.73
14	SCCL-4	ad	3.76	25.68	56.21	2.9	1.57	0.32	9.56
		dry	---	26.68	58.41	3.01	1.63	0.33	9.93
		daf	---	---	79.67	4.11	2.22	0.45	13.54
15	SCCL-5	ad	3.17	15.28	64.80	4.21	1.32	0.61	10.62
		dry	---	15.78	66.91	4.35	1.36	0.63	10.97
		daf	---	---	79.45	5.16	1.62	0.75	13.02
16	SCCL-6	ad	3.66	37.84	46.12	2.86	0.33	0.59	8.60
		dry	---	39.28	47.87	2.97	0.34	0.61	8.93
		daf	---	---	78.84	4.89	0.56	1.01	14.71
17	SCCL-7	ad	3.77	27.15	57.68	1.36	2.12	0.65	7.27
		dry	---	28.21	59.94	1.41	2.21	0.68	7.55
		daf	---	---	83.50	1.97	3.08	0.94	10.52
18	SCCL-8	ad	3.69	17.41	64.57	4.31	1.26	0.67	8.09
		dry	---	18.08	67.04	4.48	1.31	0.70	8.40
		daf	---	---	81.84	5.46	1.60	0.85	10.26

19	SCCL-9	ad	2.86	11.04	69.32	3.45	1.33	0. 54	11.46
		dry	---	11.37	71.36	3.55	1.36	0.56	11.80
		daf	---	---	80.51	4.01	1.54	0.63	13.31
20	MCL-1	ad	7.13	37.48	40.39	4.23	0.55	0.44	9.77
		dry	---	40.36	43.50	4.55	0.60	0.47	10.52
		daf	---	---	72.93	7.64	1.00	0.79	17.64
21	MCL-2	ad	6.42	35.25	43.21	4.36	1.00	0.69	9.06
		dry	---	37.66	46.18	4.66	1.07	0.74	9.68
		daf	---	---	74.09	7.47	1.72	1.18	15.54
22	MCL-3	ad	2.81	13.46	67.13	3.21	1.25	0.25	11.90
		dry	---	13.85	69.07	3.30	1.28	0.26	12.24
		daf	---	---	80.17	3.83	1.49	0.30	14.21
23	MCL-4	ad	6.63	11.20	68.12	3.12	1.11	0.23	9.58
		dry	---	12.00	72.96	3.34	1.19	0.25	10.26
		daf	---	---	82.91	3.80	1.36	0.28	11.66
24	MCL-5	ad	3.89	16.20	65.26	2.89	2.31	0.25	9.20
		dry	---	16.86	67.90	3.01	2.41	0.26	9.57
		daf	---	---	81.67	3.62	2.90	0.31	11.51
25	MCL-6	ad	6.13	37.12	37.97	4.23	3.10	0.6	10.85
		dry	---	39.54	40.45	4.51	3.31	0.64	11.56
		daf	---	---	66.90	7.45	5.47	1.06	19.12
26	MCL-7	ad	7.77	14.01	61.25	4.62	2.92	0.89	8.53
		dry	---	15.19	66.42	5.01	3.17	0.96	9.25
		daf	---	---	78.31	5.91	3.73	1.14	10.91
27	MCL-8	ad	11.71	22.74	50.89	4.57	2.47	0.76	6.86
		dry	---	25.76	57.64	5.18	2.79	0.86	7.77
		daf	---	---	77.64	6.97	3.76	1.16	10.47
28	WCL-1	ad	6.03	14.50	65.25	2.57	1.25	0.12	10.27
		dry	---	15.43	69.44	2.73	1.34	0.13	10.93
		daf	---	---	82.11	3.23	1.58	0.15	12.92
29	WCL-2	ad	4.00	22.00	61.26	2.35	1.27	0.15	8.97
		dry	---	22.92	63.81	2.45	1.32	0.16	9.35
		daf	---	---	82.78	3.18	1.71	0.20	12.13
30	WCL-3	ad	6.50	16.00	62.99	4.25	1.70	0.21	8.36
		dry	---	17.11	67.36	4.55	1.82	0.22	8.94
		daf	---	---	81.27	5.48	2.19	0.27	10.78
31	WCL-4	ad	3.50	23.10	60.25	3.36	2.30	0.25	7.24
		dry	---	23.94	62.44	3.48	2.38	0.26	7.50
		daf	---	---	82.09	4.58	3.13	0.34	9.86
32	WCL-5	ad	5.50	16.00	61.19	3.77	3.56	0.38	9.60
		dry	---	16.93	64.75	3.99	3.77	0.40	10.16
		daf	---	---	77.95	4.80	4.53	0.48	12.23
33	WCL-6	ad	6.00	17.50	59.21	4.1	1.10	0.66	11.42
		dry	---	18.61	62.99	4.36	1.17	0.70	12.15
		daf	---	---	77.40	5.36	1.44	0.86	14.93
34	WCL-7	ad	7.30	16.00	61.13	4.21	1.35	0.58	9.44
		dry	---	17.26	65.94	4.54	1.45	0.63	10.18
		daf	---	---	79.69	5.49	1.75	0.76	12.31

35	WCL-8	ad	11.00	13.50	62.12	4.12	1.21	0.45	7.59
		dry	---	15.17	69.80	4.63	1.36	0.51	8.53
		daf	---	---	82.28	5.46	1.61	0.60	10.05
36	WCL-9	ad	4.13	19.50	60.26	2.89	2.41	0.64	10.17
		dry	---	20.34	62.85	3.01	2.52	0.67	10.60
		daf	---	---	78.90	3.78	3.16	0.84	13.31
37	WCL-10	ad	4.00	16.09	63.97	3.24	3.30	0.49	8.91
		dry	---	16.76	66.63	3.38	3.44	0.51	9.28
		daf	---	---	80.05	4.05	4.13	0.61	11.15
38	NEC-1	ad	1.32	6.20	67.25	4.2	2.82	2.1	16.10
		dry	---	6.28	68.15	4.26	2.86	2.13	16.32
		daf	---	---	72.72	4.54	3.05	2.27	17.41
39	NEC-2	ad	1.90	6.90	63.89	5.6	2.57	2.4	16.74
		dry	---	7.04	65.13	5.71	2.62	2.45	17.07
		daf	---	---	70.06	6.14	2.81	2.63	18.36
40	NEC-3	ad	4.06	11.63	61.26	3.89	2.82	0.98	15.36
		dry	---	12.12	63.85	4.05	2.94	1.02	16.01
		daf	---	---	72.66	4.61	3.35	1.16	18.22
41	NEC-4	ad	2.36	11.21	63.21	3.93	1.45	0.51	17.33
		dry	---	11.48	64.74	4.02	1.48	0.52	17.75
		daf	---	---	73.14	4.55	1.68	0.59	20.05
42	NEC-5	ad	2.15	13.50	59.94	3.48	1.25	0.81	18.86
		dry	---	13.80	61.26	3.56	1.28	0.83	19.28
		daf	---	---	71.06	4.13	1.49	0.96	22.36
43	NEC-6	ad	2.53	8.31	64.26	3.25	4.31	0.58	16.76
		dry	---	8.53	65.92	3.33	4.43	0.60	17.19
		daf	---	---	72.07	3.65	4.84	0.65	18.80
44	NCL-1	ad	7.94	19.40	56.26	3.9	2.92	0.99	8.59
		dry	---	21.07	61.11	4.24	3.17	1.08	9.33
		daf	---	---	77.43	5.37	4.02	1.36	11.82
45	NCL-2	ad	8.03	19.06	54.21	4.93	1.55	0.53	11.69
		dry	---	20.72	58.95	5.36	1.68	0.58	12.71
		daf	---	---	74.36	6.76	2.12	0.73	16.03
46	IISCO-1	ad	0.82	31.57	53.94	3.49	1.15	0.81	8.21
		dry	---	31.83	54.39	3.52	1.16	0.82	8.28
		daf	---	---	79.78	5.16	1.71	1.20	12.15
47	IISCO-2	ad	0.97	27.96	51.26	4.21	4.21	0.58	10.81
		dry	---	28.23	51.76	4.25	4.25	0.59	10.92
		daf	---	---	72.12	5.92	5.93	0.82	15.21
48	BCCL-1	ad	1.39	16.30	67.21	4.53	3.25	0.32	7.00
		dry	---	16.53	68.16	4.59	3.29	0.32	7.10
		daf	---	---	81.66	5.50	3.94	0.39	8.50
49	TISCO-1	ad	1.44	15.05	68.70	4.69	2.12	0.43	7.57
		dry	---	15.27	69.70	4.76	2.16	0.44	7.68
		daf	---	---	82.26	5.62	2.54	0.51	9.06

NB: *Where, M - Moisture, A - Ash, C - Carbon, H - Hydrogen, N - Nitrogen, S - Sulphur, O – Oxygen, ad - air dried, daf - dry ash free.*

Table 4.3 Results of petrographic analysis

Sl. No.	Coal Sample	Macerals Volume (%)			
		V%	L%	I%	VMM %
1	SECL -1	18.91	5.85	53.04	22.20
2	SECL -2	17.00	6.12	52.97	23.91
3	SECL -3	32.87	5.35	49.50	12.28
4	SECL -4	31.31	3.97	57.38	7.34
5	SECL -5	58.43	1.57	24.51	15.49
6	SECL -6	49.23	6.17	33.96	10.64
7	SECL -7	28.79	6.2	33.11	31.9
8	SECL -8	39. 76	4.71	29.26	26.27
9	SECL -9	29.14	9.03	53.19	8.64
10	SECL -10	30.57	11.41	48.01	10.01
11	SCCL-1	45.88	1.76	38.83	13.53
12	SCCL-2	45.72	1.67	38.29	14.32
13	SCCL-3	42.89	6.8	33.98	16.33
14	SCCL-4	42.3	6.32	34.39	16.99
15	SCCL-5	41.66	7.22	33.96	17.16
16	SCCL-6	50.35	4.62	27.79	17.24
17	SCCL-7	53.79	4.89	30.23	11.09
18	SCCL-8	52.15	4.12	25.69	18.04
19	SCCL-9	54.71	4.71	32.54	8.04
20	MCL-1	19. 24	6.7	28.99	45.07
21	MCL-2	18. 88	7.89	31.34	41.89
22	MCL-3	21.11	9.84	20.55	48.5
23	MCL-4	39.88	7.25	35.16	17.71
24	MCL-5	33.19	7.88	16	42.93
25	MCL-6	23.78	2.76	25.12	48.34
26	MCL-7	28.2	5.11	25.23	41.46
27	MCL-8	38.67	3.35	26.11	31.87
28	WCL-1	58.62	4.55	17.23	19.60
29	WCL-2	66.74	3.56	16.63	13.07
30	WCL-3	34.85	2.77	43.96	18.42
31	WCL-4	56.55	5.75	26.19	11.51
32	WCL-5	42.18	5.94	40.59	11.29
33	WCL-6	40.07	6.03	39.88	14.02
34	WCL-7	40.97	8.76	37.88	12.39
35	WCL-8	29.15	8.52	50.93	11.40
36	WCL-9	27.44	9.16	49.74	13.66
37	WCL-10	31.47	8.38	50.23	9.92
38	NEC-1	86.87	4.32	5.10	3.71
39	NEC-2	85.21	4.45	5.83	4.51
40	NEC-3	85.94	4.73	5.76	3.57
41	NEC-4	84.18	4.56	5.42	5.84
42	NEC-5	86.35	4.18	5.39	4.08
43	NEC-6	85.81	4.37	5.94	3.88
44	NCL-1	35.08	1.6	40.94	22.38

45	NCL-2	36. 87	0.67	41.32	21.14
46	IISCO-1	59.36	2.19	30.68	7.77
47	IISCO-2	58.33	2.17	31.92	7.58
48	BCCL-1	59.94	2.79	27.32	9.95
49	TISCO-1	62.29	3.39	28.68	5.64

NB: *Where, V - Vitrinite, L - Liptinite, I - Inertinite, VMM - Visible mineral matter.*

4.1.2 Susceptibility indices

The results of susceptibility indices, viz. crossing point temperature, flammability temperature, wet oxidation potential difference, Olpinski index, and differential thermal analysis are presented in Table 4.4.

Table 4.4 Results of susceptibility indices

Coal sample	CPT ^{0}C	FT ^{0}C	ΔE mV	Olpinski index		DTA analysis			
				Sza ^{0}C/min	Szb ^{0}C/min	IIA	IIB	II	Tr ^{0}C
SECL -1	175	550	132	58.41	68	0.023	0.01	0.014	154.56
SECL -2	182	555	159	55.06	74	0.022	0.008	0.011	166.77
SECL -3	156	540	135	71.02	85	0.05	0.01	0.02	173.68
SECL -4	178	545	130	58.63	70	0.042	0.012	0.02	175.93
SECL -5	158	540	165	87.02	99	0.02	0.013	0.018	173.59
SECL -6	163	535	133	61.29	77.36	0.035	0.009	0.015	169.2
SECL -7	176	575	152	58.78	69.14	0.051	0.0105	0.017	172.58
SECL -8	182	580	125	56.2	63.26	0.028	0.009	0.013	142.82
SECL -9	154	525	116	89.43	107.89	0.05	0.015	0.029	164.12
SECL -10	188	580	140	52.79	65.42	0.072	0.0134	0.0185	171.43
SCCL-1	175	520	140	48.86	73	0.032	0.1	0.101	168.63
SCCL-2	180	500	155	49.62	67	0.045	0.11	0.12	175.03
SCCL-3	153	530	159	94.95	111	0.01	0.12	0.124	149.6
SCCL-4	179	510	151	40.88	55	0.08	0.117	0.121	178.14
SCCL-5	164	510	136	65.23	77	0.02	0.136	0.139	161.52
SCCL-6	168	500	150	48.48	78	0.01	0.114	0.137	118.69
SCCL-7	166	510	143	42.98	59	0.033	0.126	0.127	137.7
SCCL-8	157	530	125	87.33	105.74	0.056	0.126	0.128	177.34
SCCL-9	172	525	144	66.08	74.28	0.073	0.179	0.144	177.63
MCL-1	154	500	73	61.27	98	0.374	0.805	0.53	178.6
MCL-2	158	515	82	67.34	104	0.385	0.037	0.584	178.26
MCL-3	151	525	59	94.33	109	0.387	0.69	0.516	159.35
MCL-4	142	500	104	93.24	105	0.495	0.242	0.534	98.78
MCL-5	152	540	92	92.18	110	0.31	0.084	0.201	125.1
MCL-6	168	535	81	49.05	78	0.325	0.368	0.346	153.08
MCL-7	148	480	75	101.13	117.61	0.100	0.181	0.142	146.76
MCL-8	164	540	95	44.99	58.23	0.891	0.089	0.985	152.16
WCL-1	155	550	131	83.79	98	0.86	0.711	0.891	159.99
WCL-2	149	540	141	87.36	112	0.802	0.811	0.772	135.79

WCL-3	142	535	139	89.88	107	0.703	0.917	0.806	165.83
WCL-4	147	540	145	68.44	89	0.685	0.4	0.565	133.94
WCL-5	157	560	72	82.32	98	0.593	0.945	0.746	180.16
WCL-6	148	540	68	76.73	93	0.728	0.821	0.792	146.53
WCL-7	165	540	114	49.63	59.08	0.648	0.585	0.614	137.49
WCL-8	155	530	94	94.24	108.95	0.527	0.896	0.688	157.65
WCL-9	153	520	178	93.77	116.48	0.262	0.573	0.378	171.51
WCL-10	143	475	144	99.63	118.73	0.221	0.670	0.367	184.18
NEC-1	150	520	56	102.24	109	0.243	0.985	0.445	199.55
NEC-2	153	545	65	109.86	118	0.148	0.605	0.268	216.36
NEC-3	152	515	68	98.87	111.88	0.142	0.484	0.243	178.85
NEC-4	151	500	72	102.62	115.58	0.106	0.553	0.229	193.18
NEC-5	154	520	69	97.88	113.16	0.378	0.519	0.433	158.63
NEC-6	176	570	87	62.98	68.69	0.112	0.766	0.236	206.13
NCL-1	141	490	182	121.71	151	0.182	0.883	0.997	144.47
NCL-2	146	530	148	137.60	170	0.665	0.783	0.717	160.06
IISCO-1	180	570	46	30.79	45	0.032	0.141	0.123	152.7
IISCO-2	165	560	48	50.43	70	0.035	0.548	0.1	247.57
BCCL-1	178	575	55	54.03	64.55	0.038	0.724	0.148	247.14
TISCO-1	192	590	67	49.32	58.06	0.050	0.801	**0**.148	239.44

NB: *Where, CPT – Crossing point temperature, FT – Flammability temperature, ∆E - Wet oxidation potential difference, Sza – Olpinski index, Szb - Olpinski index (free of ash), IIA – Slope at stage IIA, IIB – Slope at stage IIB, II – Slope at stage II, Tr – Transition temperature.*

4.2 Discussion on Experimental Results

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 Tables 4.1 to 4.3. The results of proximate analysis shows that for three non-coking coal samples (SECL-9, MCL-8, and WCL-8), the moisture content was very high i.e. ≥ 11% matches with the field observations while 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 coalfields (NEC-1 – NEC-6), it ranged from 6.2% - 13.5% and 43.26% - 56.30% while for coking coals, the ash and volatile matter contents were between 15.05% - 31.57% and 14.24% - 18.48%. High inherent moisture and volatile matter coals have a higher tendency to spontaneous heating [17]. Therefore, only three parameters of proximate analysis, viz. moisture (M), ash (A) and volatile matter (VM) on air dried basis were considered to ascertain the tendency of coal to spontaneous heating.

The results of the petrographic analysis are summarized in Table 4.3. The degree of proneness to spontaneous combustion increases with the rise of vitrinite and liptinite, but decreases with the rise of inertinite content [151]. Vitrinite content is richer in North-Eastern coalfields, it ranged from 84.18% - 86.87% while for coking coals, the values were between 58.33% - 62.29%. Liptinite and inertinite were in the ranges of 0.67% - 11.41% and 5.1% - 57.38% respectively in the investigated coal samples. In North-Eastern coalfields, less liptinite (4.18% - 4.73%) and inertinite (5.1% - 5.94%) were present. Hence, three macerals (V, L, and I) were considered as the most influencing parameters of petrographic analysis for assessment of spontaneous heating of coals.

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 [120]. Pyrite might have an appreciable effect if its concentration in finely dispersed form exceeds 5-10%. The effect would be not of much importance if the pyrite present is less than 5% [144]. Indian coals have low-sulphur content except in North-Eastern coalfield, and the pyrite is one of the key factors of the susceptibility of coal to spontaneous combustion. The results show that NEC coals have sulphur content less than 3%, which might not be reflected 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 in accordance to the percentage of carbon, hydrogen, and oxygen in coal [45]. Therefore, only carbon (C), hydrogen (H) and oxygen (O) were considered and they play a vital role as compared to other elements nitrogen (N) and sulphur (S) of ultimate analysis.

The results of the susceptibility indices i.e. crossing point temperature, flammability temperature, wet oxidation potential, Olpinski index free of ash, and differential thermal analysis are summarized in Table 4.4. The graphs are plotted for CPT, ΔE, Sza and DTA thermograms of all investigated coal samples and are depicted in Appendices A1, A2, A3, and A4 respectively. 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 [98]. The tendency of coal to spontaneous combustion increases with high wet oxidation potential difference. If Szb increases, it implies increase in the susceptibility of coal to spontaneous heating. In FT, coal that is more susceptible towards aerial oxidation burns at low temperature as compared to less susceptible coals. In case of DTA, if stage II is dragged to a considerable range of temperature, it delays the initiation of stage III in poorly susceptible coals [151]. The sharpness of the slope of the thermograms in stage II can also be considered as set criteria for categorizing coals.

4.3 Statistical Analysis

Univariate and multivariate statistical analysis was carried out using Microsoft Excel-2010 to find out the best-correlated parameters. For that, intrinsic properties and susceptibility indices were considered as independent and dependent variables respectively.

4.3.1 Univariate analysis

Univariate analysis between intrinsic properties, viz. parameters of proximate analysis the (M, VM and A), elements of ultimate analysis (C, H and O), macerals of petrographic analysis (V, L and I) and susceptibility indices (CPT, FT, ΔE, Szb, Slope IIA, Slope IIB, Slope II and Tr) were carried out on different basis. It revealed that the elements of ultimate analysis (C, H, and O) on dry ash free basis show significant correlation with all investigated susceptibility indices (CPT, FT, ΔE and Szb) as compared to other independent and dependent variables based on correlation coefficient, r and standard error, SE (Table 4.5).

Table 4.5 Univariate analysis between intrinsic properties on different basis and the susceptibility indices

Sl. No.	Susceptibility indices → / Intrinsic properties ↓	Univariate analysis	CPT	FT	ΔE	Sz_b	Slope IIA	Slope IIB	Slope II	Tr
1	M_{ad}	r	0.98	0.98	0.91	0.85	0.71	0.61	0.73	0.72
		SE	0.24	1.02	0.49	0.48	0.26	0.41	0.30	1.53
2	VM_{ad}	r	0.95	0.98	0.91	0.95	0.67	0.75	0.72	0.82
		SE	0.49	1.54	0.49	0.29	0.27	0.34	0.30	1.26
3	A_{ad}	r	0.92	0.91	0.88	0.85	0.62	0.63	0.68	0.73
		SE	0.61	2.12	0.56	0.48	0.29	0.40	0.32	1.51
4	C_{ad}	r	0.98	0.99	0.94	0.95	0.67	0.76	0.73	0.84
		SE	0.24	0.65	0.40	0.27	0.27	0.33	0.30	1.18
5	H_{ad}	r	0.92	0.98	0.91	0.94	0.66	0.75	0.72	0.82
		SE	0.33	1.02	0.49	0.30	0.27	0.34	0.30	1.28
6	O_{ad}	r	0.95	0.96	0.87	0.94	0.65	0.78	0.71	0.81
		SE	0.48	1.48	0.57	0.30	0.28	0.32	0.31	1.30
7	C_{daf}	r	0.99	0.99	0.95	0.95	0.68	0.75	0.74	0.84
		SE	0.15	0.36	0.36	0.27	0.27	0.34	0.29	1.20
8	H_{daf}	r	0.97	0.97	0.90	0.95	0.67	0.73	0.73	0.80
		SE	0.37	1.21	0.50	0.33	0.27	0.35	0.30	1.32
9	O_{daf}	r	0.96	0.97	0.90	0.95	0.66	0.76	0.73	0.81
		SE	0.40	1.25	0.53	0.29	0.27	0.33	0.30	1.30
10	V	r	0.94	0.94	0.86	0.90	0.63	0.76	0.69	0.80
		SE	0.54	1.73	0.59	0.41	0.28	0.33	0.32	1.34

11	**L**	r	0.54	0.54	0.93	0.55	0.33	0.50	0.38	0.46
		SE	0.37	4.50	1.08	0.79	0.35	0.44	0.41	1.98
12	**I**	r	0.92	0.92	0.93	0.88	0.61	0.66	0.67	0.78
		SE	0.61	2.04	0.43	0.44	0.29	0.38	0.32	1.39

4.3.2 Multivariate analysis

Multivariate analysis was carried out on the combined parameters of the proximate analysis (M, VM and Ash), ultimate analysis (C, H and O), and the macerals of petrographic analysis (V, L and I) with the investigated susceptibility indices. From the results shown in Table 4.6, it can be inferred that CPT, FT, ΔE and Szb show significant correlation results with the parameters of ultimate analysis on dry ash free basis based on correlation coefficient, r (0.99, 0.99, 0.95 and 0.96), standard error, SE (0.13, 0.27, 0.38 and 0.25), and variance, σ (0.01, 0.07, 0.14 and 0.06) as compared to the other parameters. The macerals and other susceptibility indices show no significant correlation due to lower r, high SE and high σ.

Table 4.6 Multivariate analysis between intrinsic properties on different basis and the susceptibility indices

Sl. No.	Independent variable	Multivariate analysis	CPT	FT	ΔE	Szb	Slope IIA	Slope IIB	Slope II	Tr
1.	M_{ad}, VM_{ad} and A_{ad}	**r**	0.98	0.98	0.94	0.95	0.69	0.74	0.75	0.82
		SE	0.28	0.89	0.39	0.27	0.26	0.35	0.29	1.25
		μ	1.61	5.32	1.13	0.9	0.24	0.39	0.33	1.86
		σ	0.01	0.07	0.14	0.06	0.07	0.11	0.07	0.14
2.	C_{ad}, H_{ad} and O_{ad}	**r**	0.98	0.99	0.93	0.96	0.65	0.77	0.73	0.84
		SE	0.29	0.61	0.42	0.25	0.27	0.33	0.30	1.19
		μ	1.61	5.32	1.13	0.90	0.24	0.38	0.32	1.85
		σ	0.01	0.07	0.14	0.06	0.02	0.11	0.08	1.44
3.	C_{daf}, H_{daf} and O_{daf}	**r**	0.99	0.99	0.95	0.96	0.68	0.75	0.74	0.84
		SE	0.13	0.27	0.38	0.25	0.27	0.33	0.29	1.21
		μ	1.61	5.32	1.13	0.90	0.24	0.38	0.32	1.85
		σ	0.01	0.07	0.14	0.06	0.07	0.11	0.08	1.44
4.	V, L and I	**r**	0.97	0.97	0.91	0.93	0.64	0.77	0.71	0.82
		SE	0.36	1.13	0.48	0.32	0.28	0.33	0.31	1.25
		μ	1.61	5.32	1.13	0.9	0.29	0.38	0.32	1.85
		σ	0.01	0.07	0.14	0.06	0.07	0.11	0.08	1.44

***NB:** Where, r – Correlation coefficient, SE – Standard error, μ – Mean, σ – Variance.*

4.4 Discussion on Statistical Analysis

From the univariate and multivariate analysis of the investigated coals, it can be concluded that elements of ultimate analysis (C, H and O) on dry ash free basis can be used for classification of fire risk of Indian coals with susceptibility indices (CPT, FT, ΔE and Szb). The empirical relationship between the combined parameters of ultimate analysis (C, H and

O) on dry ash free basis and the different susceptibility indices of the Indian coals are presented in Table 4.7. These empirical equations can predict the related dependent variables (CPT, FT, Szb, ΔE, Slope IIA, Slope IIB, Slope II and Tr) based on input parameters of ultimate analysis (C, H and O) on dry ash free basis. The results obtained using empirical relation will be helpful to ascertain the fire risk of Indian coals.

Table 4.7 Empirical relationship between the combined parameters of ultimate analysis (C, H, and O) on dry ash free basis and the susceptibility indices

Independent variable	Empirical relation
C_{daf}, H_{daf}, and O_{daf}	$CPT = 0.56\ C_{daf} + 2.66\ H_{daf} - 0.2\ O_{daf} + 107.15$
	$FT = 0.03\ C_{daf} + 2.54\ H_{daf} - 1.16\ O_{daf} + 533.05$
	$S_{Zb} = -\ 0.05\ C_{daf} - 1.28\ H_{daf} + 2.09\ O_{daf} + 73.68$
	$\Delta E = 5.69\ C_{daf} + 1.8\ H_{daf} + 1.42\ O_{daf} - 361.24$
	$\text{Slope IIA} = 0.01\ C_{daf} + 0.02\ H_{daf} + 0.01\ O_{daf} - 0.96$
	$\text{Slope IIB} = -\ 0.06\ C_{daf} - 0.1\ H_{daf} - 0.04\ O_{daf} + 6.53$
	$\text{Slope II} = -\ 0.02\ C_{daf} - 0.01\ H_{daf} - 0.01\ O_{daf} + 1.87$
	$Tr = -7.2\ C_{daf} - 3.8\ H_{daf} - 6.57\ O_{daf} + 839.02$

CHAPTER – 5

APPLICATION OF SOFT COMPUTING TECHNIQUES FOR THE ASSESSMENT OF FIRE RISK OF INDIAN COALS

Literature review reveals that limited work has been carried out on the fire risk assessment of Indian coals using soft computing techniques. Therefore, in this chapter an attempt has been made to develop mathematical models using soft computing techniques viz. artificial neural network techniques viz. multilayer perceptron network, functional link artificial neural network, and random basis function network. The most precise developed ANN model can help the mine management to predict in advance the fire risk of Indian coals and thereby adopt appropriate strategies and effective action plans to prevent occurrence and spread of fire.

5.1 Introduction

Soft computing is considered as an emerging approach to computing, which parallels the remarkable ability of human mind to reason and learn in a circumstance of uncertainty and imprecision. The pioneer of soft computing, Prof. Lotfi A. Zadeh of the University of California, Berkeley, USA [163], has pointed that, the guiding principle of soft computing was to exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution cost, and better rapport with reality. In contrast with hard computing methods that only deal with precision, certainty and rigor, soft computing is effective in acquiring imprecise or sub-optimal but economic and competitive solutions. It takes advantage of intuition, which implies the human mind-based intuitive and subjective thinking. The motivation of applying the human intuition is that hard computing methods cannot solve a large number of real-world problems, due to the fact either they are too complex to handle or they cannot be described or catalogued by any analytical and exact models. Prof. Zadeh also emphasizes precise measurement and control approaches are not always effective in coping with such difficult problems, but perception can often help. Therefore, the goal of soft computing is to exploit the imprecision and uncertainty in human decision making procedure and achieve simple, reliable and low-cost solutions. Because of the aforementioned unique features, soft computing has drawn increasing research attention from people in different communities [52].

The principal constituents of soft computing (SC) are: Fuzzy Logic (FL), Neural Computing (NC), Evolutionary Computation (EC), Machine Learning (ML) and Probabilistic Computing (PC). That is, it is evolving the above relevant techniques together with the important advances in other new computing methods, such as artificial immune systems, common sense reasoning, probabilistic computing, intelligent agents and chaos theory. The principal constituent methodologies in soft computing are complementary rather than competitive. Furthermore, soft computing may be viewed as a foundation component for the emerging field of conceptual intelligence [164].

Associated of the symbiotic relationship between FL, NC, EC and PC is the growing visibility of information/intelligent systems that employ the constituent methodologies of soft computing in combination rather than segregation [97]. The advantages of three methods (NC, FL, EC) are listed in Table 5.1.

Table 5.1 Soft computing constituents [94]

Methodology	Advantage
Artificial Neural Network	Learning and Approximation
Fuzzy systems	Approximate reasoning
Evolutionary algorithms	Systematic random search

The primary contribution of probabilistic computing is the machinery of probability theory and the subsidiary techniques for decision-making under uncertainty, belief networks, cluster analysis and analysis of stochastic systems. During the past decades, the application of soft computing has covered a variety of areas. Besides control and instrumentation, other important fields include speech recognition, signal processing, telecommunications, power electronics systems, and system diagnosis. Soft computing has, in fact, shown a superior performance to the hard computing-based solutions in manipulating these real-world problems. With the rapid development of hardware platforms, e.g., digital signal processing (DSP) and neural networks/fuzzy logic chips, it is becoming more and more feasible to apply soft computing methods into practice [62, 68].

In this dissertation, an attempt has been made to classify the fire risk of Indian coals using soft computing technique such as Artificial Neural Network (ANN) techniques.

5.2 Data Normalization

Normalization of the data that lie in the range of 0 to 1 is necessary before using it in ANN models. It can be observed from the literature survey that, techniques such as Min-Max normalization, Z-Score normalization, and decimal scaling are being used for normalizing the data. In this work Min-Max normalization [61, 147] technique is used to normalize the data. Min-Max normalization performs a linear transformation on the original data. Each of the actual data d of attribute p is mapped to a normalized value d' that lies in the range of 0 to 1. The Min-Max normalization is calculated by using the equation:

$$\text{Normalized (d)} = d' = \frac{\mathrm{d} - \min(p)}{\max(p) - \min(p)} \tag{5.1}$$

Where, min (p) and max (p) represent the minimum and maximum value of the attribute p respectively.

5.3 Cross-Validation Method

Cross-validation is the most common adopted statistical learning method to evaluate and compare the models by partitioning the data into two parts. One part 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 [71, 76]. In K-fold cross-validation, the data are first partitioned into K equal (or nearly equally) sized parts 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 work, 5-folds cross-validation was used for designing and comparing the models.

5.4 Application of Artificial Neural Network (ANN) Techniques

ANN represents a promising modeling technique, especially for data sets having non-linear relationships that are frequently encountered in engineering. In terms of model specification, artificial neural networks require no knowledge of the data source but, since they often contain many weights that must be estimated, they require large training sets. Also, ANNs can combine and incorporate both literature-based and experimental data to solve problems. A distinct advantage of neural computation is that, after proper training, a neural network completely bypasses the repeated use of complex iterative processes for new cases presented to it. For engineering applications, the simple models are very usable. Thus the neural models given in this work can also be used for many engineering applications and purposes [48,118]. 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 [8, 141].

In the proposed model, three types of artificial neural network techniques were applied to predict the fire risk of Indian coals. These include Multilayer Perceptron (MLP), Functional Link Artificial Neural Network (FLANN), and Radial Basis Function Network (RBFN). Supervised learning and iterative based training methods were applied and adopted in all specified network system. During training, the inter unit connections are optimized until the error in predictions was minimized and the system reaches the specified level of accuracy. Once the network is trained, new unseen input information was entered into the system to calculate the output for the test. In this work, MATLAB R2014b was used for the development of neural-based models.

5.4.1 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 [49, 50, 51, 66]. The structure of MLP is shown in Figure 5.1. MLP is widely used for pattern classification, recognition, prediction, and approximation.

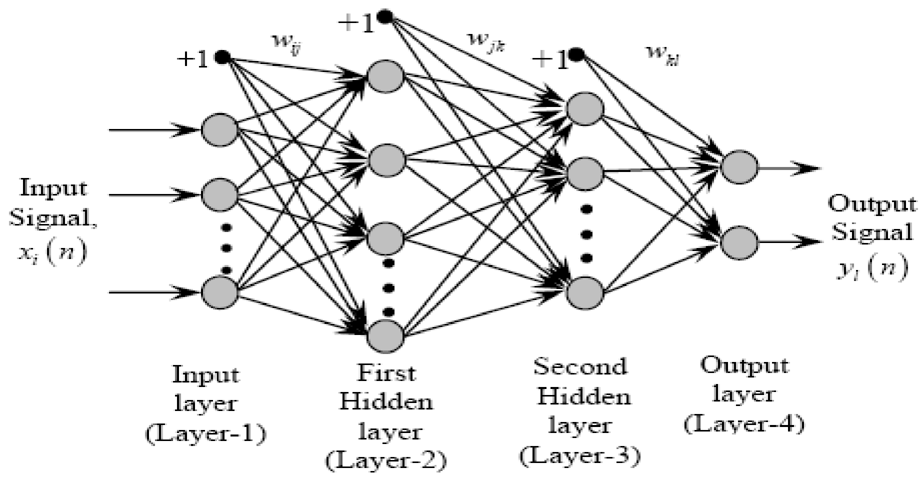


Figure 5.1 Structure of MLP

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:

$$f_j = \varphi_j\left[\sum_{i=1}^{N} w_{ij}\, x_i\ (n) + \ b_j\ \right], i = 1, 2, 3, \ldots\ldots, N, j = 1,2,3, \ldots\ldots, P_1 \qquad (5.2)$$

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:

$$f_k = \varphi_k \left[\sum_{j=1}^{P_1} w_{jk} f_j + b_k \right], k = 1, 2, 3, \ldots\ldots, P_2 \tag{5.3}$$

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

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

$$y_1\,(n) = \varphi_l [\sum_{k=1}^{P_2} w_{kl} f_k + b_l], l = 1, 2, 3, \ldots\ldots, P_3 \tag{5.4}$$

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:

$$y_1\,(n) = \varphi_n \left[\sum_{k=1}^{P_2} w_{kl}\, \varphi_k \left(\sum_{j=1}^{P_1} w_{jk}\, \varphi_j \left\{ \sum_{i=1}^{N} w_{ij}\, x_i\,(n) + b_j \right\} + b_k \right) + b_l \right] \tag{5.5}$$

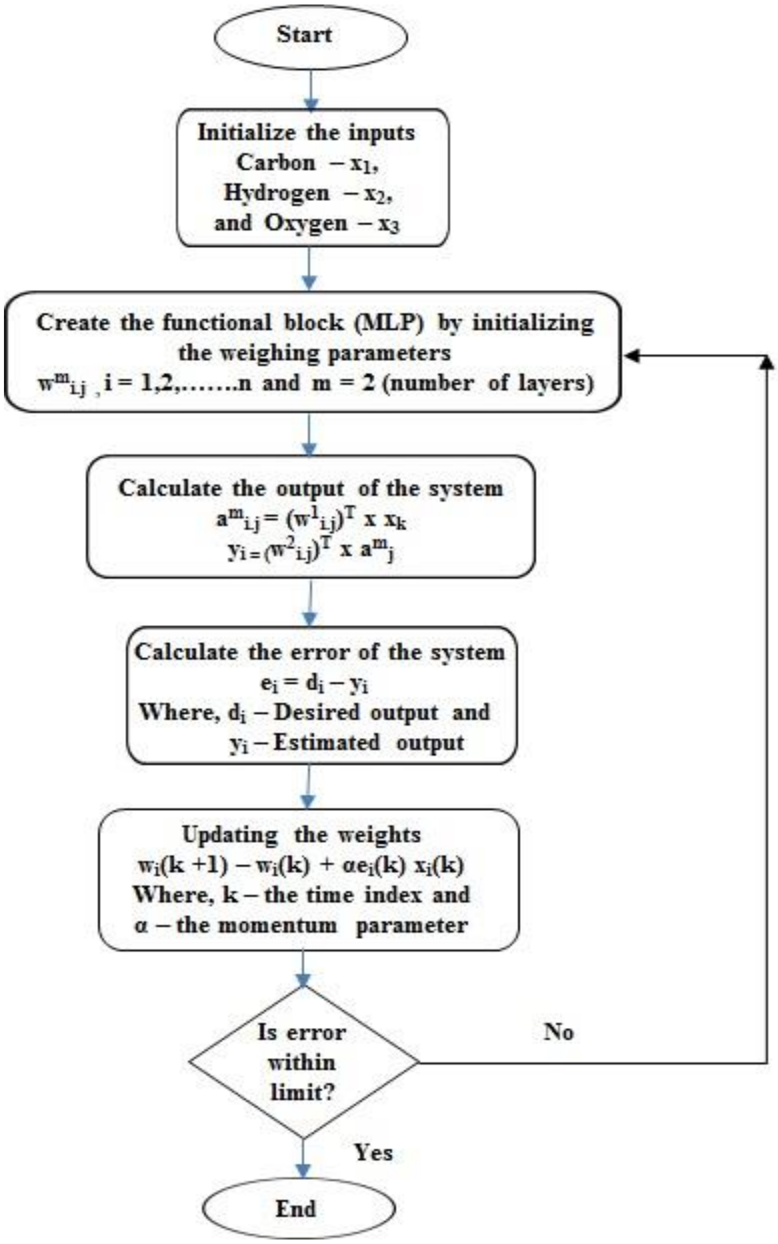


Figure 5.2 Flowchart representing training process of MLP

5.4.1.1 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 was used for the minimization of error [90, 124, 132].

5.4.1.1.1 Algorithm for training MLP based fire risk model

The algorithm for training MLP [50, 99] based fire risk model has been represented (Figure 5.2) 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).

$w^m_{i,j} \leftarrow Rand(w^m_{i,j}(0))$ (5.6)

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

$b^m_{i,j} \leftarrow Rand(b^m_{i,j}(0))$ (5.7)

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

$a^m_{i,j} = \varphi((w^1_{i,j})*x_k + bias)$ (5.8)

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:

$Y_j = \varphi((W^2_{i,j})* a^m_{j} + bias)$ (5.9)

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:

$e_l(n)=d(n) - y_l(n)$ (5.10)

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

$$\xi(n) = \frac{1}{n}\sum_{i=1}^{n} e^2(n) \quad (5.11)$$

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

$S_1 = \dot{f}^2(n^2) = \frac{d}{dn}(n) = 1$ (5.12)

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

$$S_2 = \dot{f}^1(n) = \frac{d}{dn}\left[\frac{1}{1+\exp^{-n}}\right] = \left[1 - \frac{1}{1+\exp^{-n}}\right] * \left[\frac{1}{1+\exp^{-n}}\right]$$

$$= \left(1 - a_{i,j}^{m}\right) * a_{i,j}^{m} \quad (5.13)$$

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

a) Updating the weight for output layer:

$$W_{i,j}^{1}(\text{new}) = W_{i,j}^{1}(\text{old}) + \eta S_j^1 \quad (5.14)$$

b) Updating the weight for hidden layer:

$$W_{i,j}^{2}(\text{new}) = W_{i,j}^{2}(\text{old}) + \eta S_j^2 (a_{i,j}^{1}) \quad (5.15)$$

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.

5.4.2 Functional link artificial neural network (FLANN)

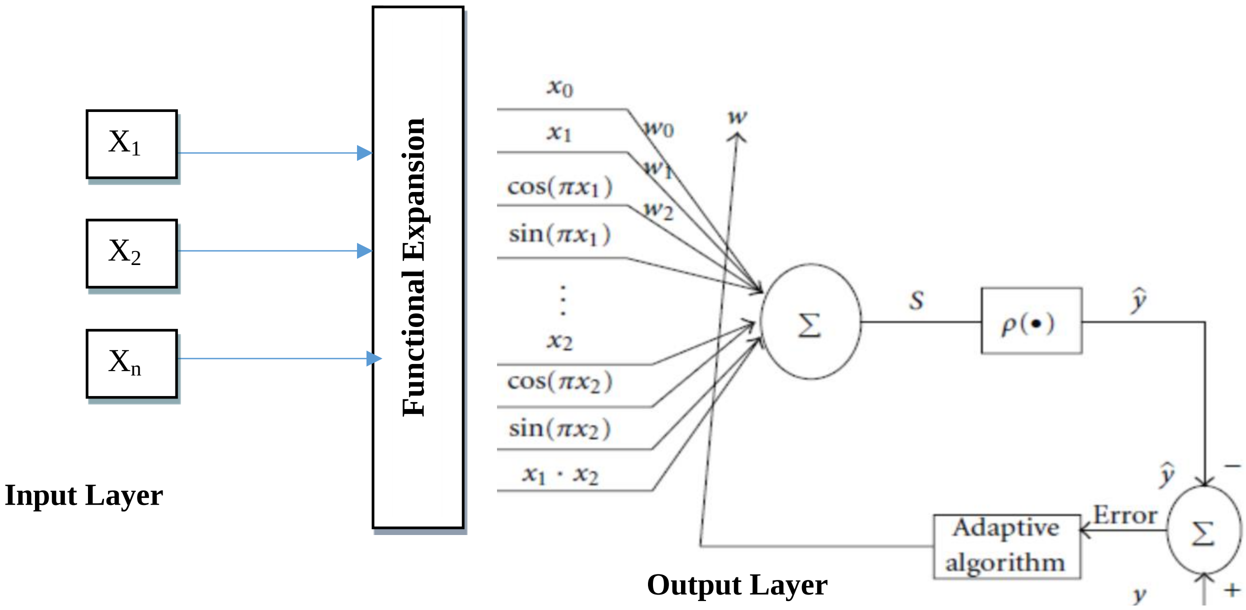


Figure 5.3 Structure of FLANN [96]

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 [90, 112, 127], and the structure has been represented in Figure 5.3.

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:

$$X(K) = x_k \,, 1 \leq K \leq N \tag{5.16}$$

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:

$$s_i = \begin{Bmatrix} x_k & \text{for } i = 1 \\ \sin(l\pi x_k) & \text{for } i = 2,4, \ldots., M \\ \cos(l\pi x_k) & \text{for } i = 3,5, \ldots., M+1 \end{Bmatrix} \tag{5.17}$$

The bias input is unity and the enhanced pattern can be obtained by the trigonometric function $X = [x_1 \ \cos(\pi x_1) \ \sin(\pi x_1) \cdot\cdot\cdot x_2 \ \cos(\pi x_2) \ \sin(\pi x_2) \cdot\cdot\cdot x_1 x_2]^T$ 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.

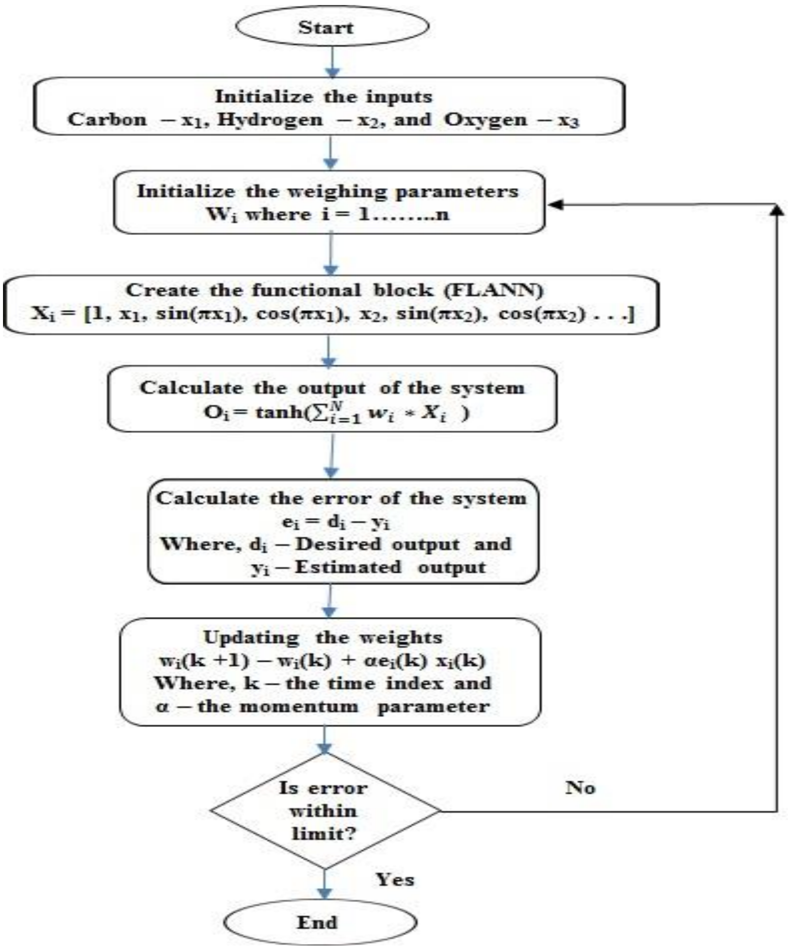


Figure 5.4 Flowchart representing training process of FLANN

5.4.2.1 Algorithm for training FLANN fire risk model

The algorithm for training FLANN [95] based fire risk model has been represented (Figure 5.4) 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

$$w_i \leftarrow \text{Rand}(w_i(0)) \qquad (5.18)$$

Step 4: The functional block can be represented as:

$$Xi = [1, x_1, \sin(\pi x_1), \cos(\pi x_1), x_2, \sin(\pi x_2), \cos(\pi x_2) \ldots] \qquad (5.19)$$

Step 5: The output was calculated as follows:

$$O_i = \tanh(\textstyle\sum_{i=1}^{N} w_i * X_i) \qquad (5.20)$$

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:

$$w_i(k + 1) = w_i(k) + \alpha e_i(k)\, X_i(k) \qquad (5.21)$$

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.

5.4.3 Radial basis function (RBF) network

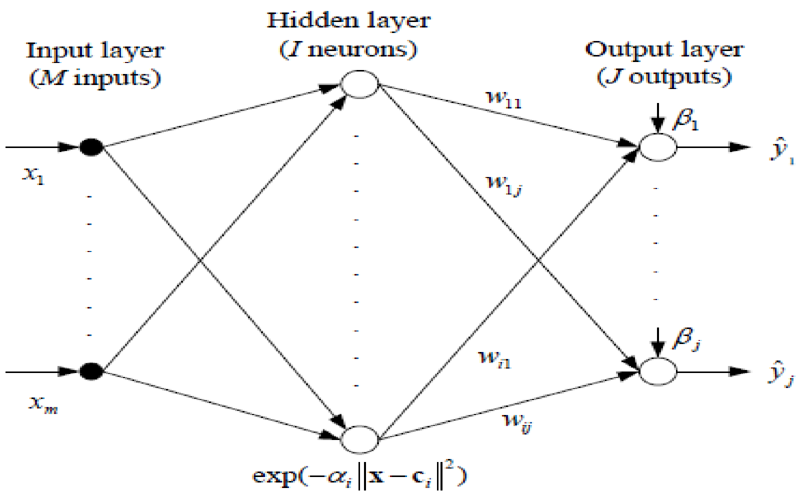


Figure 5.5 Network architecture of RBF [77]

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) [128]. An RBF network has only output neuron.The structure of RBF network has been depicted in Figure 5.5.

Gradient Descent **(**GD) [133] is a first-order derivative-based optimization algorithm used for finding a local minimum of a function. The Gaussian radial function is used as a radial 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 [128] has been written as:

$$\hat{Y} = F(x) = \sum_{j=1}^{L} w_j \phi_j \,(||x - c_j\,||) \tag{5.22}$$

Where, L is the number of hidden neurons, x ∈ R^p is the input and w_j are the output layer weights of the RBF network and ϕ(x) is the Gaussian Radial basis function given by:

$$\phi_j\,(||x - c_j||) = exp\,(-\frac{||x - c_j||^2}{(\sigma_j)^2}) \tag{5.23}$$

Where, ||.|| denotes the Euclidean distance, c_j ∈ R^p is the center of the j^{th} hidden neuron and $\sigma_j{}^2$ is the width of the j^{th} hidden neuron.

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

$$E = \sum (Y - \hat{Y})^2 \tag{5.24}$$

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:

$$\mathrm{w_{ij}} = \mathrm{w_{ij}} - \eta\,\frac{\partial \mathrm{E}}{\partial \mathrm{w_{ij}}} \tag{5.25}$$

$$\mathrm{c_i} = \mathrm{c_i} - \eta\,\frac{\partial \mathrm{E}}{\partial \mathrm{c_i}} \tag{5.26}$$

Where, η is the step size [133].

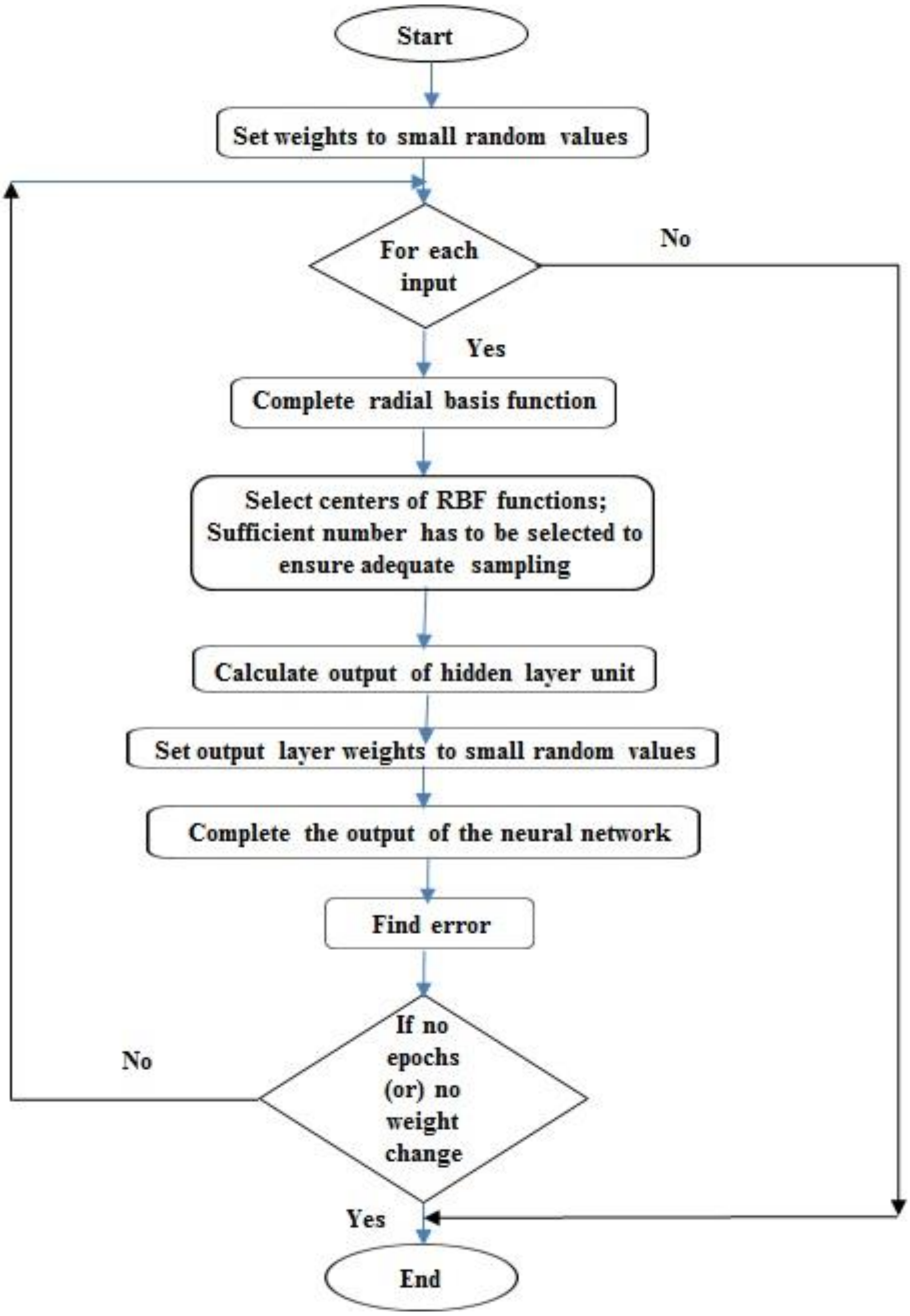


Figure 5.6 Flowchart representing training process of RBF network [141]

5.4.3.1 Algorithm for training RBF network based fire risk model

The algorithm for training RBF network [141] based fire risk model has been represented (Figure 5.6) 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:

$$\nu_i(x_i) = \frac{\exp\left[-\sum_{j=1}^{r}\left(x_{ji}-\hat{x}_{ji}\right)^2\right]}{\sigma_i^2} \tag{5.27}$$

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:

$$y_{net} = \sum_{i=1}^{k} w_{im}\, \nu_i(x_i) + w_0 \tag{5.28}$$

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.

5.5 Performance Evaluation Parameters

To assess the performance of prediction models, the most widely used evaluation criterion is the Mean Magnitude of Relative Error (MMRE) [26, 152]. Further, software accuracy for a designed model was determined by using performance evaluation parameters [128, 147] 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 [27, 78].

5.5.1 Mean absolute error (MAE)

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(|y_i' - y_i|\right) \tag{5.29}$$

Where, n is the number of samples, y_i is the actual value, and y_i' is predicted value.

5.5.2 Magnitude of relative error (MRE)

The MRE for each observation i can be obtained as:

$$MRE_i = \frac{|\text{Actual Effort}_i - \text{Predicted Effort}_i\,|}{\text{Actual Effort}_i} \tag{5.30}$$

5.5.3 Mean magnitude of relative error (MMRE)

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

$$\mathrm{MMRE} = \sum_{1}^{N} \mathrm{MRE_i} \tag{5.31}$$

5.5.4 Root mean square error (RMSE)

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

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \tag{5.32}$$

5.5.5 Standard error of the mean (SEM)

It is the deviation of predicted value from the actual.

$$\mathrm{SEM} = \frac{\mathrm{SD}}{\sqrt{n}} \tag{5.33}$$

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

5.6 Simulation Results and Discussion

To validate the performance of ANN models for prediction of fire risk of Indian coals, three ANN models i.e. MLP, FLANN and RBF networks were used. Best correlated parameters of ultimate analysis (C_{daf}, H_{daf} and O_{daf}) were chosen as inputs for the simulation process. Simulation studies were carried out using MATLAB R2014b. 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 forty-nine coal 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 and required less computation time. The Mean Square Error (MSE) vs. Epochs plot of all the applied ANN models are represented in Figures 5.7-5.9. They indicated 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 seconds computation time respectively with 2000 epochs.

Further, to assess the performance of prediction models, the most widely used evaluation criterion is the Mean magnitude of relative error (MMRE). Table 5.2 shows that average MMRE is less in Szb, viz. MLP (0.56), FLANN (0.72) and RBF network (0.49) and are graphically represented in Figure 5.10. It implies that RBF network model shows lowest average MMRE as compared to MLP and FLANN and can provide better prediction of fire risk of Indian coals with Szb.

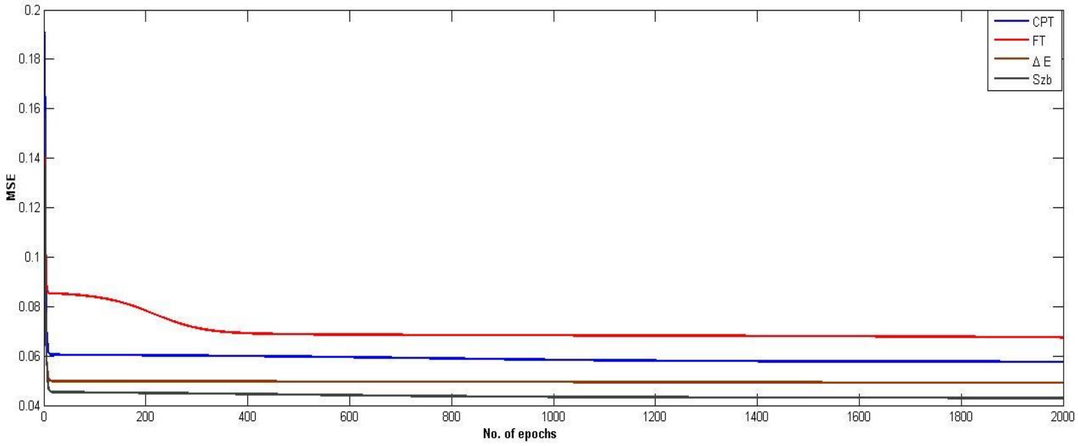


Figure 5.7 Performance curve of MLP

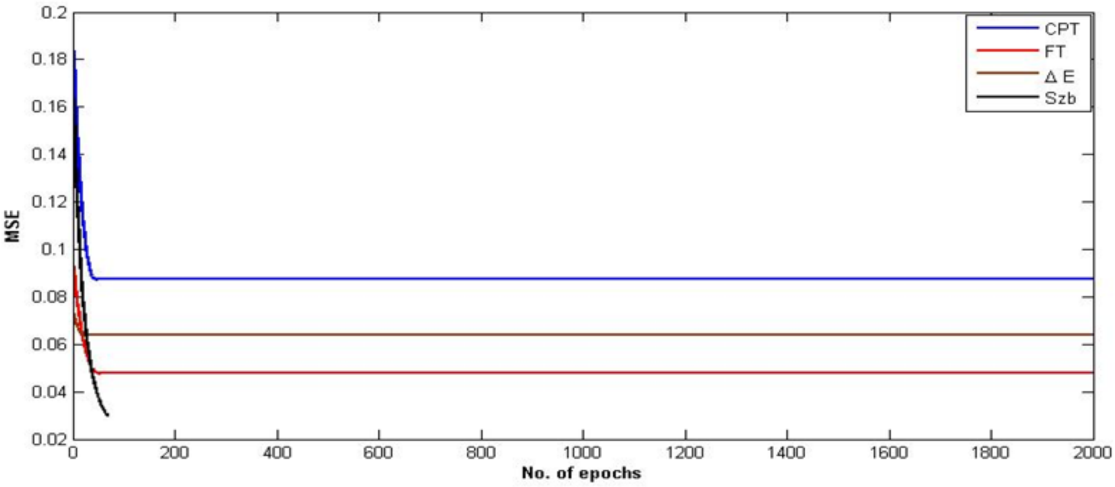


Figure 5.8 Performance curve of FLANN

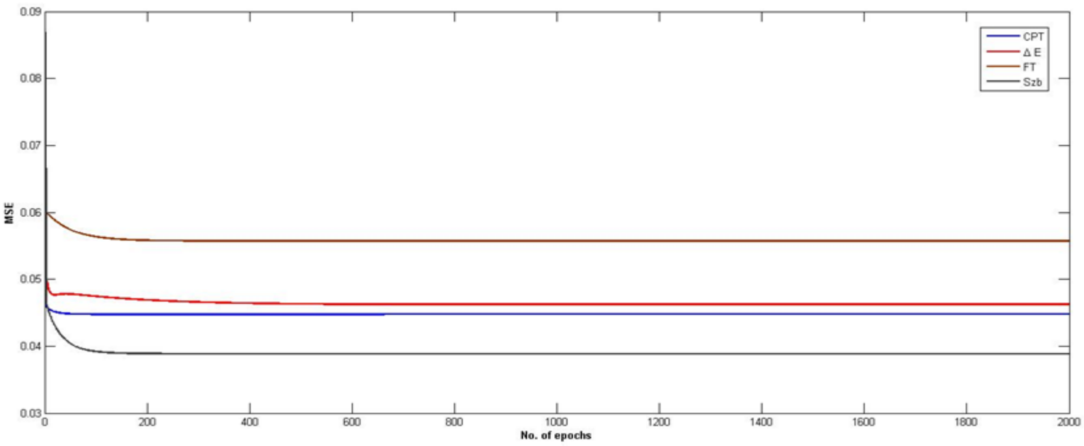


Figure 5.9 Performance curve of RBF network

Table 5.2 Performance evaluation parameters of MLP, FLANN and RBF network models with respect to susceptibility indices

CPT MLP				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.27	0.34	0.32	0.01
2	0.22	0.36	0.25	0.03
3	0.27	1.37	0.31	0.03
4	0.21	0.90	0.24	0.02
5	0.28	0.90	0.33	0.03
Avg.	0.25	0.77	0.29	0.02

CPT FLANN				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.59	0.83	0.64	1.35E-45
2	0.51	0.82	0.54	4.94E-32
3	0.23	0.60	0.28	3.97E-12
4	0.22	0.64	0.25	7.02E-36
5	0.47	0.70	0.57	1.31E-16
Avg.	0.40	0.72	0.45	7.90E-13

CPT RBF				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.28	0.39	0.33	0.04
2	0.26	0.41	0.30	0.05
3	0.27	1.31	0.36	0.05
4	0.35	1.35	0.40	0.11
5	0.35	1.30	0.41	0.08
Avg.	0.30	0.95	0.36	0.07

FT MLP				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.20	0.24	0.26	0.003
2	0.22	0.58	0.24	0.01
3	0.17	0.61	0.23	0.03
4	0.14	0.67	0.20	0.01
5	0.28	0.50	0.32	0.004
Avg.	0.20	0.52	0.25	0.01

FT FLANN				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.67	0.87	0.69	3.96E-59
2	0.33	0.76	0.35	1.15E-50
3	0.44	0.77	0.48	2.08E-21
4	0.47	0.75	0.50	3.67E-42
5	0.61	0.82	0.68	2.09E-22
Avg.	0.51	0.79	0.54	4.60E-22

FT RBF				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.21	0.25	0.26	0.04
2	0.25	0.63	0.27	0.06
3	0.29	0.71	0.33	0.06
4	0.23	0.64	0.28	0.07
5	0.32	0.57	0.39	0.08
Avg.	0.26	0.56	0.31	0.06

ΔE MLP				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.21	0.25	0.24	0.02
2	0.21	0.27	0.22	0.02
3	0.20	0.62	0.24	0.05
4	0.21	0.61	0.25	0.03
5	0.33	1.68	0.40	0.06
Avg.	0.23	0.69	0.27	0.03

ΔE FLANN				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.68	0.87	0.69	3.97E-72
2	0.67	0.86	0.70	8.60E-41
3	0.40	0.76	0.44	5.49E-14
4	0.40	0.72	0.50	4.20E-40
5	0.29	0.55	0.44	1.14E-20
Avg.	0.49	0.75	0.55	1.10E-14

∆E RBF				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.42	0.54	0.44	0.02
2	0.35	0.47	0.37	0.04
3	0.20	0.50	0.23	0.03
4	0.19	0.37	0.23	0.04
5	0.39	2.00	0.48	0.14
Avg.	0.31	0.77	0.35	0.05

Szb MLP				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.15	0.50	0.16	0.009
2	0.17	0.62	0.19	0.01
3	0.21	0.46	0.23	0.03
4	0.15	0.30	0.17	0.02
5	0.28	0.90	0.33	0.02
Avg.	0.19	0.56	0.22	0.02

Szb FLANN				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.26	0.70	0.29	8.76E-40
2	0.28	0.69	0.31	9.64E-24
3	0.44	0.79	0.46	5.54E-19
4	0.46	0.80	0.48	2.39E-26
5	0.40	0.66	0.52	1.39E-14
Avg.	0.37	0.73	0.41	2.80E-15

Szb RBF				
Fold	**MAE**	**MMRE**	**RMSE**	**SEM**
1	0.18	0.54	0.19	0.03
2	0.16	0.45	0.21	0.04
3	0.26	0.48	0.29	0.04
4	0.14	0.23	0.18	0.03
5	0.27	0.75	0.38	0.06
Avg.	0.20	0.49	0.25	0.04

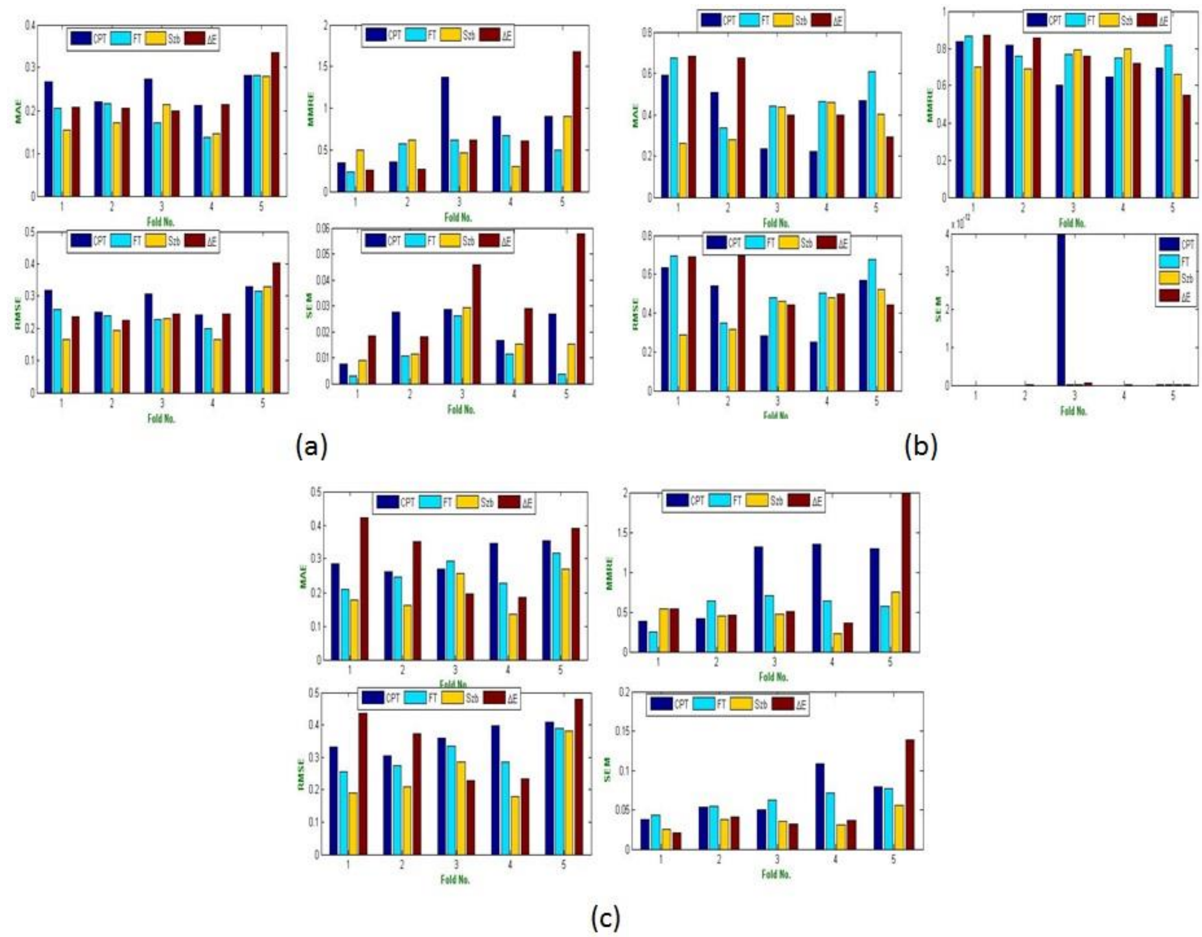


Figure 5.10 Graphical representation of performance of evaluation parameters in (a) MLP (b) FLANN (c) RBF network models

In addition to the above said results, residual boxplots have been drawn for all the ANN techniques (MLP, FLANN, and RBF network) used for forty-nine Indian coal samples. Figure 5.11 shows the Pearson residual boxplots. The line in the middle of each box represents the median of the Pearson residual. Figure 5.11 indicates that Szb provides better accuracy as compared to other susceptibility indices (CPT, FT, and ΔE). It can also be interpreted that RBFN has the narrowest box and the smallest whiskers as well as few numbers of outliers in case of Szb. Also the median residual is close to zero. FLANN has the narrowest box but the median residual is slight away from zero. MLP has the widest box of all. Based on these boxplots, it is concluded that RBFN model presents best estimation accuracy as compared to other two models i.e. MLP and FLANN.

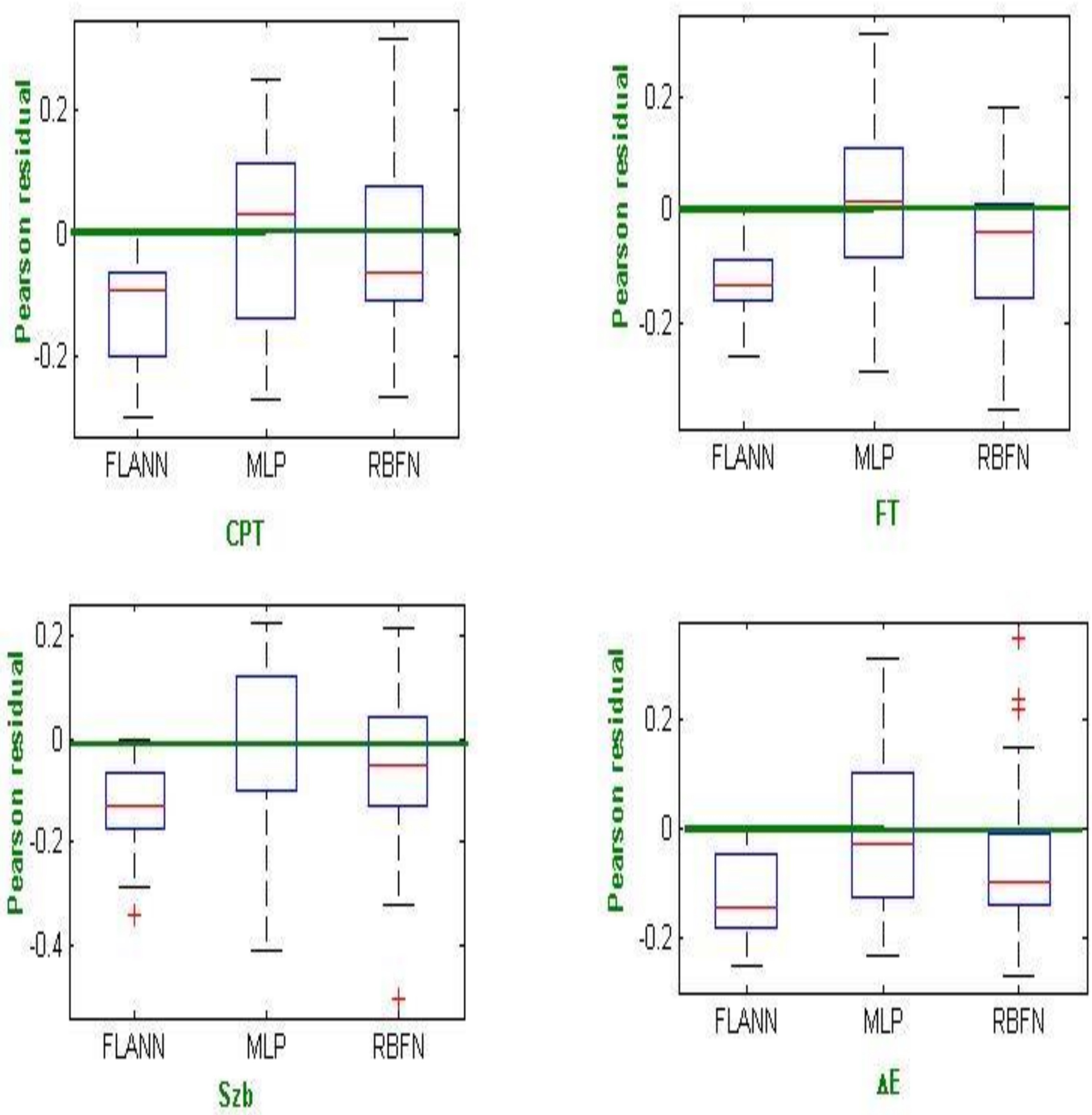


Figure 5.11 Residual boxplots

Results of the soft computing techniques i.e. ANN indicates that RBF network model provides more precise results with Szb and hence, Olpinski index can be used as a reliable susceptibility index for assessing fire risk of coals. The investigated coals can be categorized into three categories based on fire risk rating using Olpinski index and are summarized in Table 5.3.

Table 5.3 Fire risk of investigated coal samples

Susceptibility Index	Fire risk classification		
	Low	Medium	High
Szb	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

The results (Table 5.3) showed that all the coking coals (IISCO-1, IISCO-2, BCCL-1 and TISCO-1) are poorly susceptible, NCL coals are highly susceptible to spontaneous combustion, while rest of the investigated coals were classified into low and medium fire risk category based on Szb. The results of the investigated coals (Table 5.3) were observed to match closely with the field records and the fire history of the concerned mines. Thus, Olpinski index can be used as a reliable index to predict the proneness of Indian coals to fire risk.

CHAPTER – 6

CONCLUSIONS

In this thesis, the experimentation was carried out to determine the different intrinsic parameters as well as susceptibility indices of forty-nine coal samples collected from the different coalfields of India. Univariate and multivariate statistical regression analysis were carried out to determine the best-correlated parameters as inputs to the soft computing models. Further, soft computing techniques viz. artificial neural network techniques were used to develop an intelligent and most appropriate model to predict the proneness of Indian coals to spontaneous combustion.

The following conclusions were drawn from the research investigations:

- Olpinski index provides better results as compared to commonly adopted crossing point temperature method and can be used as one of the reliable susceptibility indices for categorization of fire risk proneness of Indian coals.
- From the statistical analysis, it could be inferred that there was no significant correlation between macerals and any of the susceptibility indices due to the low correlation coefficient and high standard error.
- Differential thermal analysis was used to assess the propensity of Indian coals to spontaneous combustion indicated that there was no significant correlation with the intrinsic properties in the investigated coals and could not be used as a sole indicator for the assessment of sponcom risk.
- From the statistical analysis (univariate and multivariate), it could be interpreted that parameters of ultimate (C, H and O) analysis of dry ash free basis showed significant correlation with Olpinski index (Szb) [free of ash correction] as compared to other susceptibility indices, viz. crossing point temperature (CPT), flammability temperature (FT), wet oxidation potential analysis and differential thermal analysis (DTA), and can be used as input parameters to ANN models.
- The performance analysis of ANN models (MLP, FLANN and RBF network) revealed that Szb provided more precise results as compared to CPT, FT and ΔE and can be used for the prediction of fire risk of Indian coals.

- The performance evaluation through cross-validation implied that RBF network model can provide better prediction of fire risk of Indian coals with Szb than MLP and FLANN based on least MMRE.
- The simulation study showed that RBF model provides the most accurate fire risk prediction with Szb as compared to MLP and FLANN.
- The investigated coals were classified into low, medium and high fire risk categories based on Olpinski index and are summarized in the Table given below:

Name of the Coal Samples	Fire Risk
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	Low
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	Medium
NCL-1,2	High

- The ANN-based fire risk prediction results revealed that all the coking coals (IISCO-1, IISCO-2, BCCL-1 and TISCO-1) were poorly susceptible to spontaneous combustion.
- The fire risk prediction results of the investigated coal samples based on the Olpinski index were observed to match closely with the field records and the fire history of the concerned mines. Hence, Olpinski index can be used as a reliable index to predict the proneness of Indian coals to spontaneous combustion, so that mine managers/planners/field engineers can adopt appropriate strategies and effective action plans in advance to prevent the occurrence of spontaneous combustion of coals and spread of fire.

Scope for Future Work

The following aspects may be investigated in future:

- Extrinsic properties should be taken into consideration for evaluating the risk of Indian coals to spontaneous heating.
- Vitrinite reflectance may be added as a rank indicator while assessing the coals to spontaneous combustion.
- Porosity, structure of coal and differential scanning calorimetry (DSC) studies can be initiated to evaluate the proneness of Indian coals to spontaneous heating.

- Other soft computing techniques (e.g. Genetic algorithm, Fuzzy system etc.) can also be tried to assess the susceptibility of Indian coals to spontaneous combustion for comparison purpose.

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APPENDICES

APPENDIX-1

CROSSING POINT TEMPERATURE CURVES

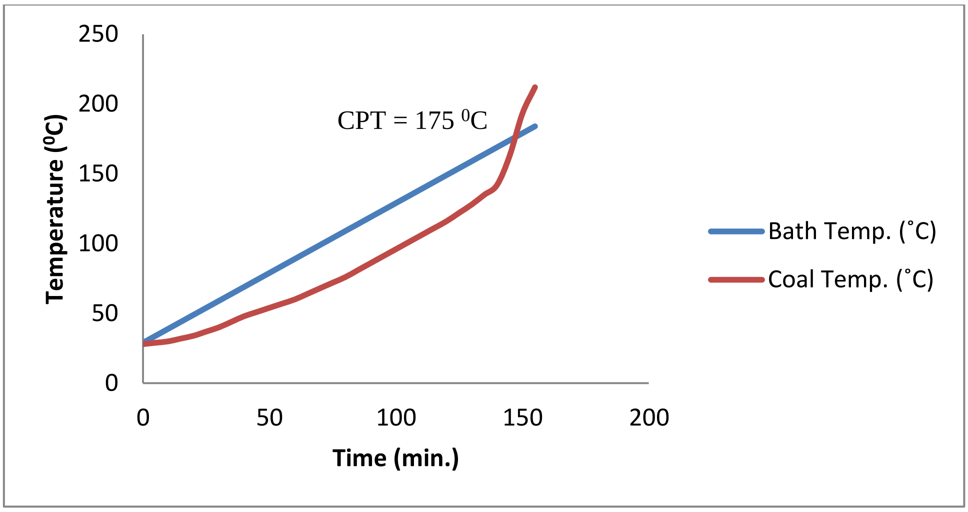


Figure A1.1 CPT curve of SECL-1 coal sample

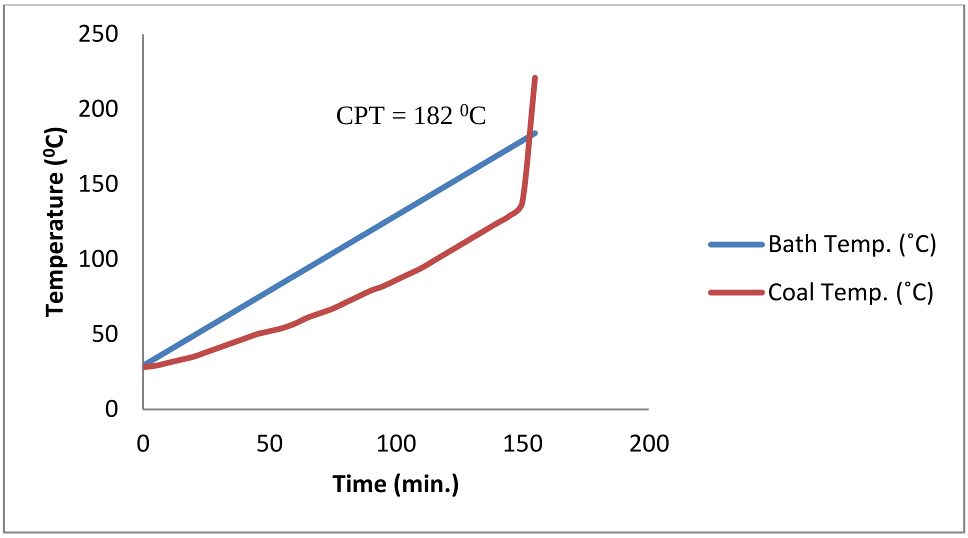


Figure A1.2 CPT curve of SECL-2 coal sample

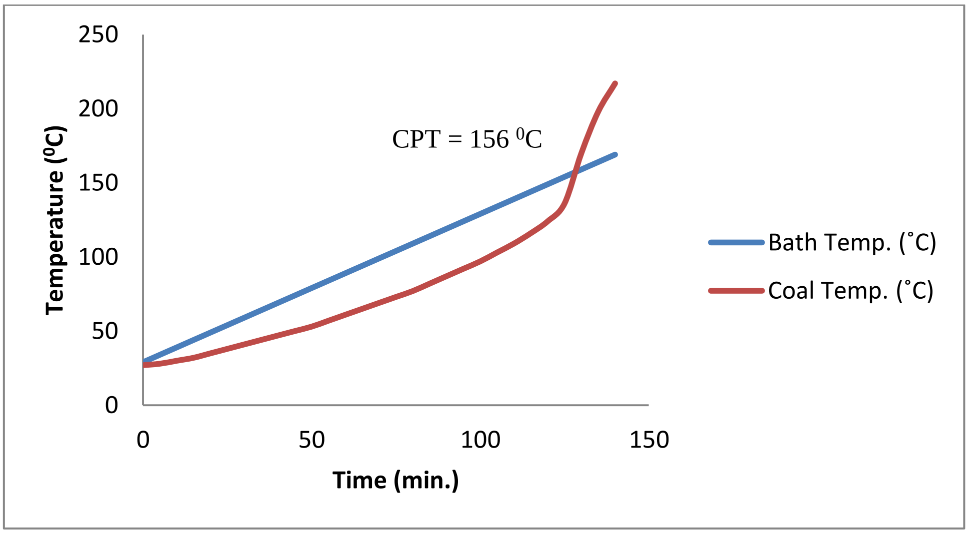


Figure A1.3 CPT curve of SECL-3 coal sample

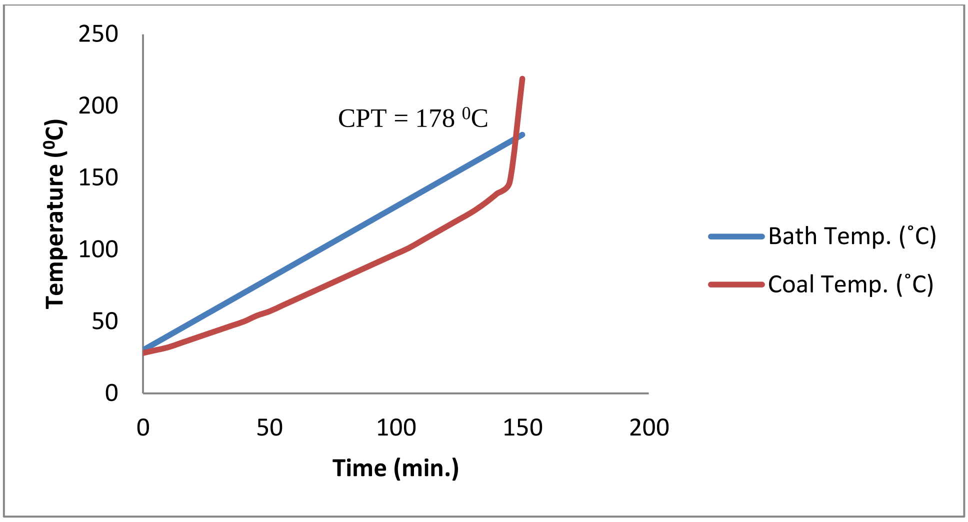


Figure A1.4 CPT curve of SECL-4 coal sample

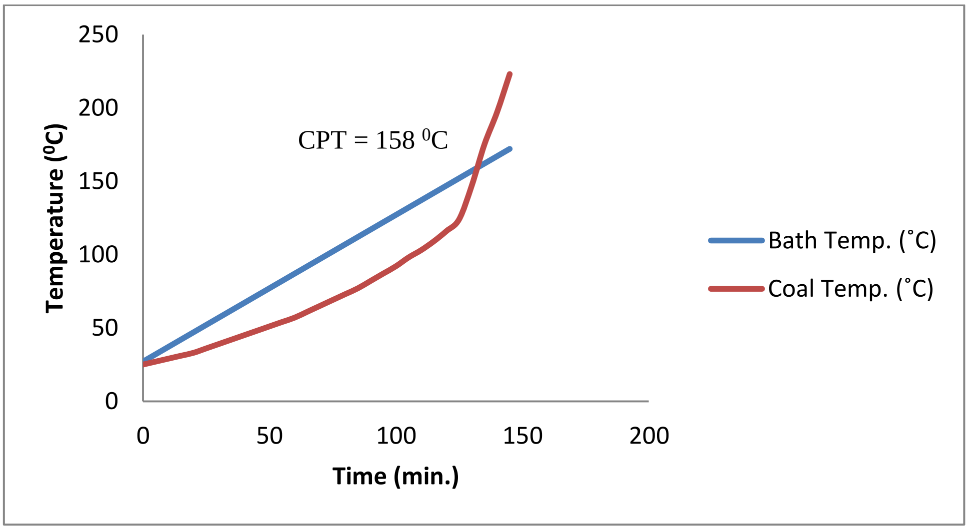


Figure A1.5 CPT curve of SECL-5 coal sample

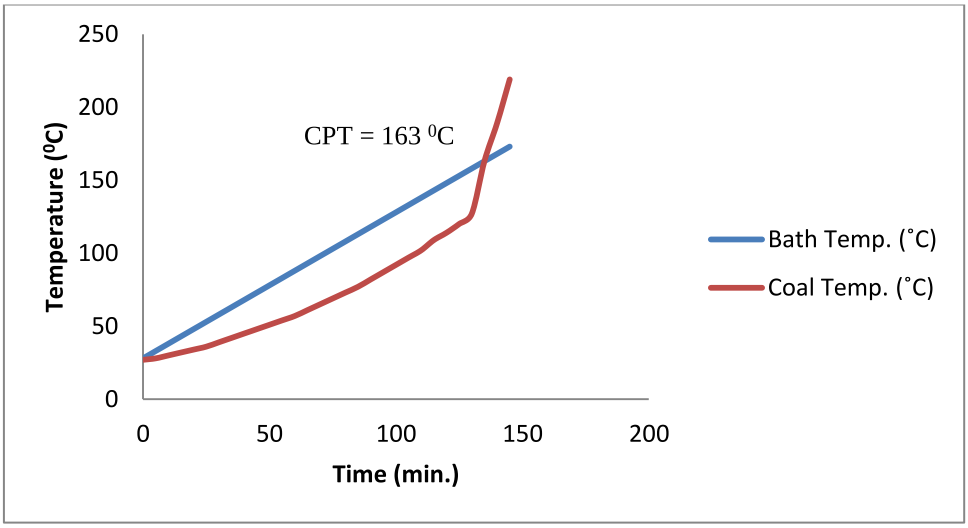


Figure A1.6 CPT curve of SECL-6 coal sample

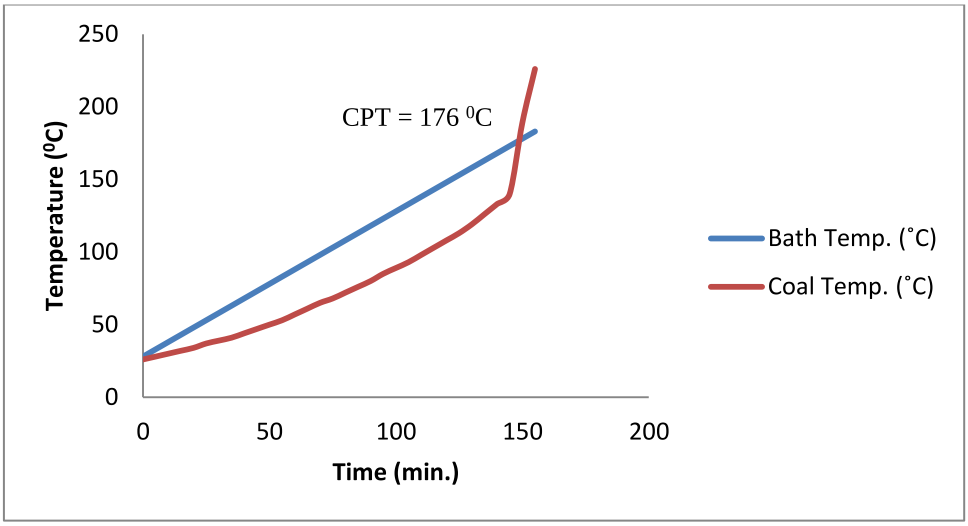


Figure A1.7 CPT curve of SECL-7 coal sample

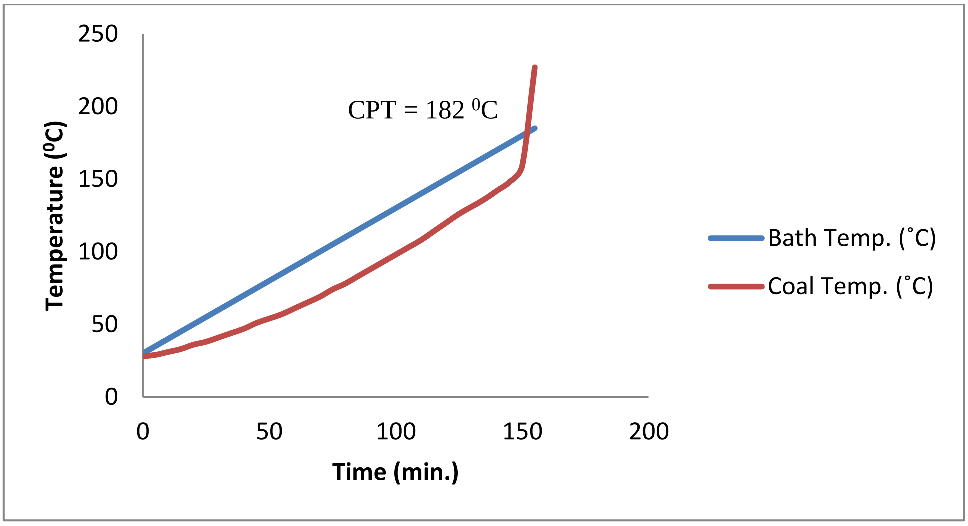


Figure A1.8 CPT curve of SECL-8 coal sample

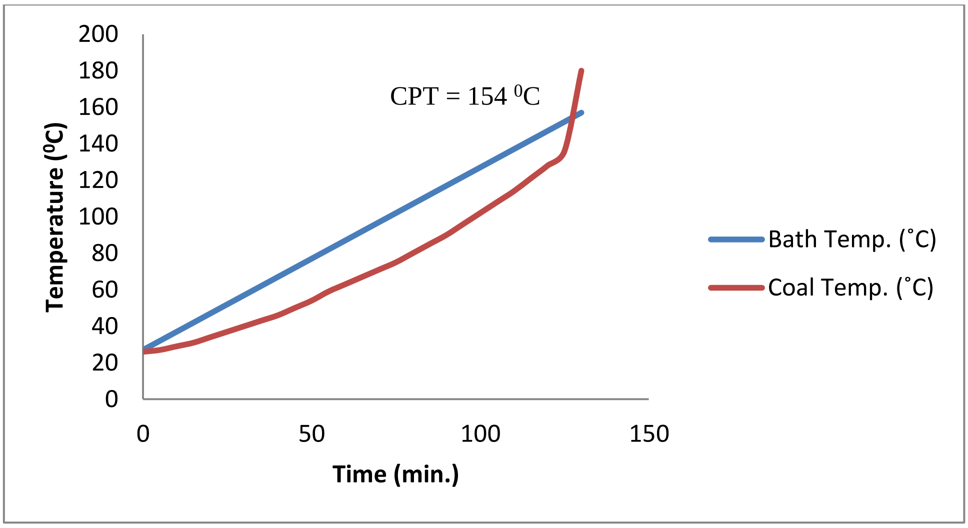


Figure A1.9 CPT curve of SECL-9 coal sample

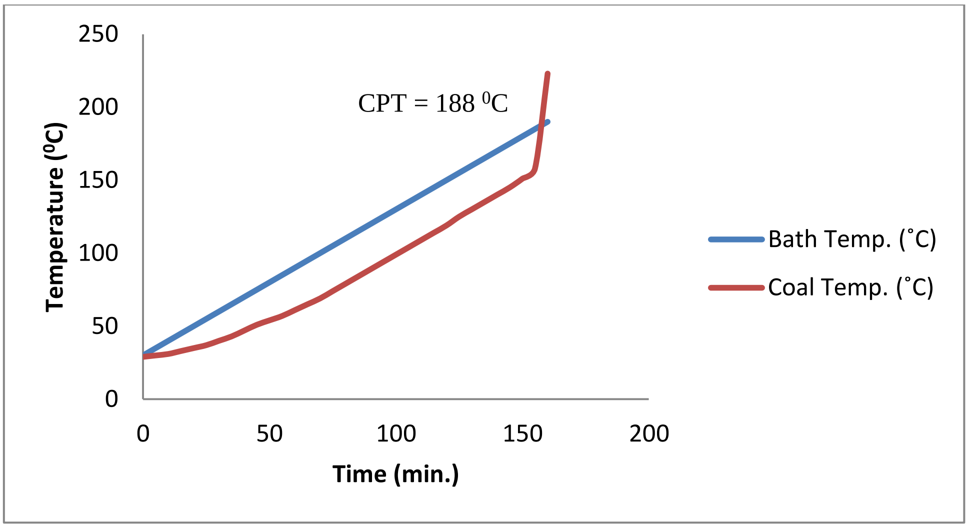


Figure A1.10 CPT curve of SECL-10 coal sample

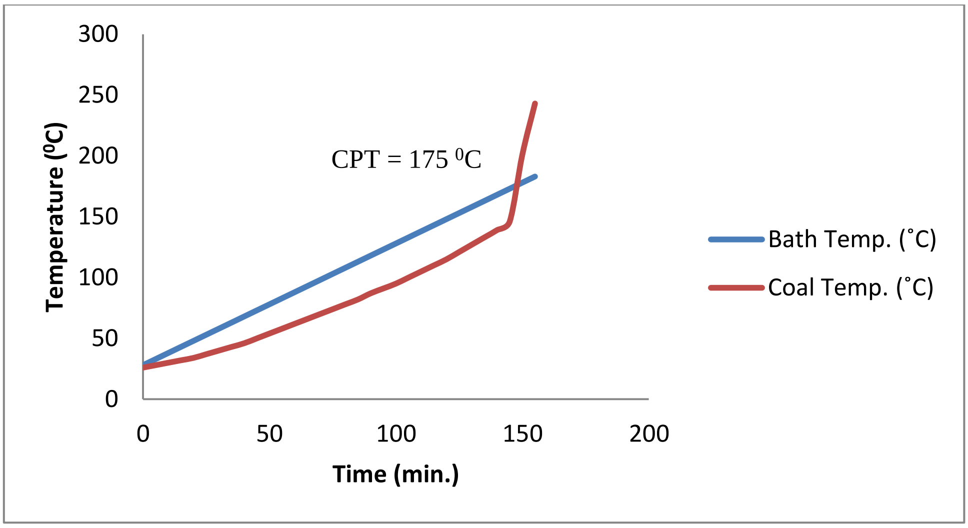


Figure A1.11 CPT curve of SCCL-1 coal sample

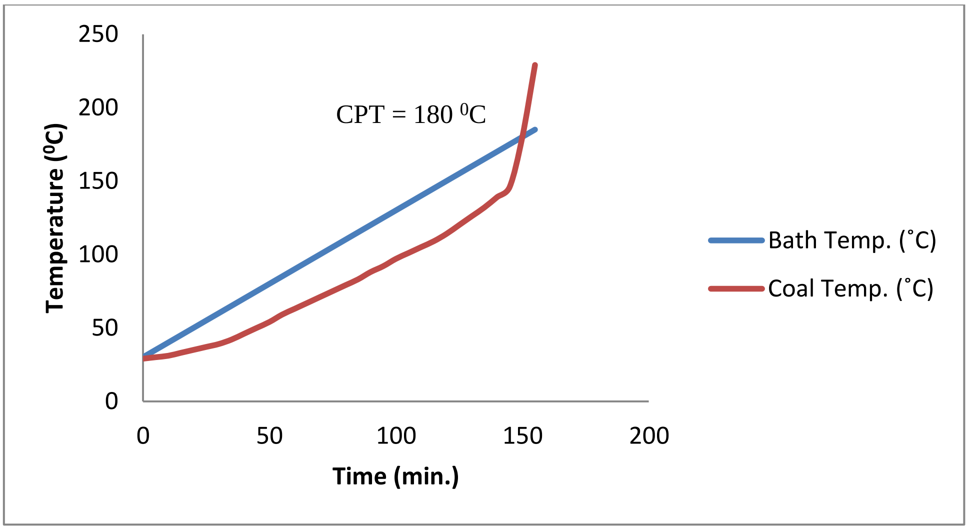


Figure A1.12 CPT curve of SCCL-2 coal sample

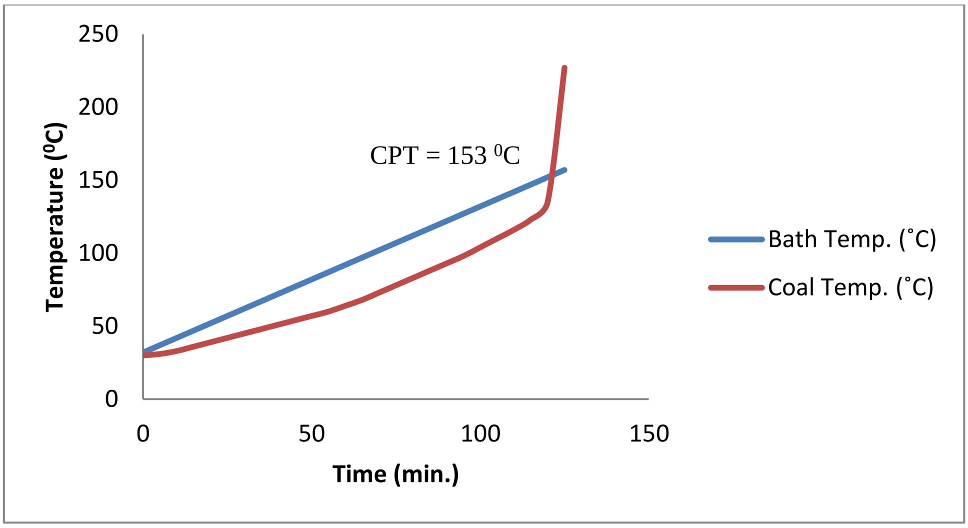


Figure A1.13 CPT curve of SCCL-3 coal sample

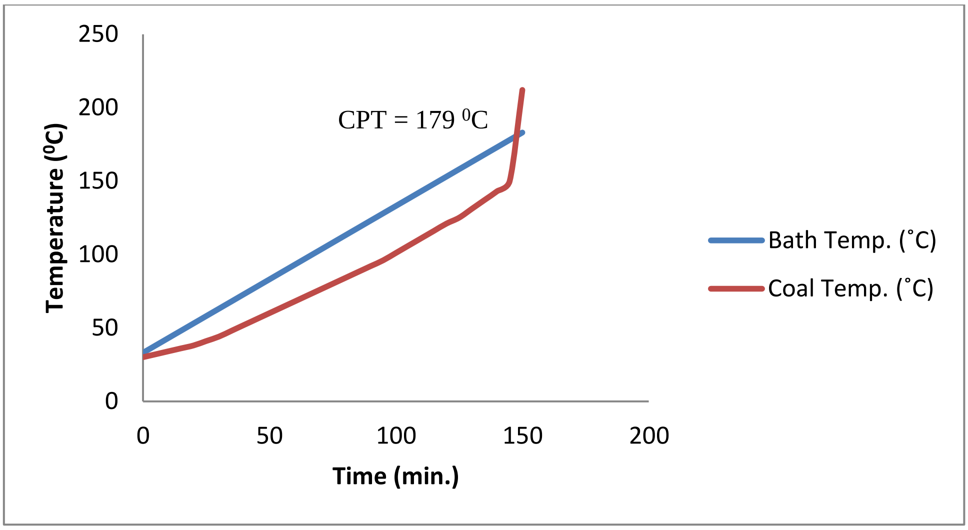


Figure A1.14 CPT curve of SCCL-4 coal sample

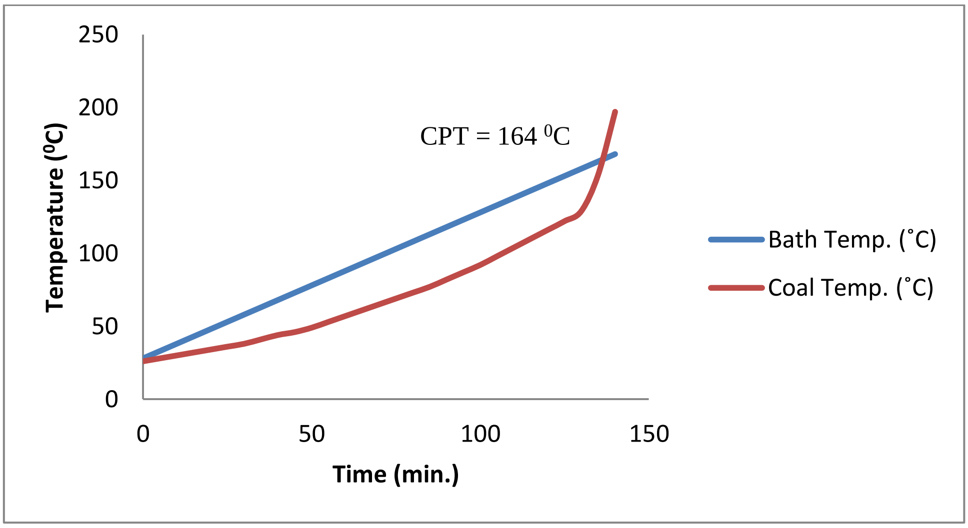


Figure A1.15 CPT curve of SCCL-5 coal sample

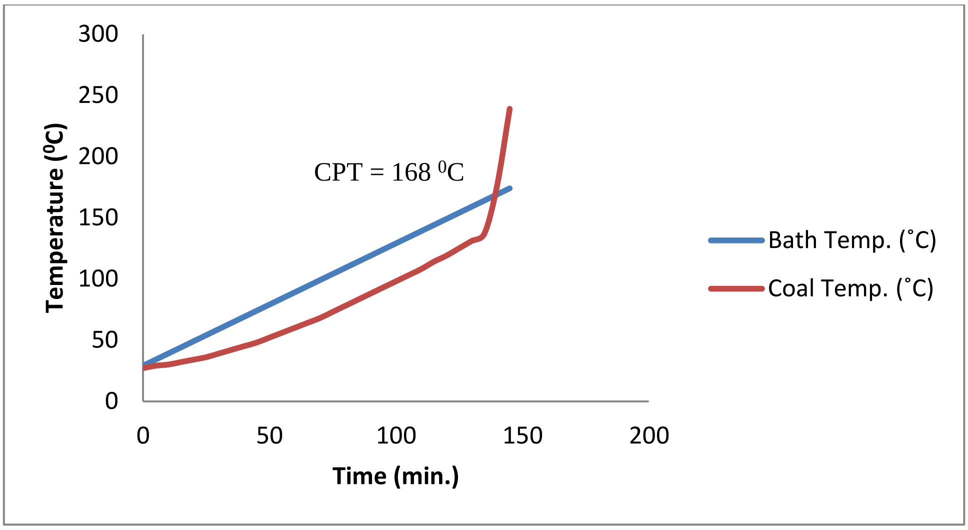


Figure A1.16 CPT curve of SCCL-6 coal sample

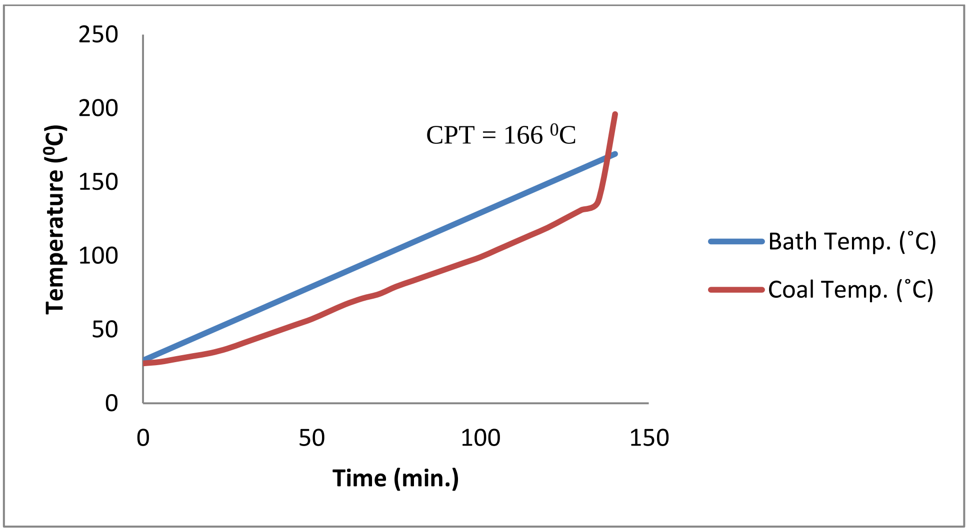


Figure A1.17 CPT curve of SCCL-7 coal sample

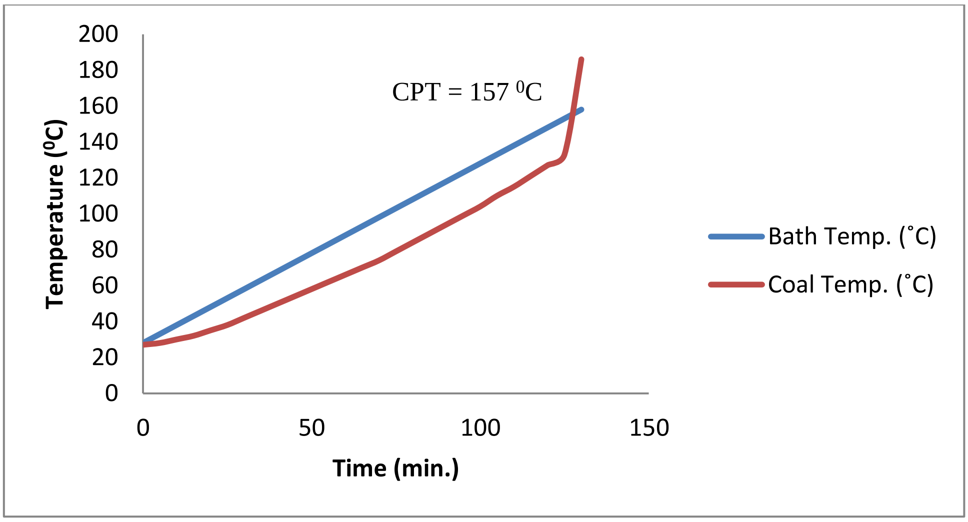


Figure A1.18 CPT curve of SCCL-8 coal sample

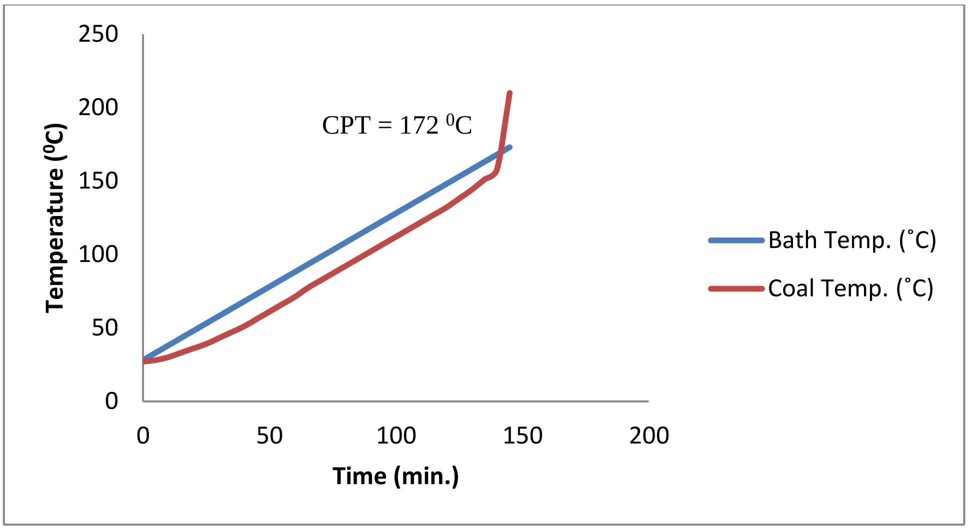


Figure A1.19 CPT curve of SCCL-9 coal sample

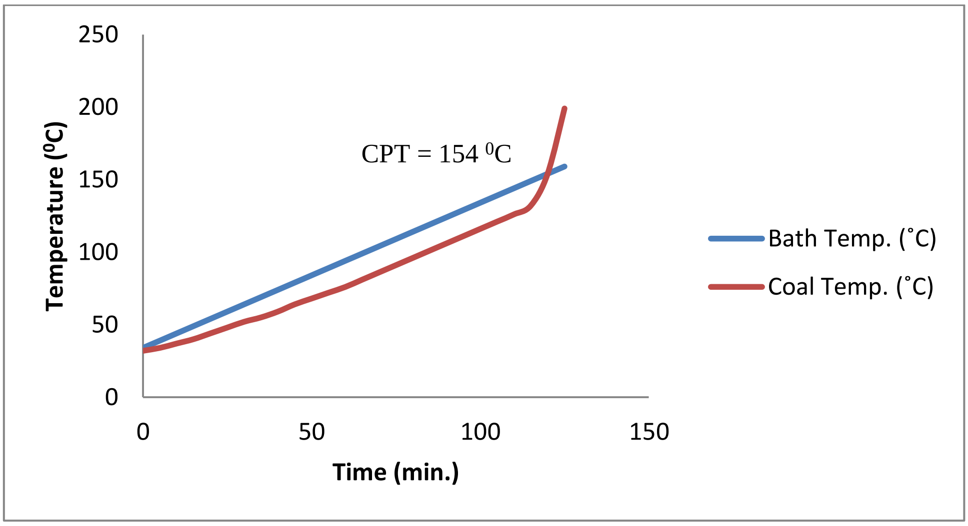


Figure A1.20 CPT curve of MCL-1 coal sample

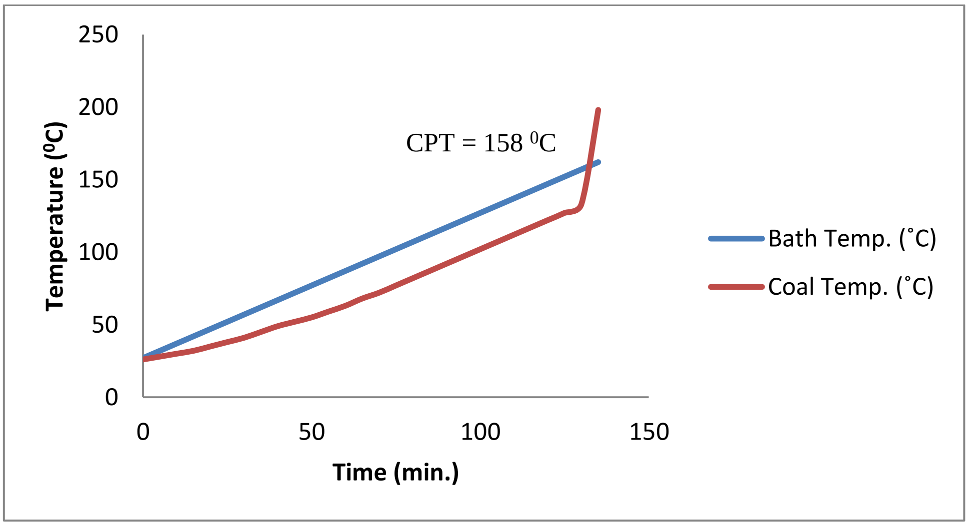


Figure A1.21 CPT curve of MCL-2 coal sample

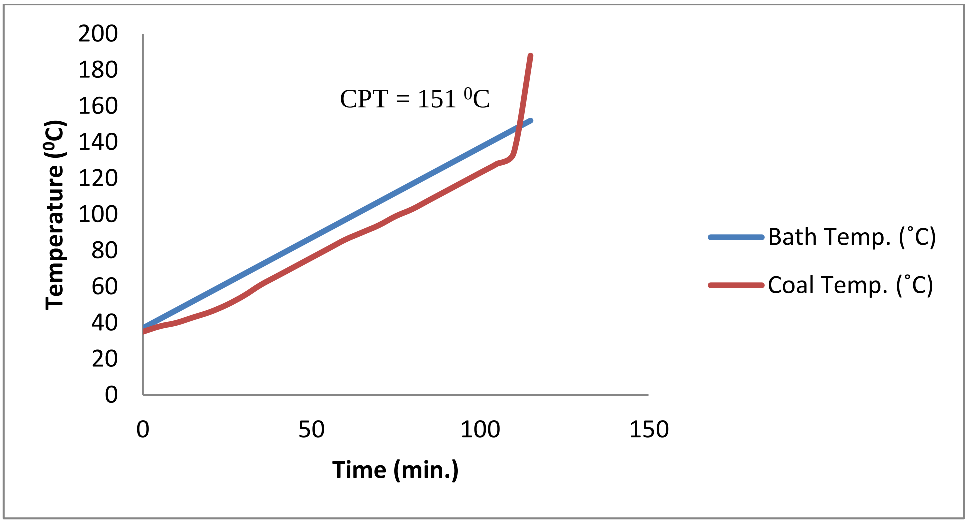


Figure A1.22 CPT curve of MCL-3 coal sample

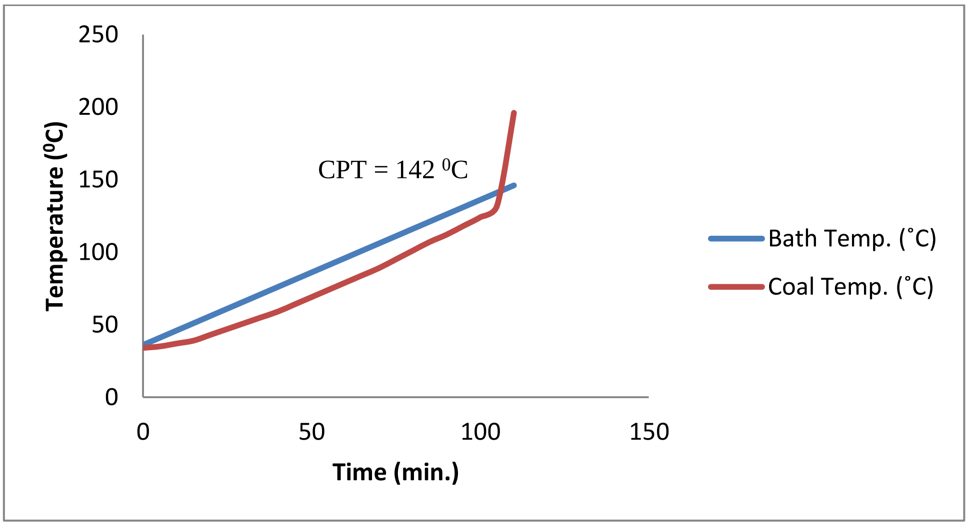
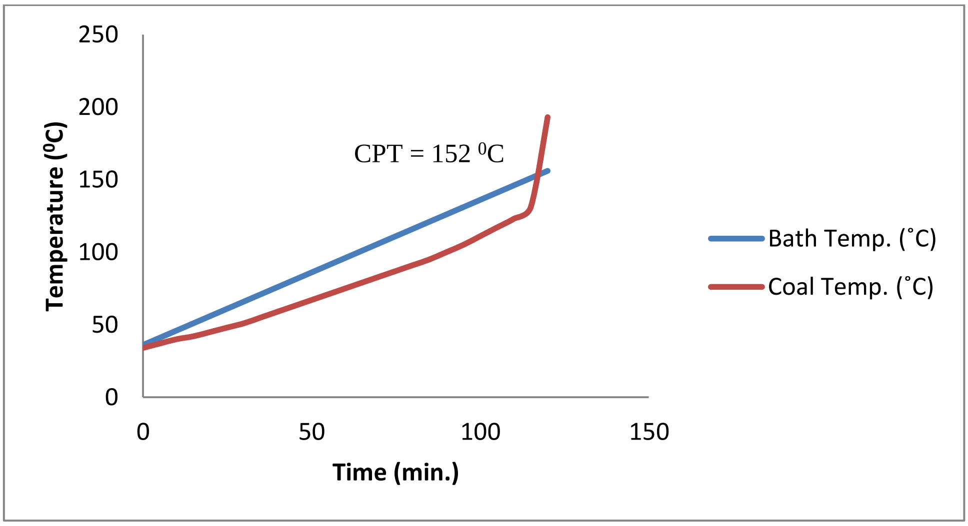


Figure A1.23 CPT curve of MCL-4 coal sample



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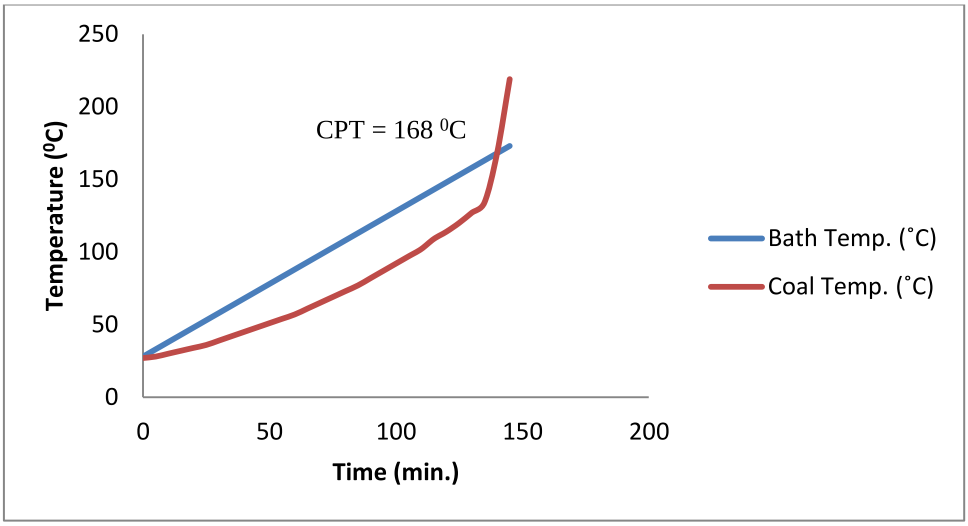

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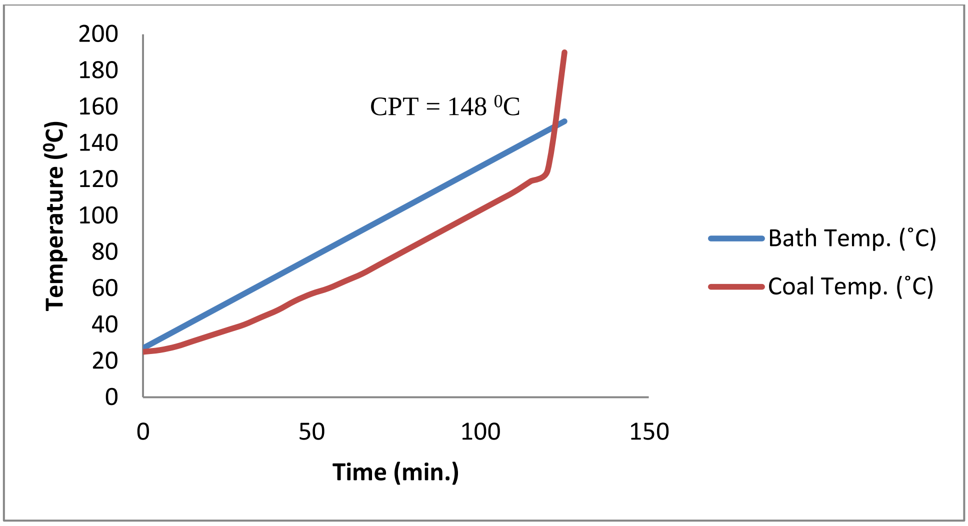


Figure A1.26 CPT curve of MCL-7 coal sample

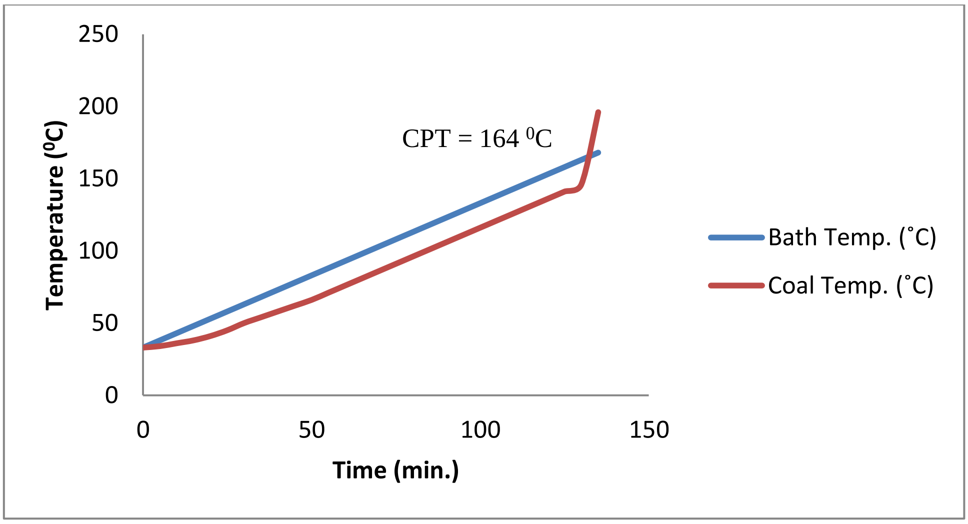


Figure A1.27 CPT curve of MCL-8 coal sample

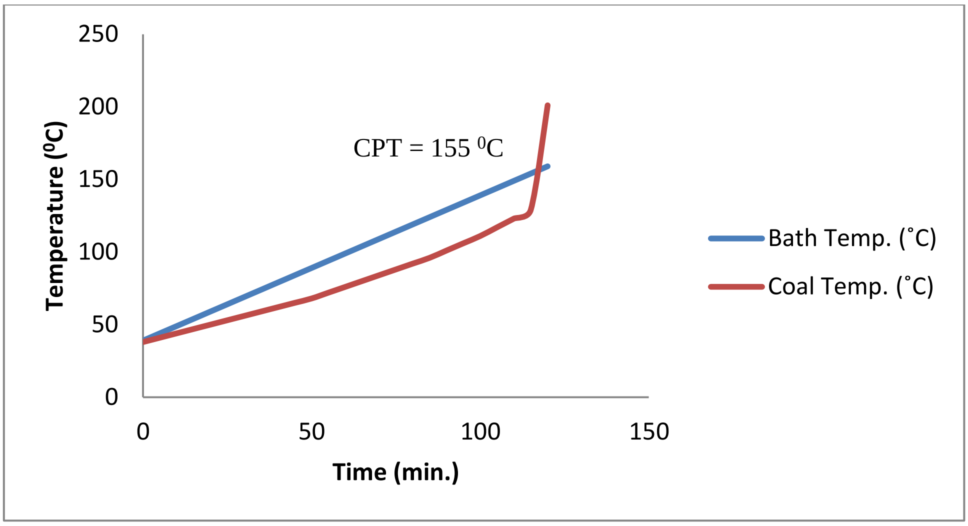


Figure A1.28 CPT curve of WCL-1 coal sample

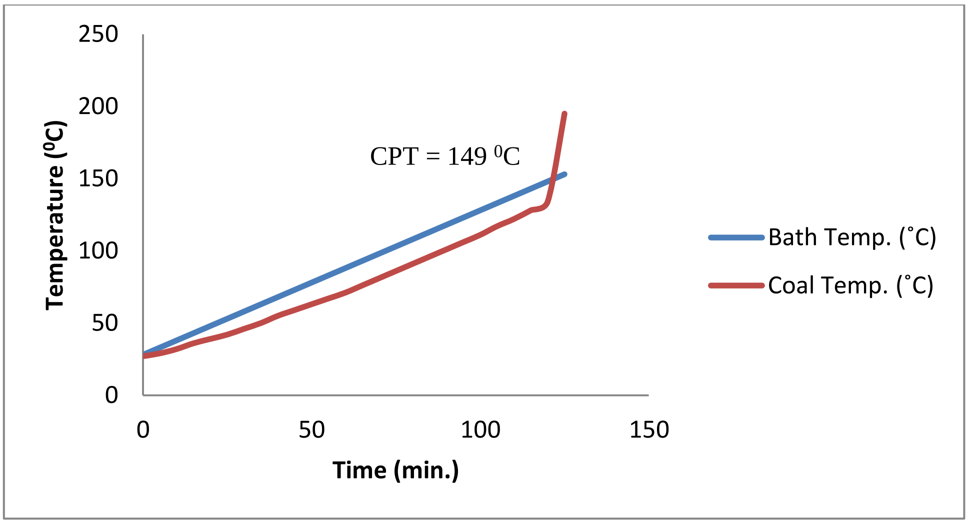
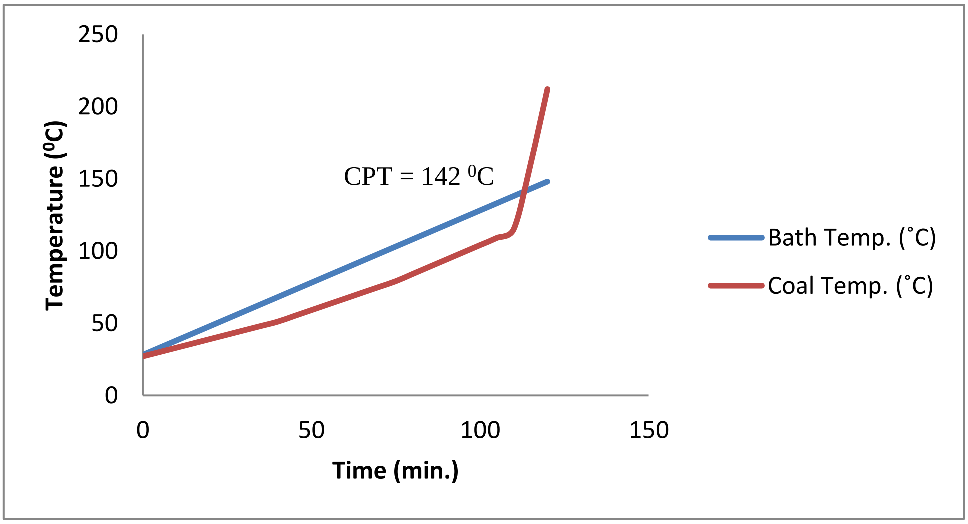


Figure A1.29 CPT curve of WCL-2 coal sample



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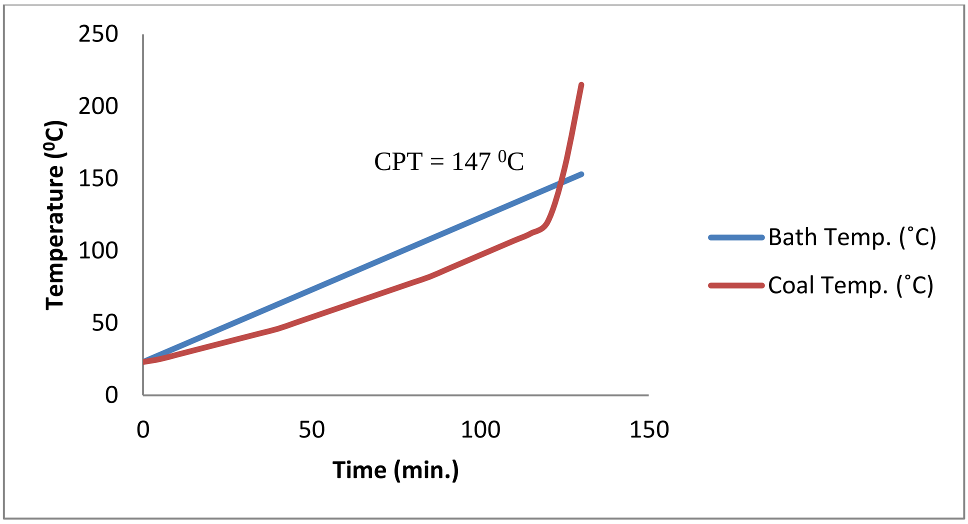

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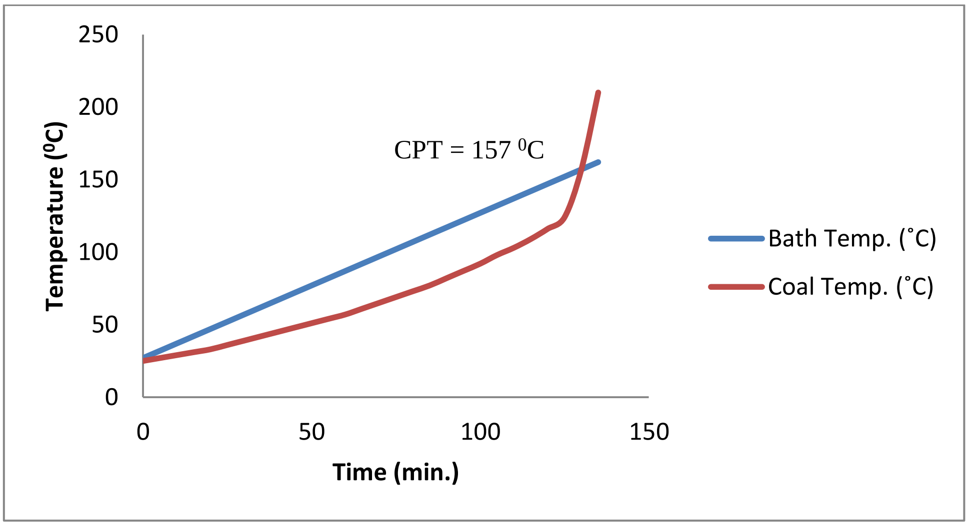

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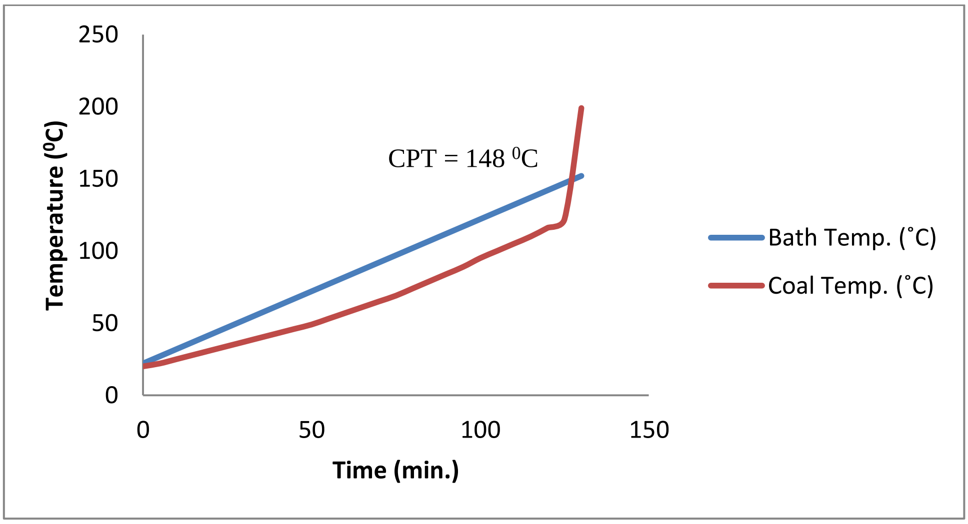

Figure A1.33 CPT curve of WCL-6 coal sample

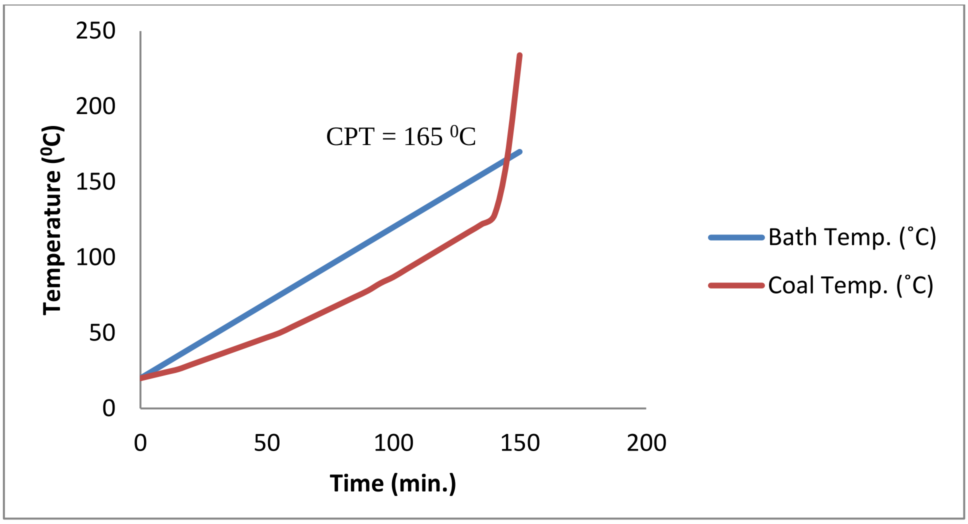

Figure A1.34 CPT curve of WCL-7 coal sample

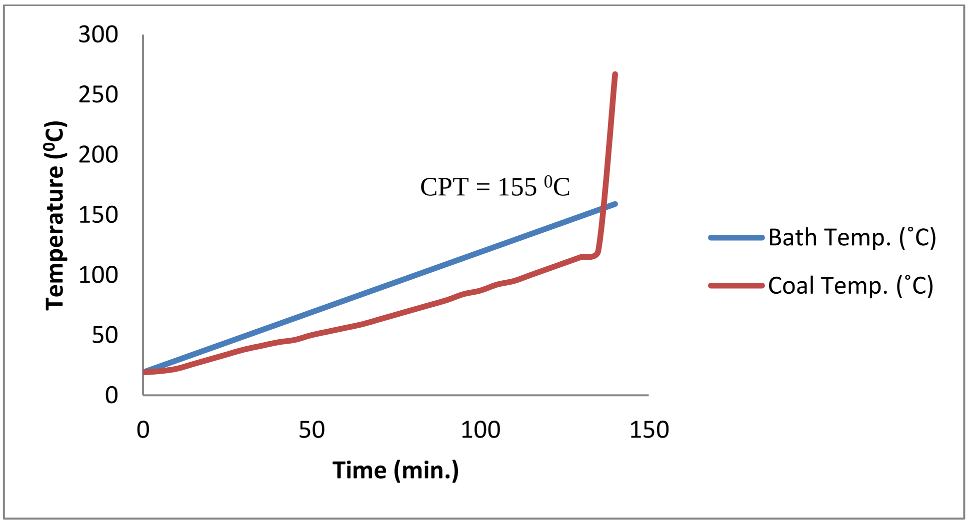

Figure A1.35 CPT curve of WCL-8 coal sample

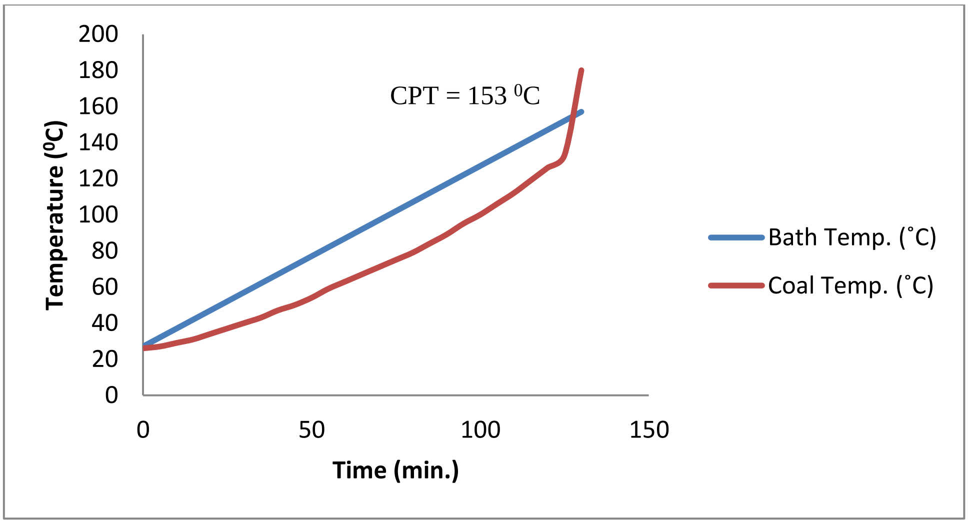

Figure A1.36 CPT curve of WCL-9 coal sample

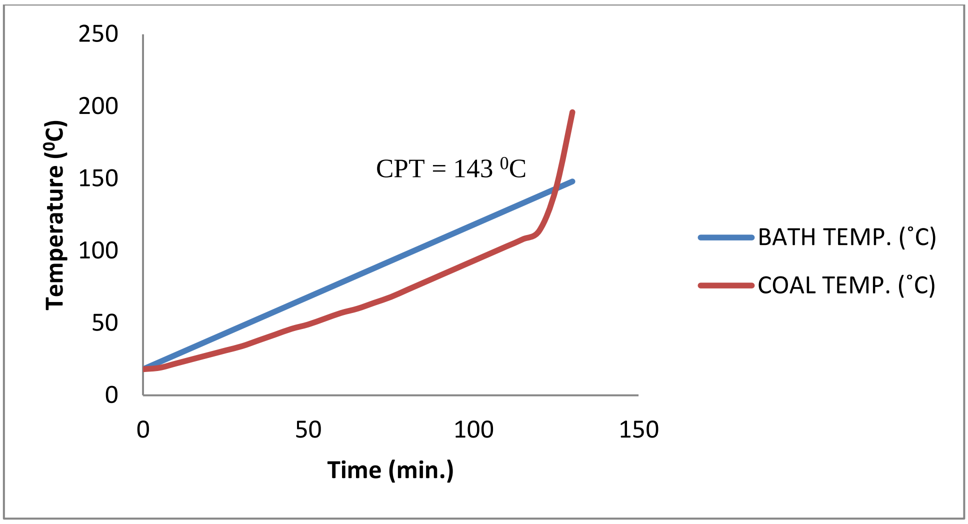

Figure A1.37 CPT curve of WCL-10 coal sample

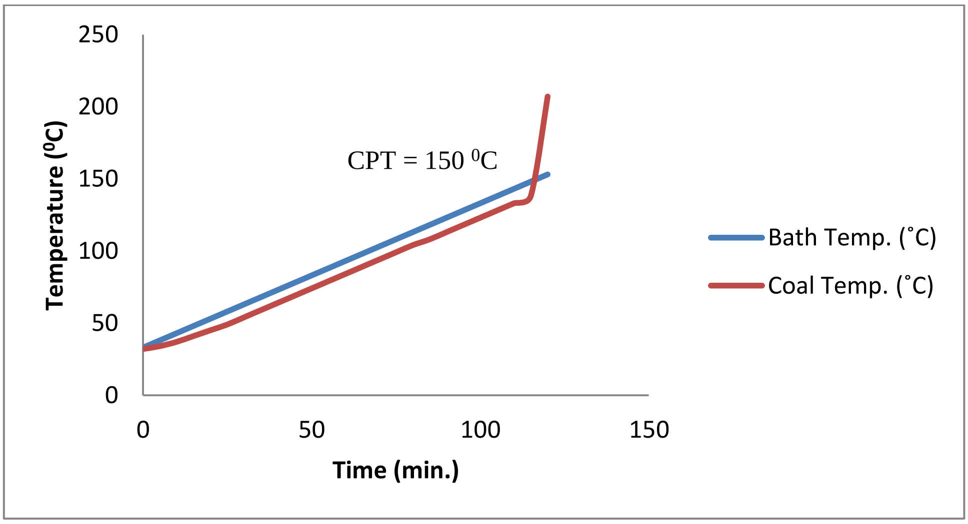

Figure A1.38 CPT curve of NEC-1 coal sample

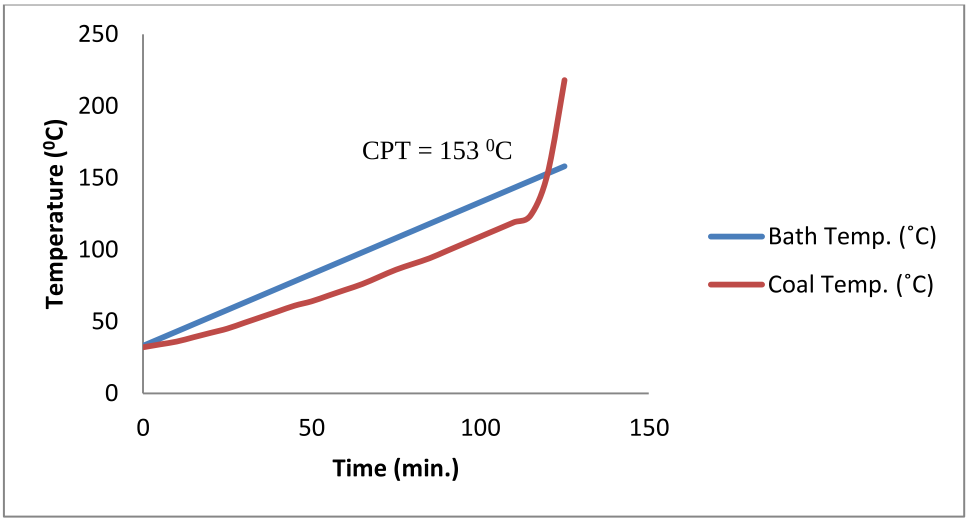

Figure A1.39 CPT curve of NEC-2 coal sample

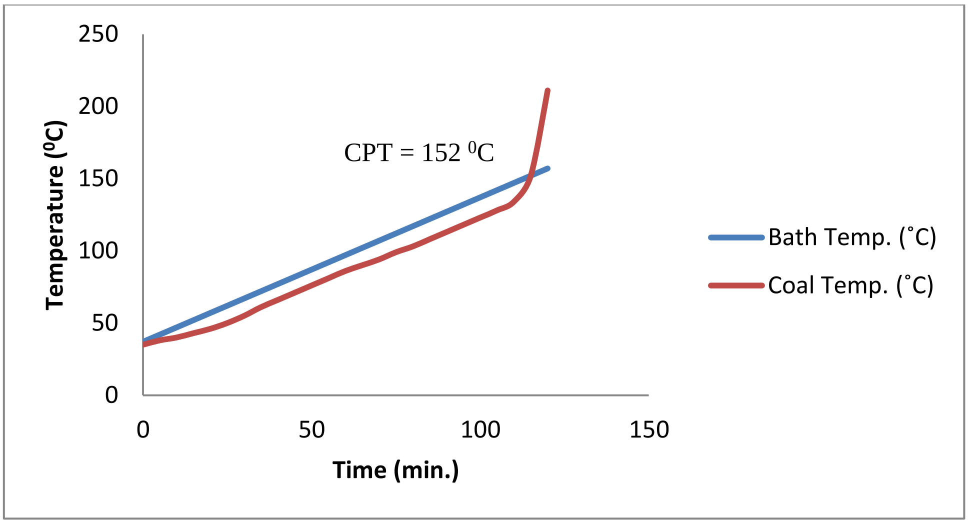

Figure A1.40 CPT curve of NEC-3 coal sample

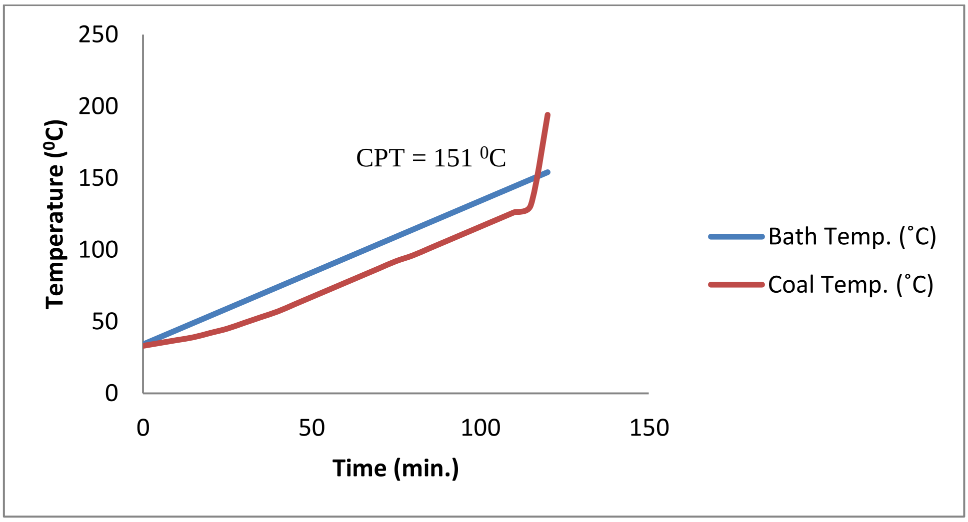

Figure A1.41 CPT curve of NEC-4 coal sample

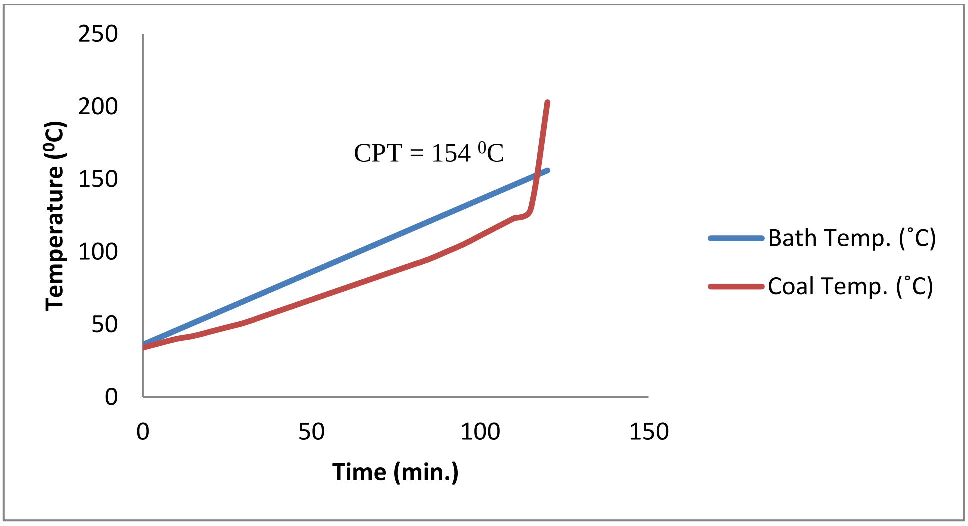

Figure A1.42 CPT curve of NEC-5 coal sample

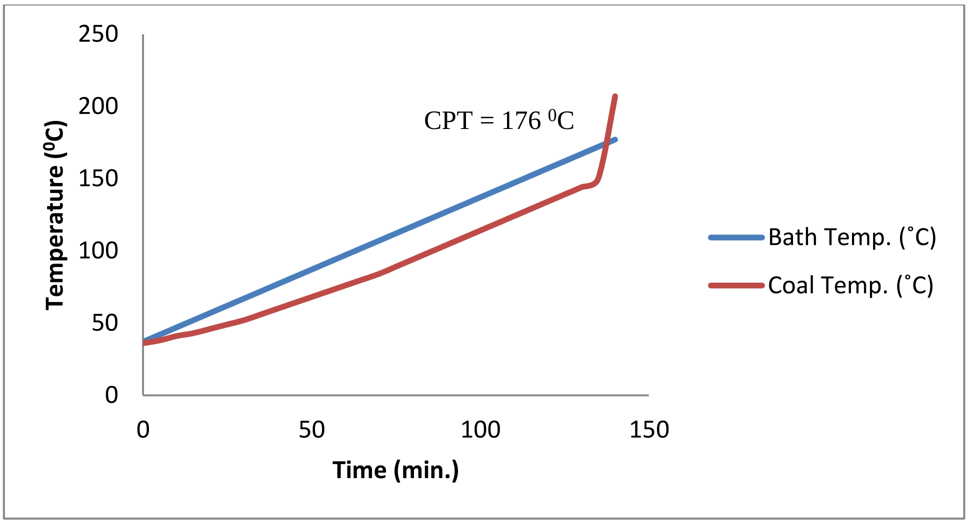

Figure A1.43 CPT curve of NEC-6 coal sample

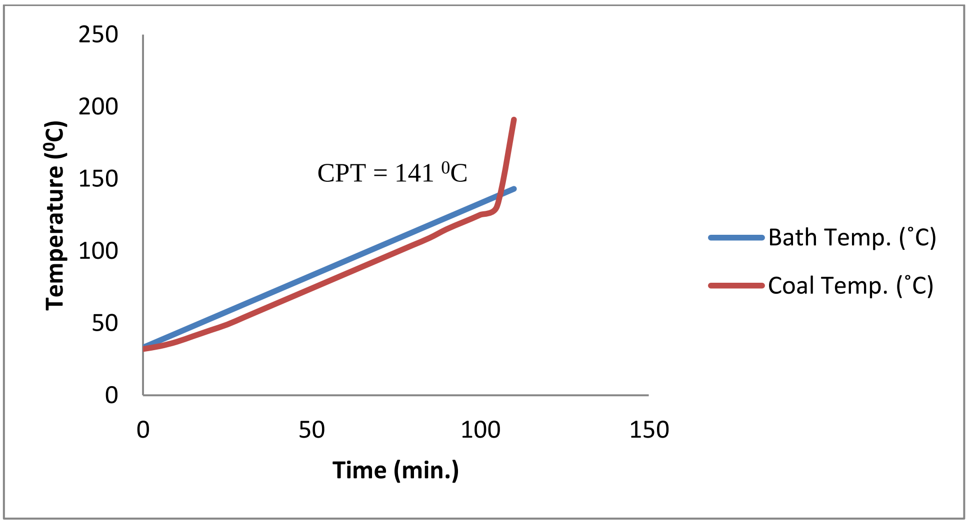

Figure A1.44 CPT curve of NCL-1 coal sample

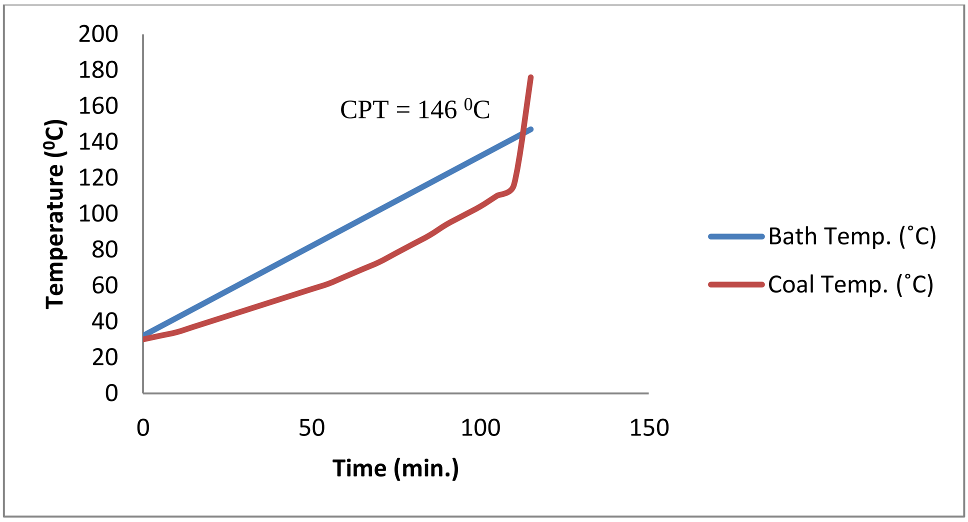

Figure A1.45 CPT curve of NCL-2 coal sample

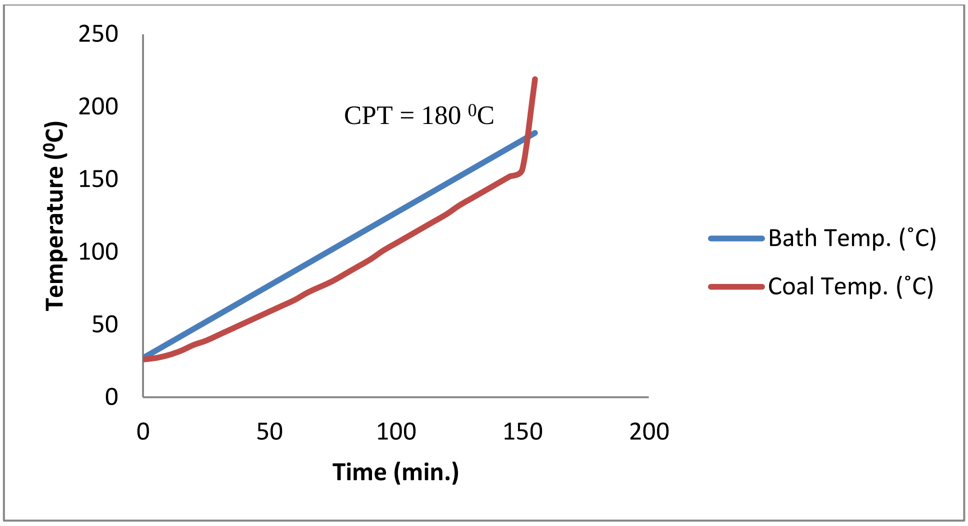

Figure A1.46 CPT curve of IISCO-1 coal sample

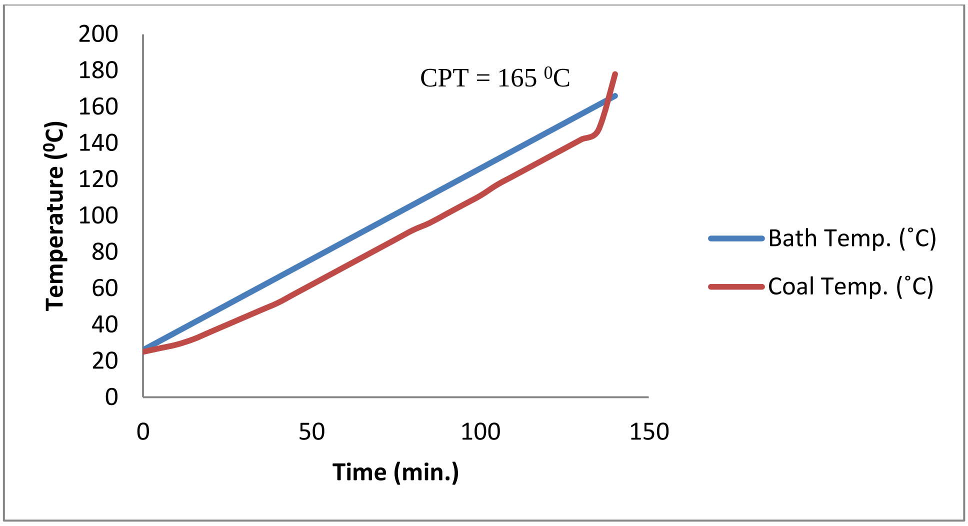

Figure A1.47 CPT curve of IISCO-2 coal sample

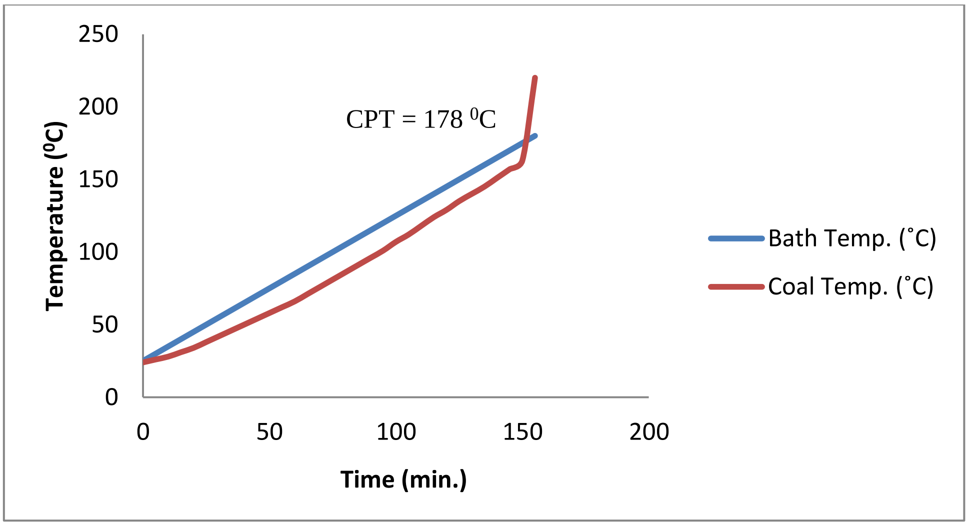

Figure A1.48 CPT curve of BCCL-1 coal sample

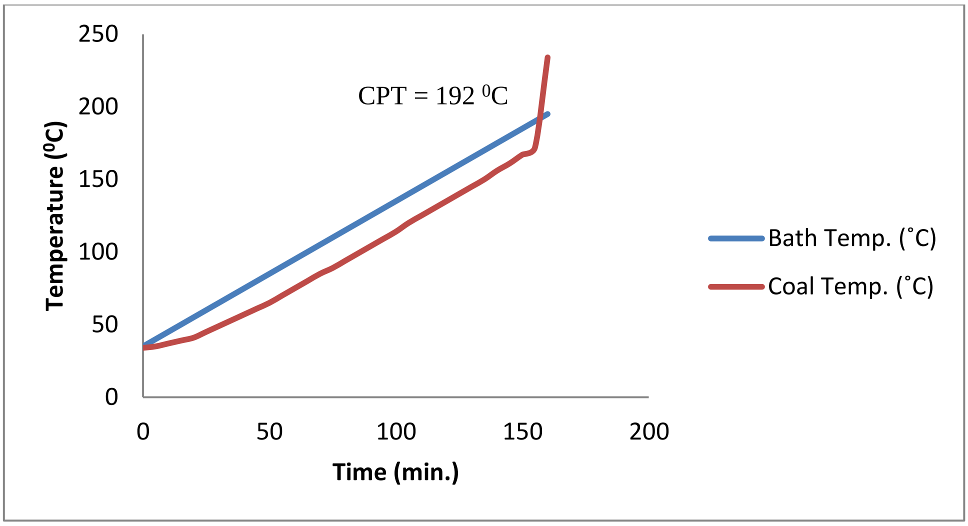

Figure A1.49 CPT curve of TISCO-1 coal sample

APPENDIX-2

WET OXIDATION POTENTIAL DIFFERENCE CURVES

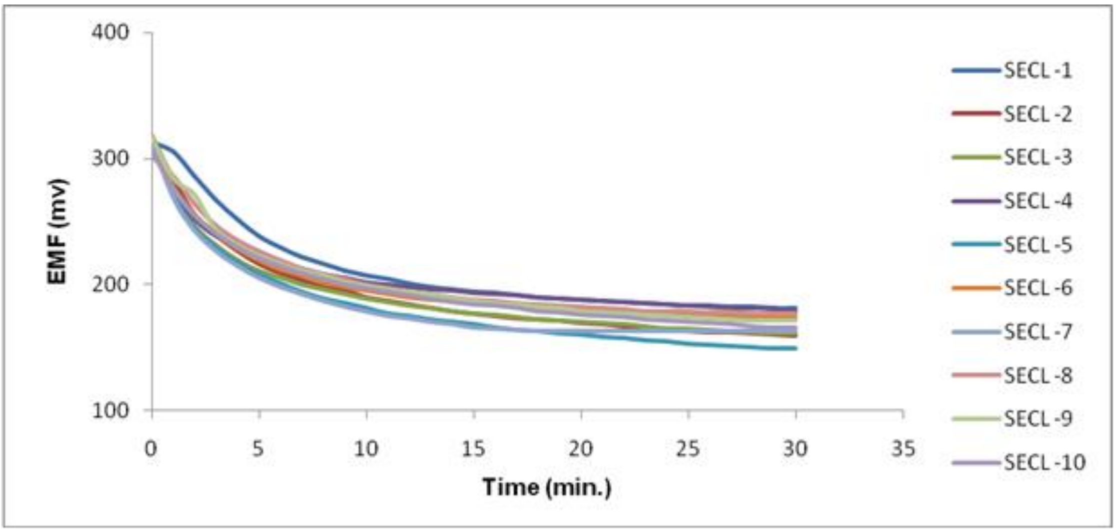

Figure A2.1 Wet oxidation potential difference curves of SECL samples

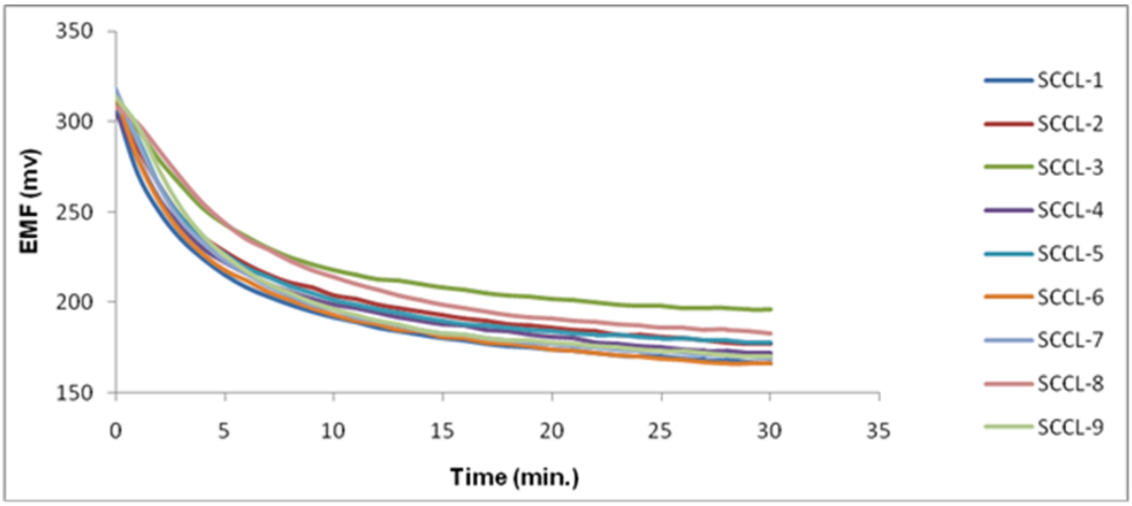

Figure A2.2 Wet oxidation potential difference curves of SCCL samples

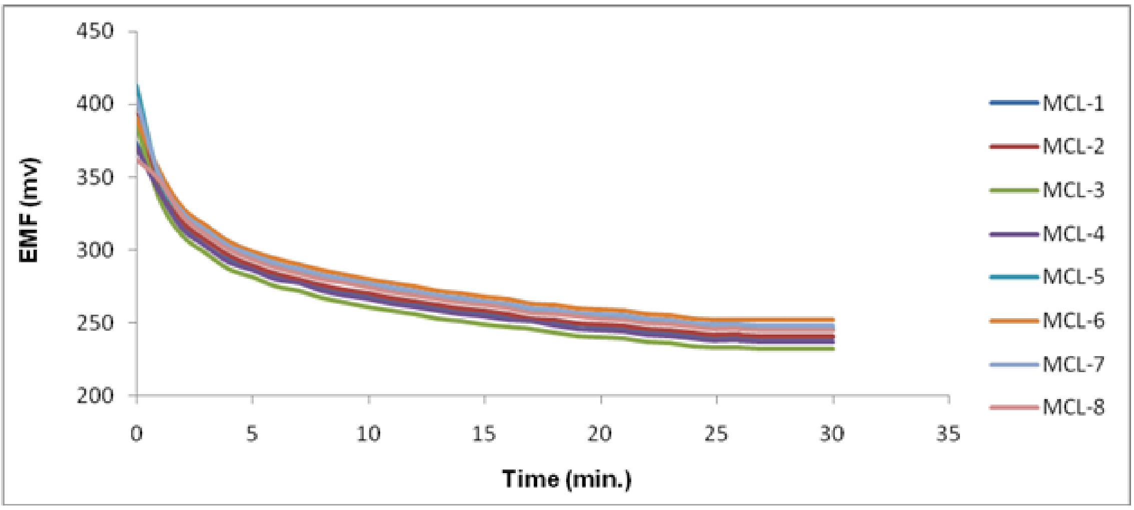

Figure A2.3 Wet oxidation potential difference curves of MCL samples

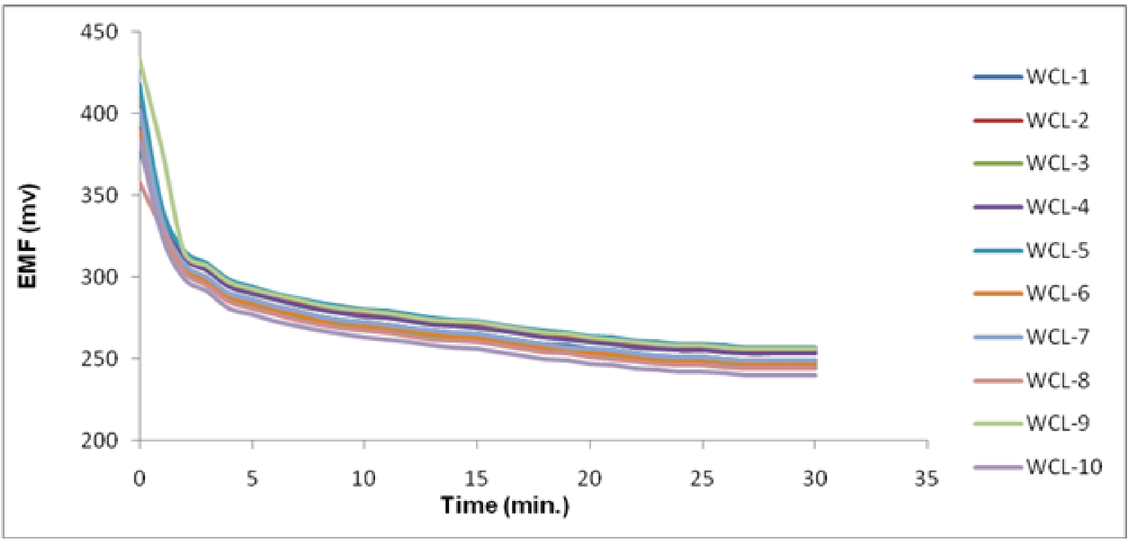

Figure A2.4 Wet oxidation potential difference curves of WCL samples

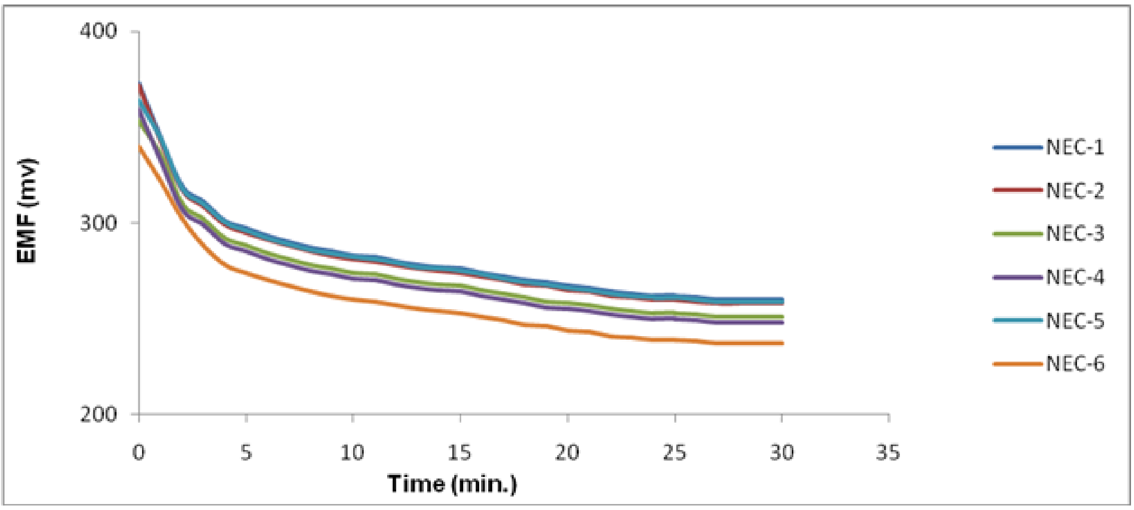

Figure A2.5 Wet oxidation potential difference curves of NEC samples

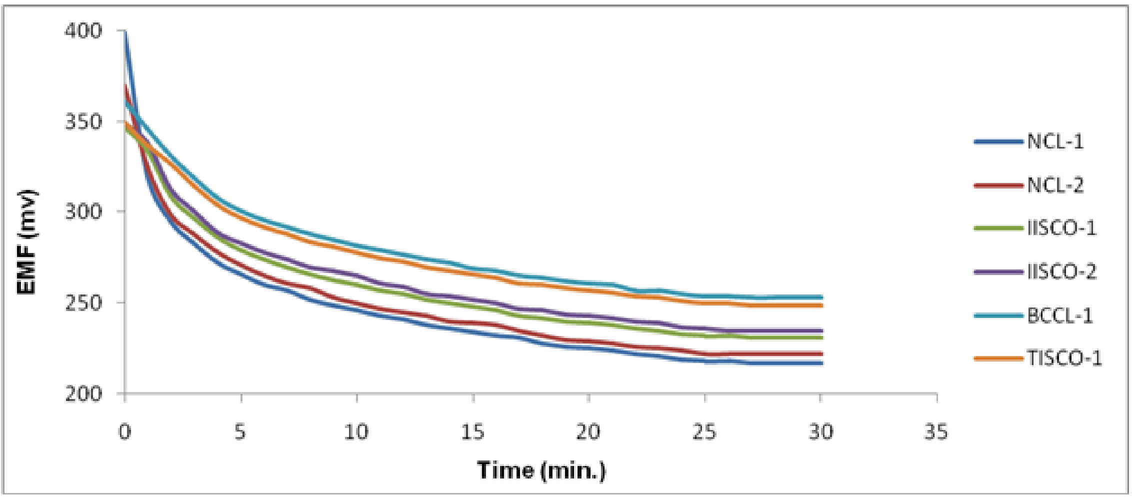

Figure A2.6 Wet oxidation potential difference curves of NCL, IISCO, BCCL & TISCO samples

APPENDIX-3

OLPINSKI INDEX CURVES

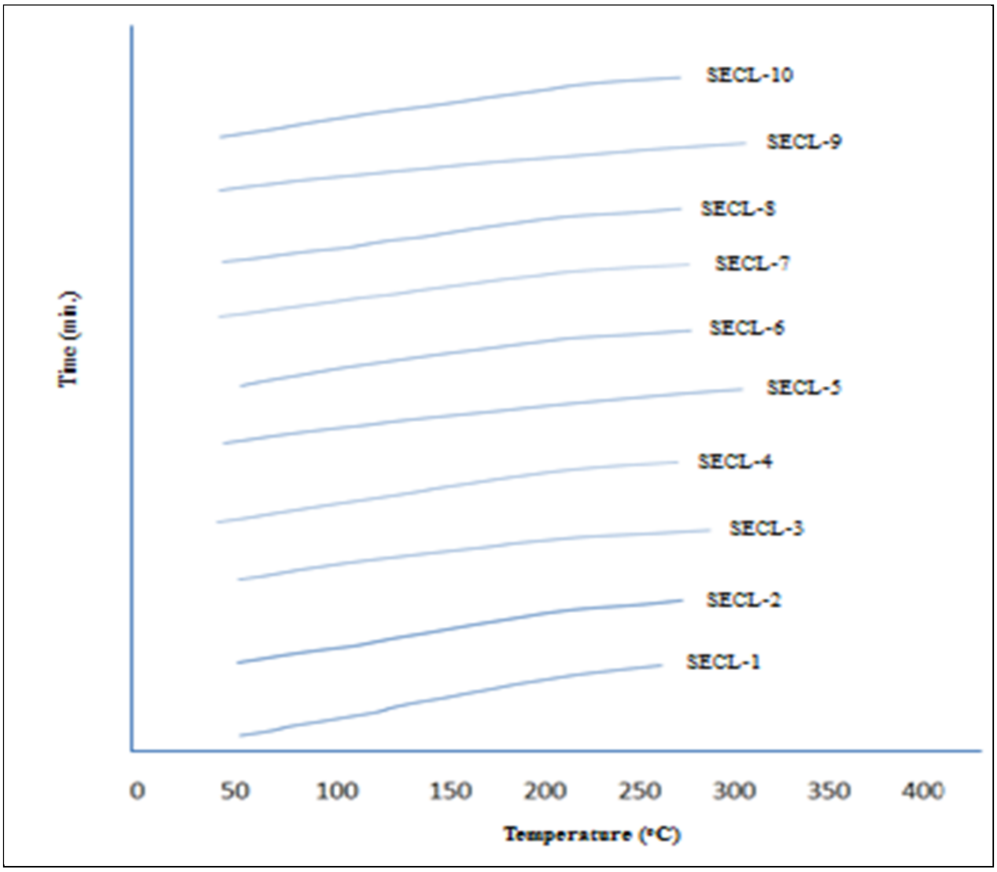

Figure A3.1 Olpinski index curves of SECL coal samples

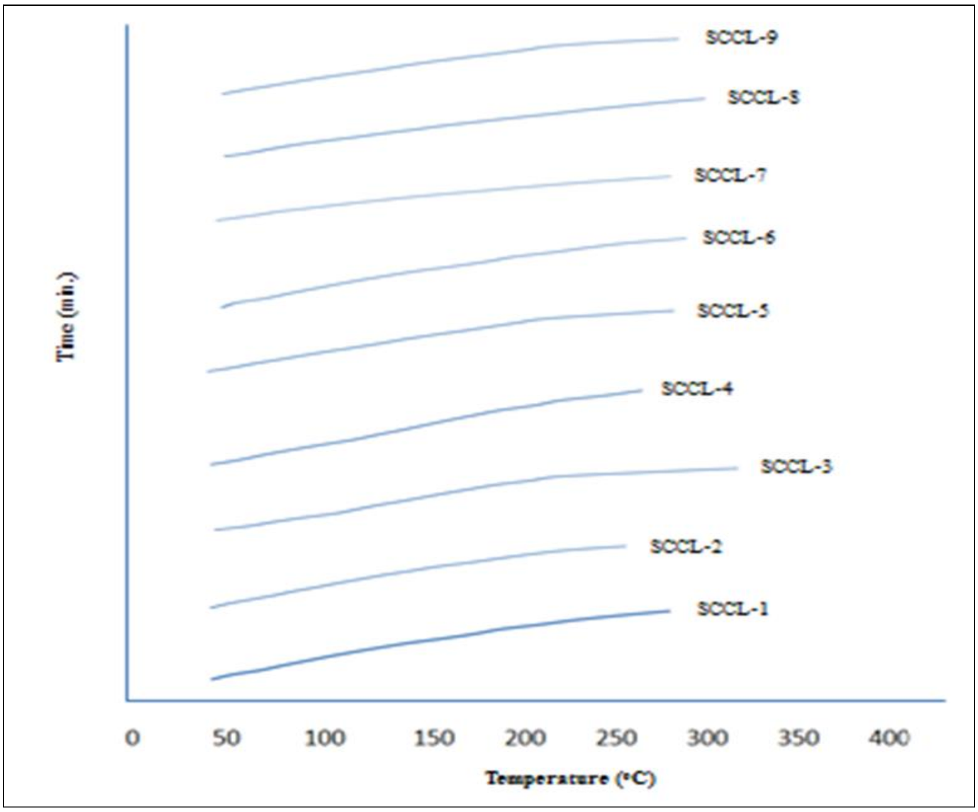

Figure A3.2 Olpinski index curves of SCCL coal samples

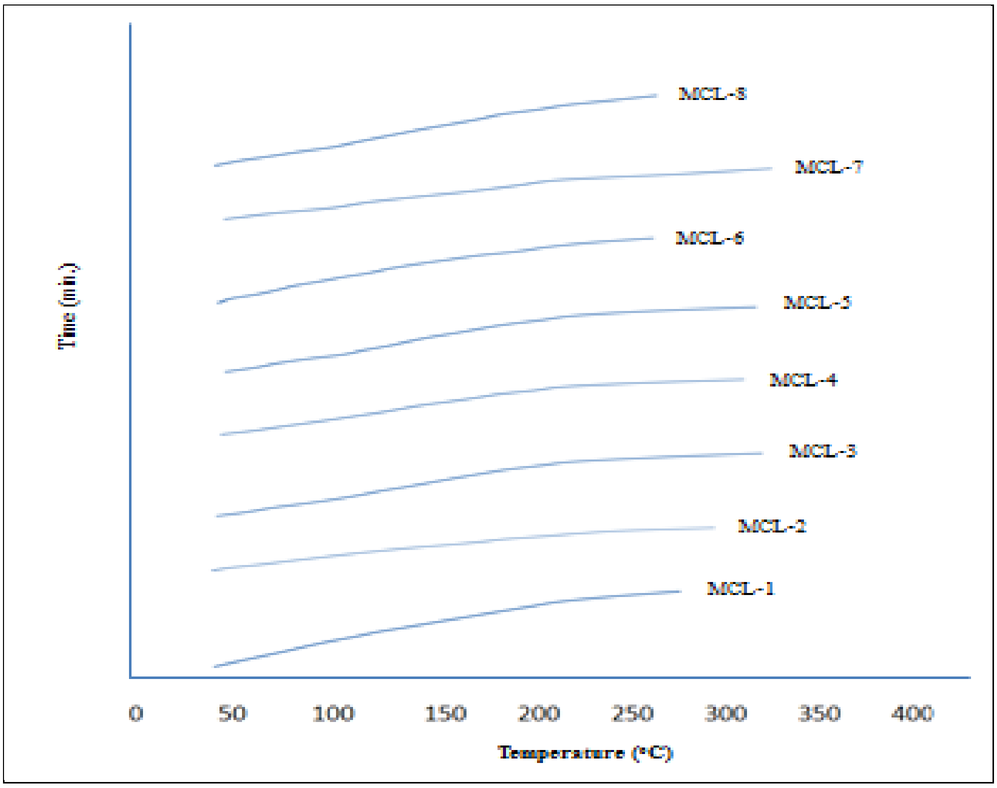

Figure A3.3 Olpinski index curves of MCL coal samples

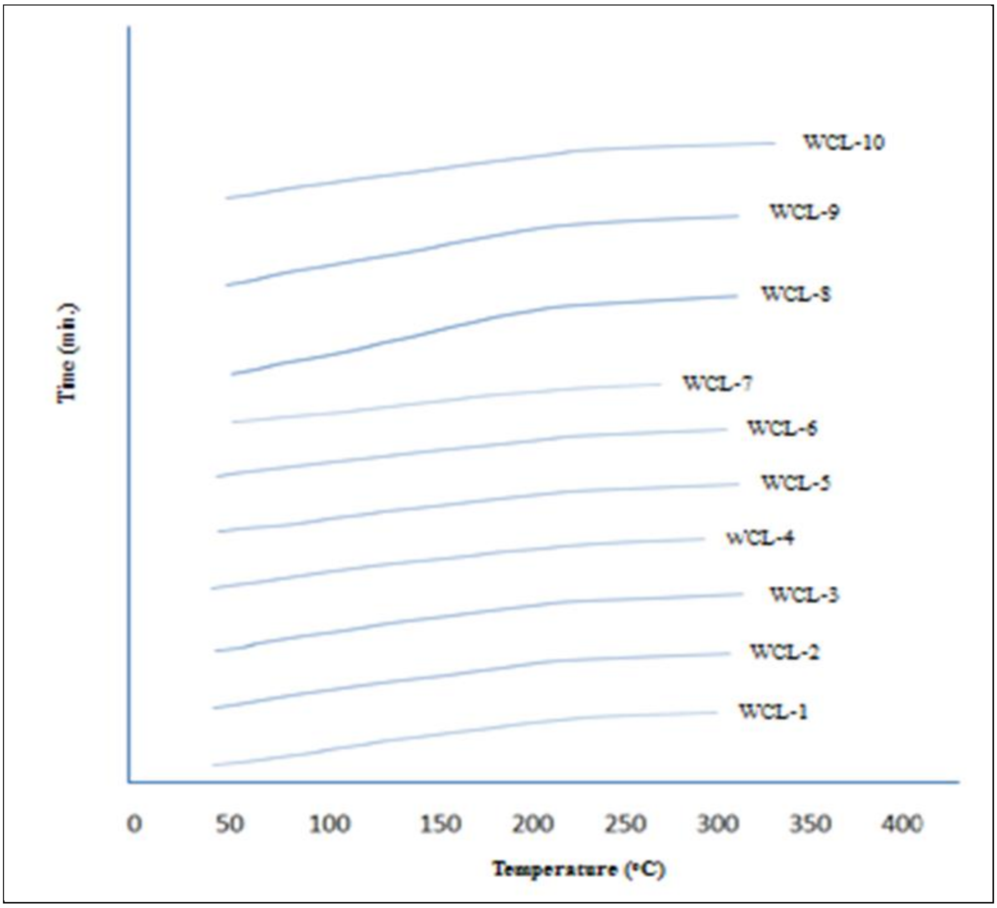

Figure A3.4 Olpinski index curves of WCL coal samples

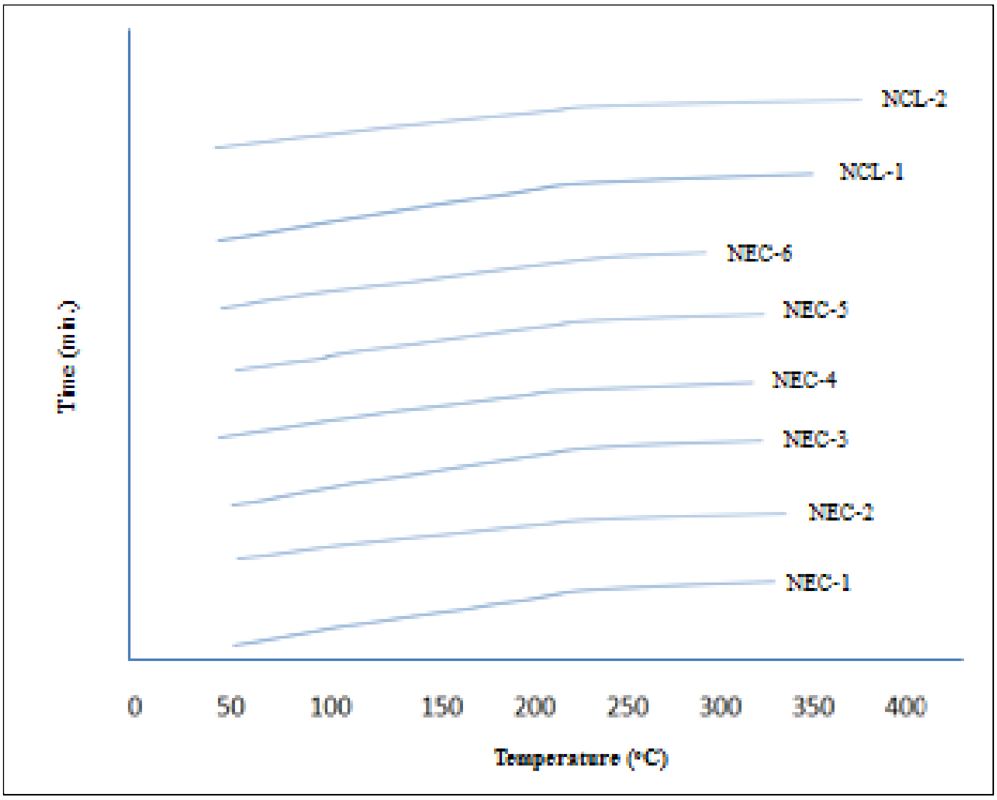

Figure A3.5 Olpinski index curves of NEC and NCL coal samples

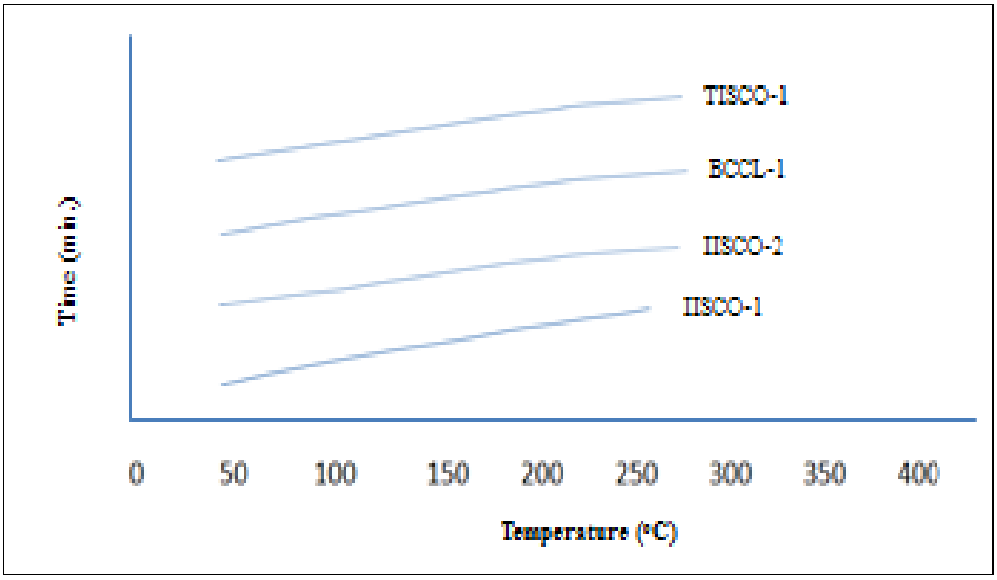

Figure A3.6 Olpinski index curves of IISCO, BCCL and TISCO coal samples

APPENDIX-4

DIFFERENTIAL THERMAL ANALYSIS THERMOGRAMS

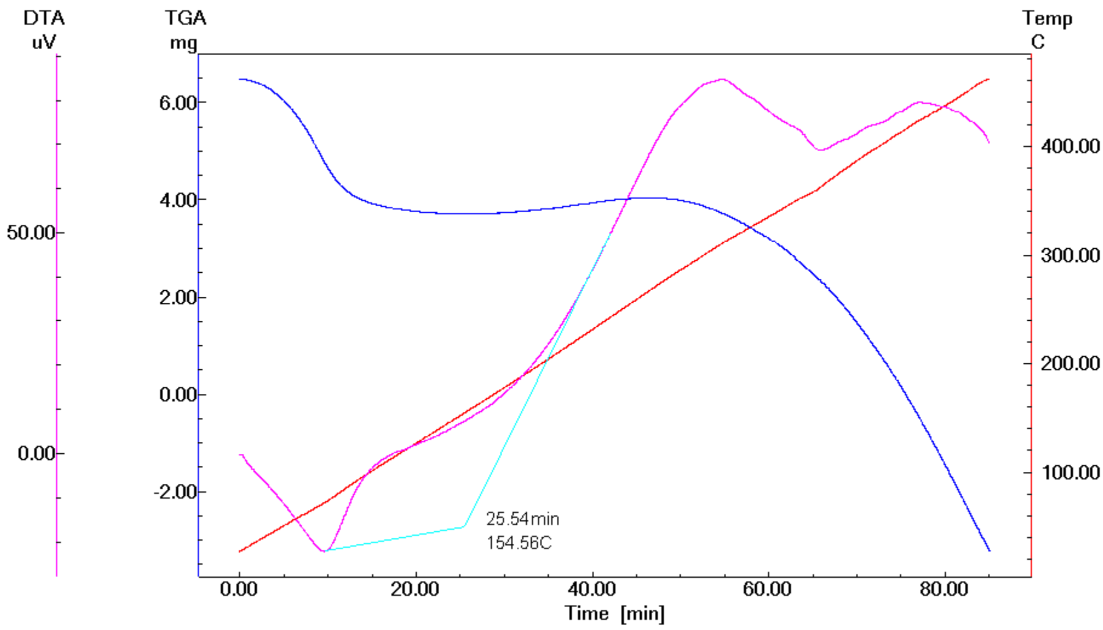

Figure A4.1 DTA thermogram of SECL -1 coal sample

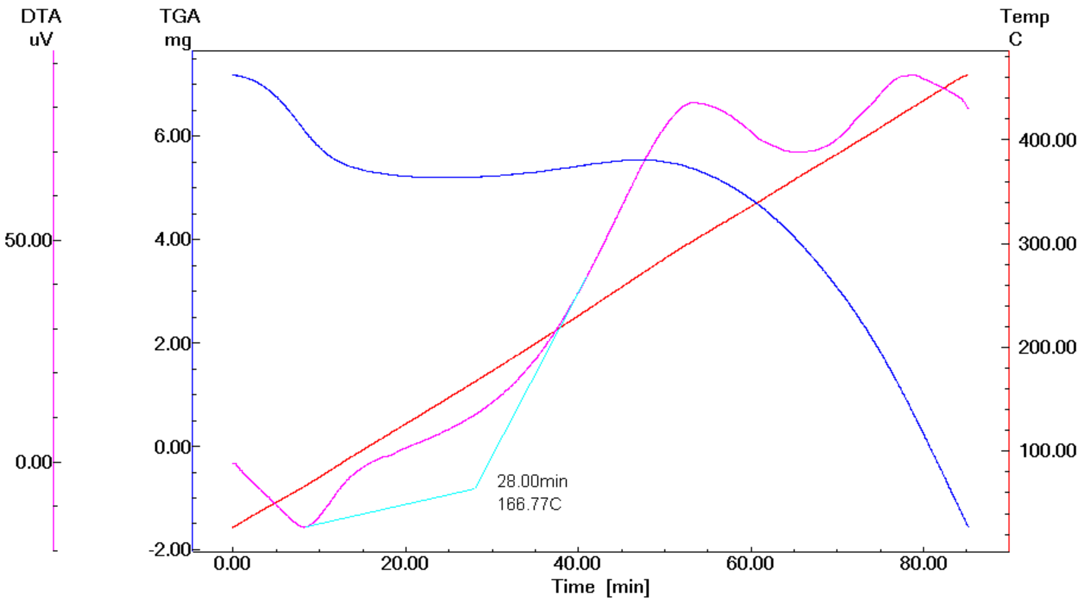

Figure A4.2 DTA thermogram of SECL -2 coal sample

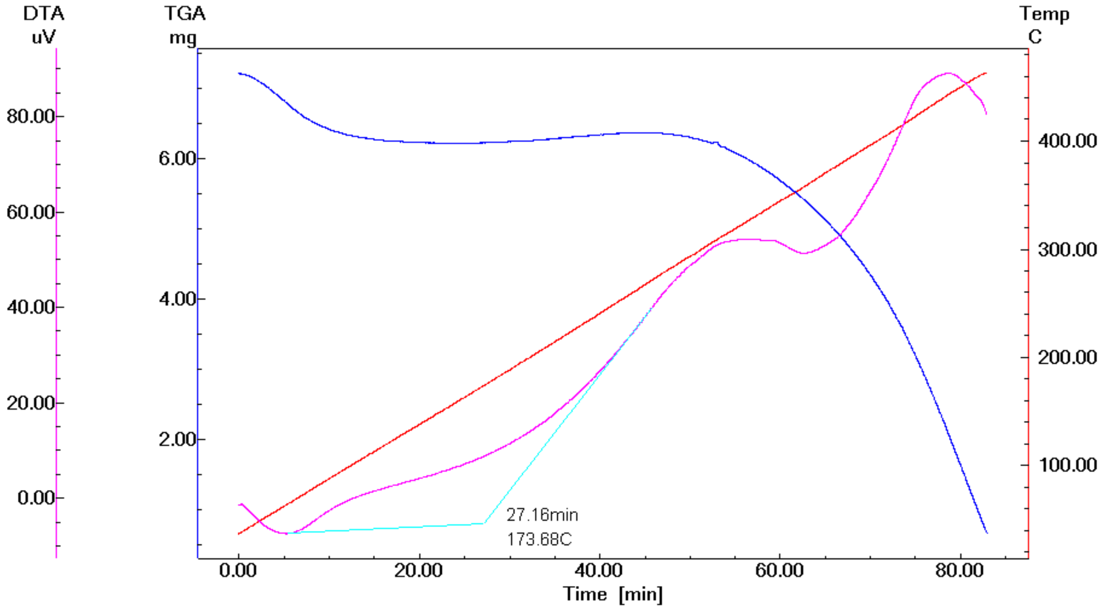

Figure A4.3 DTA thermogram of SECL -3 coal sample

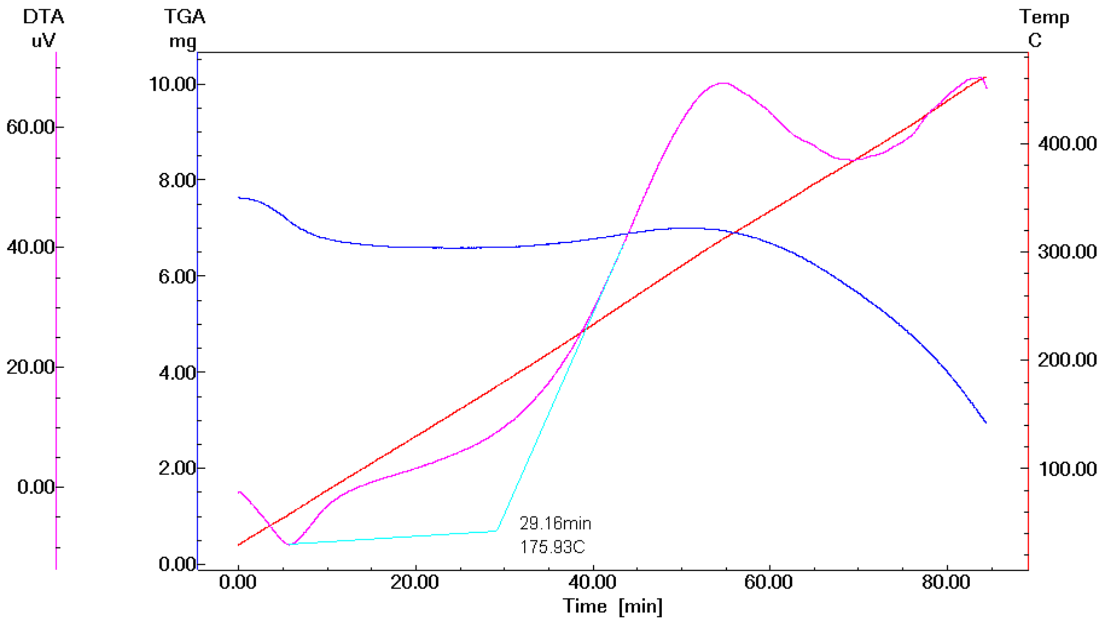

Figure A4.4 DTA thermogram of SECL - 4 coal sample

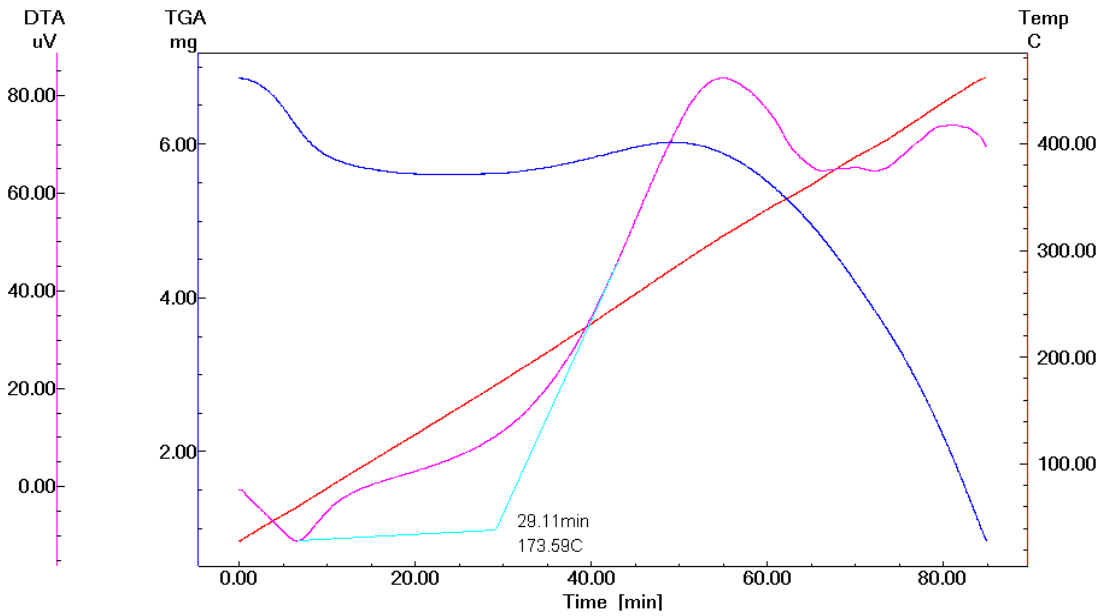

Figure A4.5 DTA thermogram of SECL – 5 coal sample

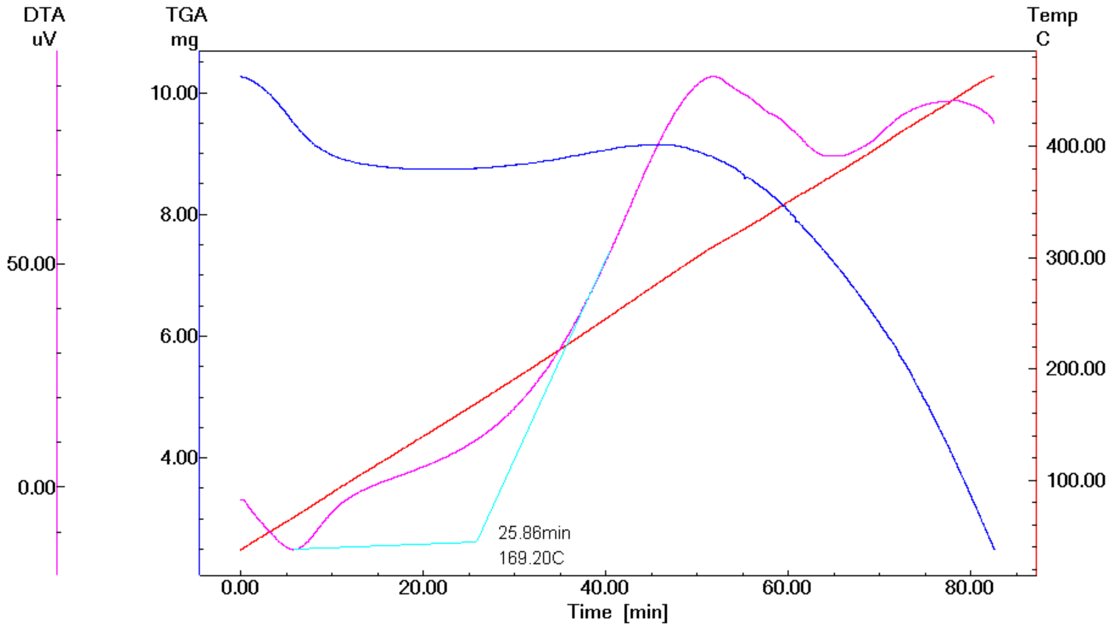

Figure A4.6 DTA thermogram of SECL - 6 coal sample

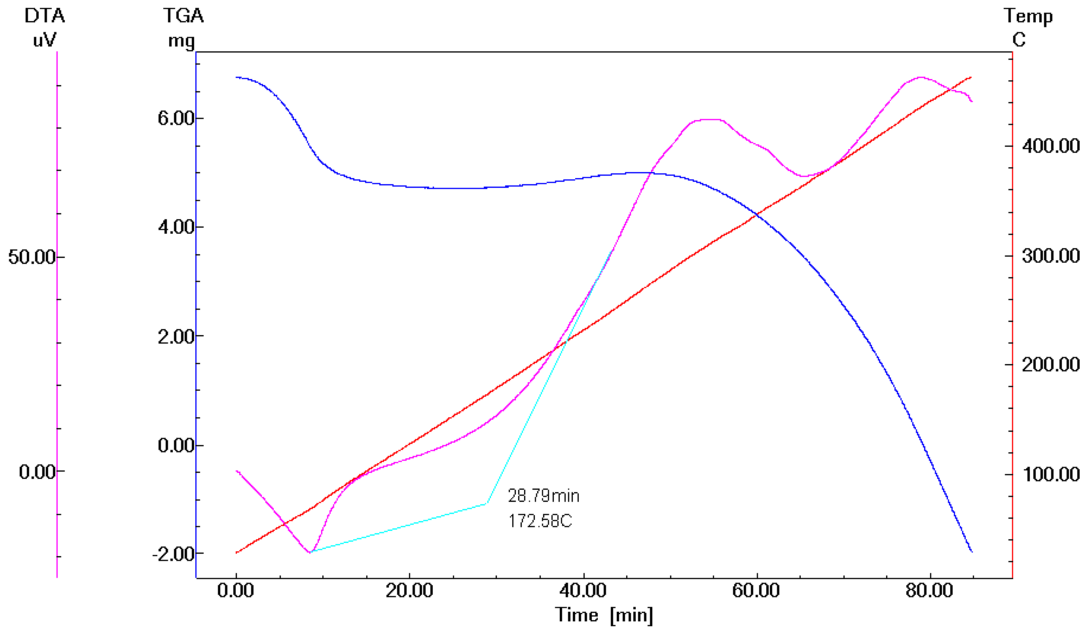

Figure A4.7 DTA thermogram of SECL -7 coal sample

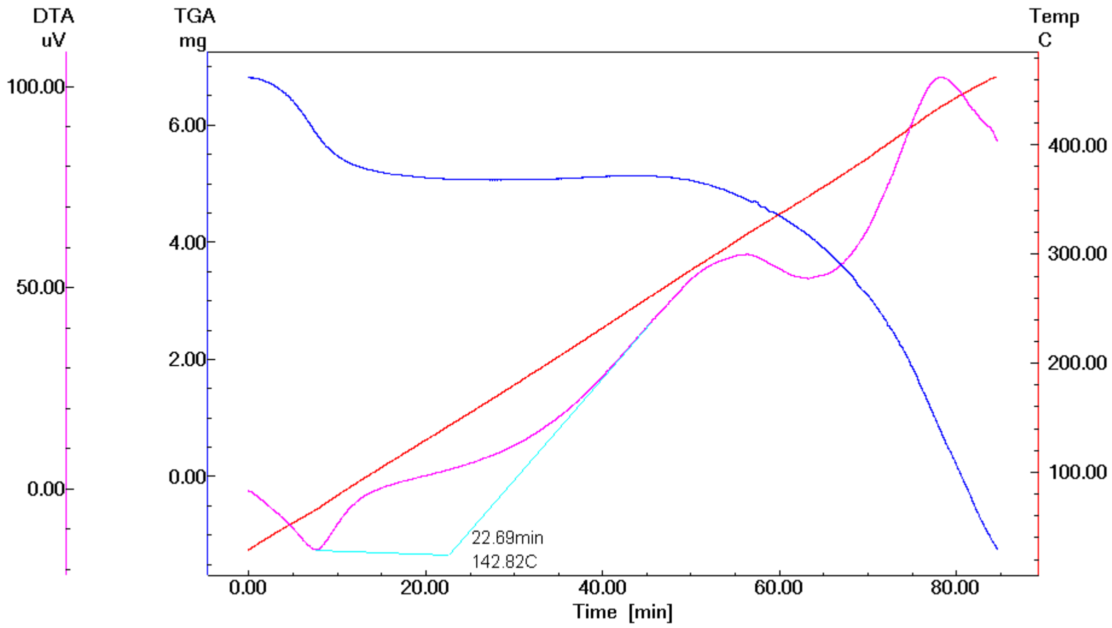

Figure A4.8 DTA thermogram of SECL -8 coal sample

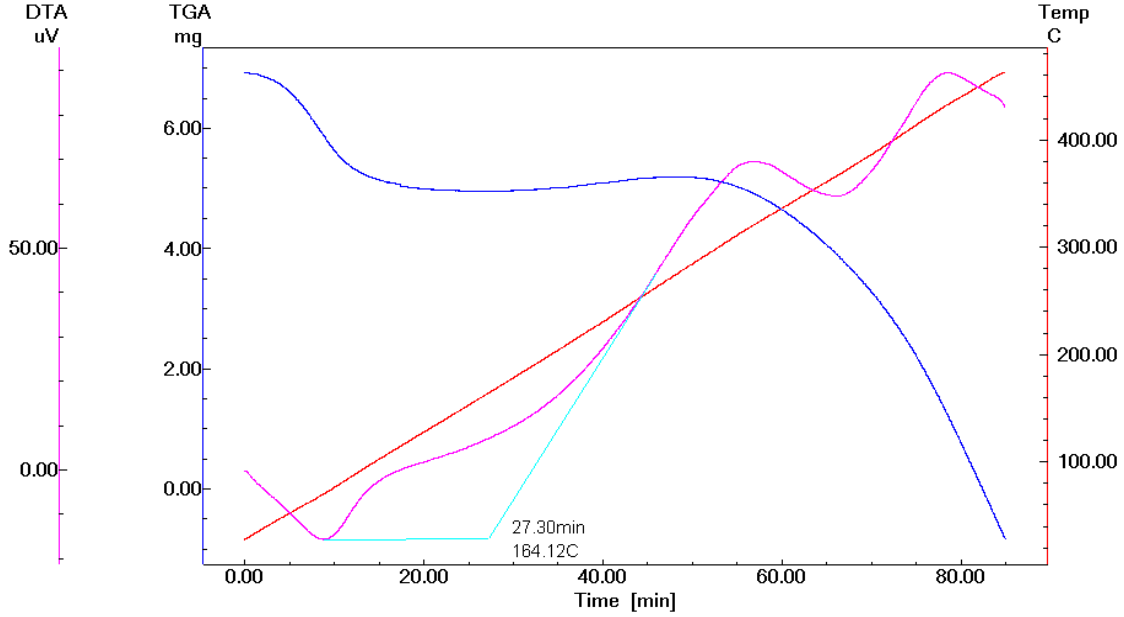

Figure A4.9 DTA thermogram of SECL – 9 coal sample

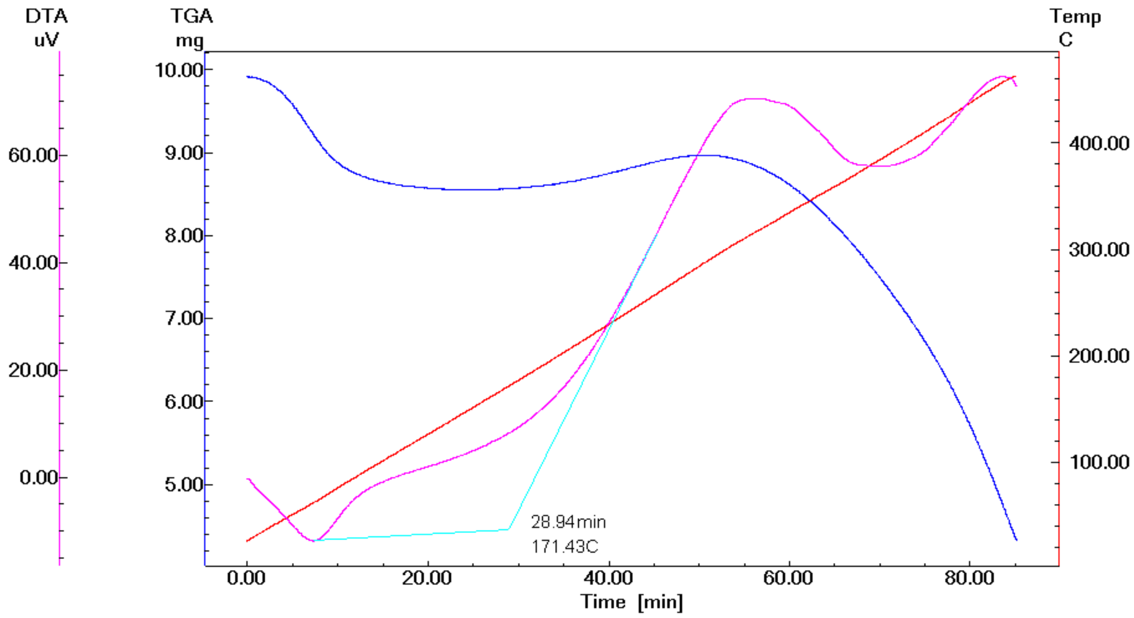

Figure A4.10 DTA thermogram of SECL -10 coal sample

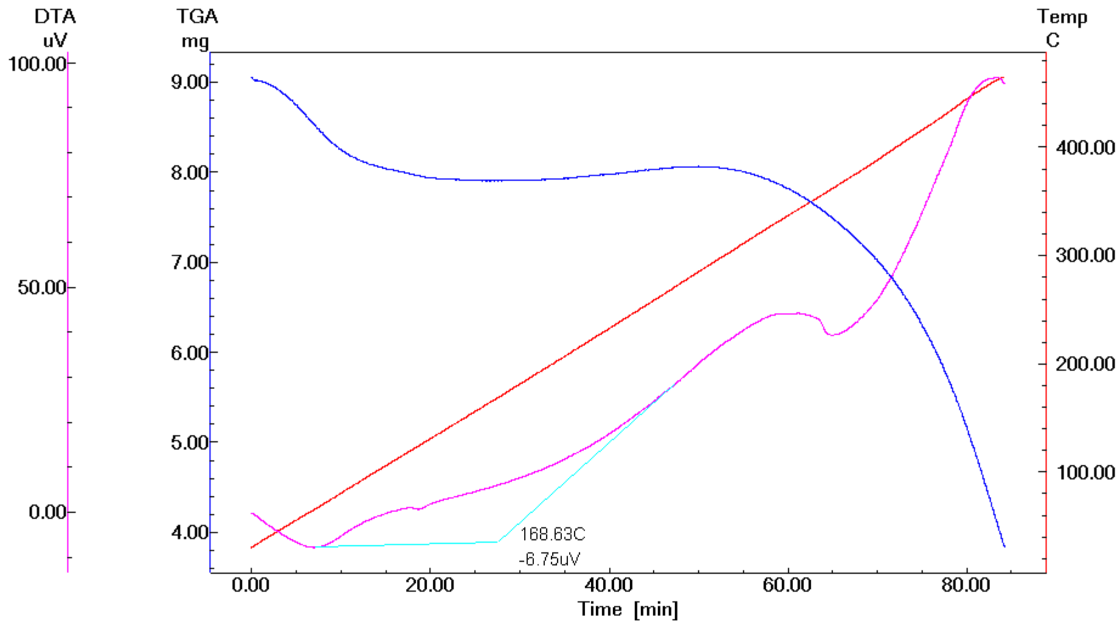

Figure A4.11 DTA thermogram of SCCL -1 coal sample

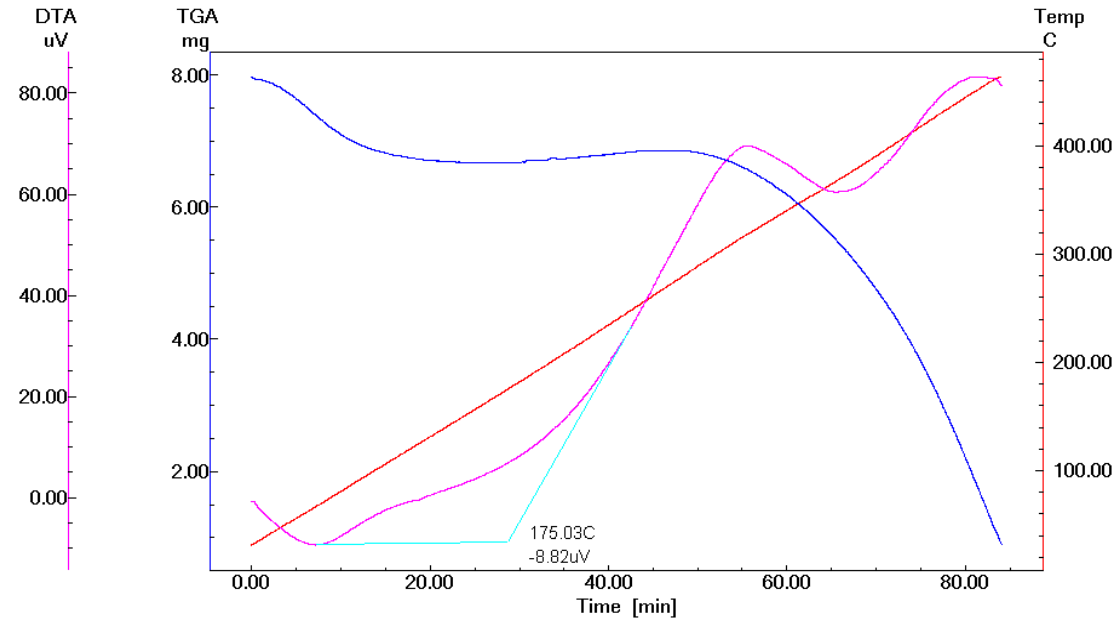

Figure A4.12 DTA thermogram of SCCL - 2 coal sample

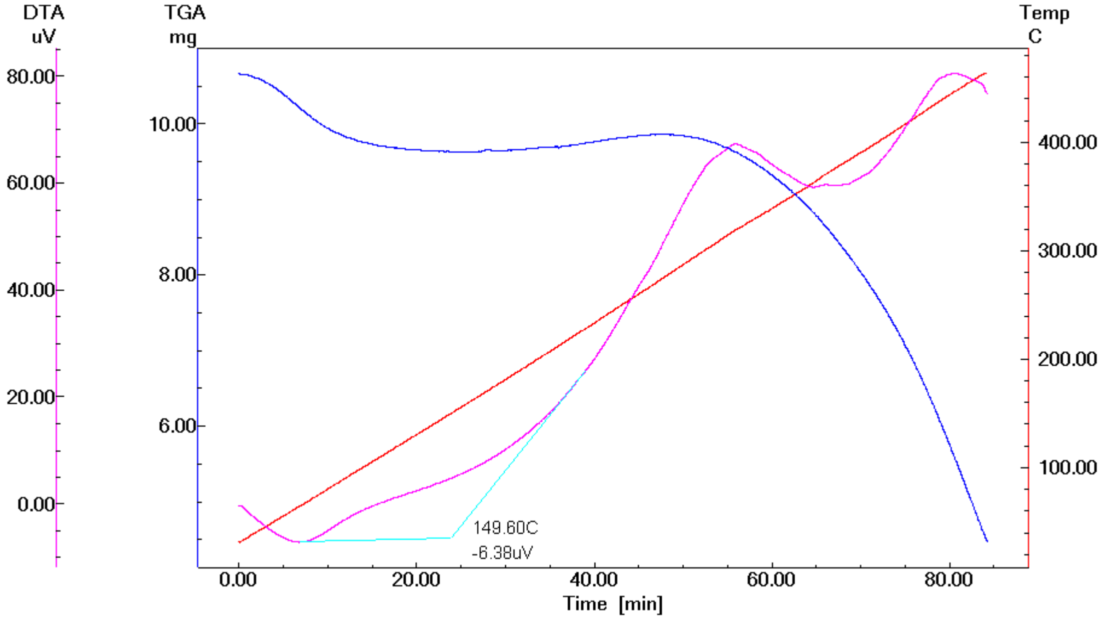

Figure A4.13 DTA thermogram of SCCL – 3 coal sample

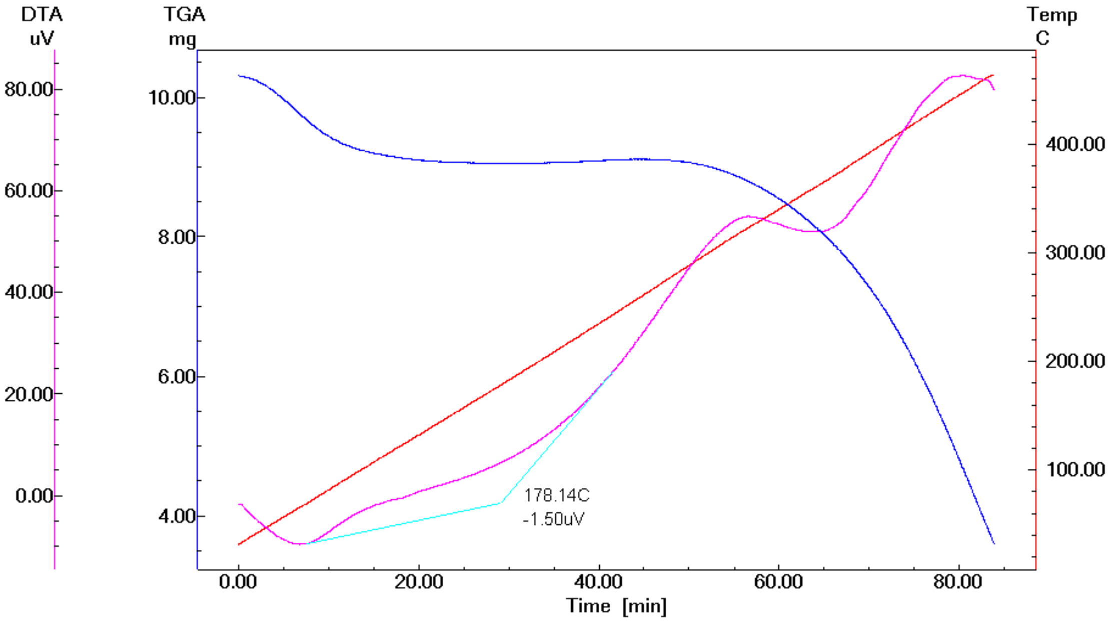

Figure A4.14 DTA thermogram of SCCL - 4 coal sample

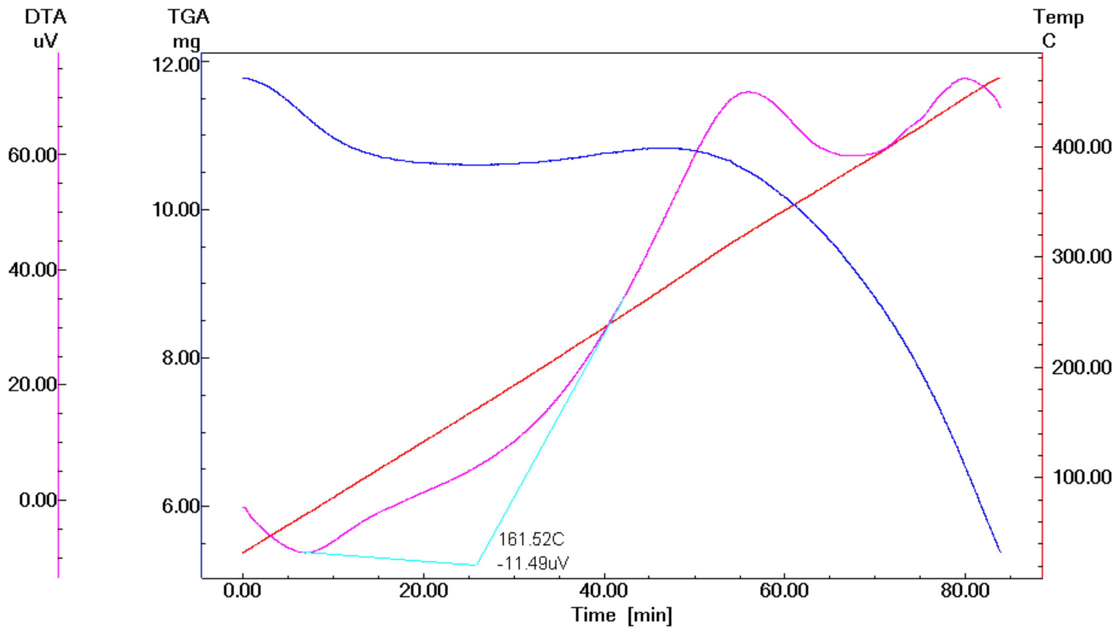

Figure A4.15 DTA thermogram of SCCL – 5 coal sample

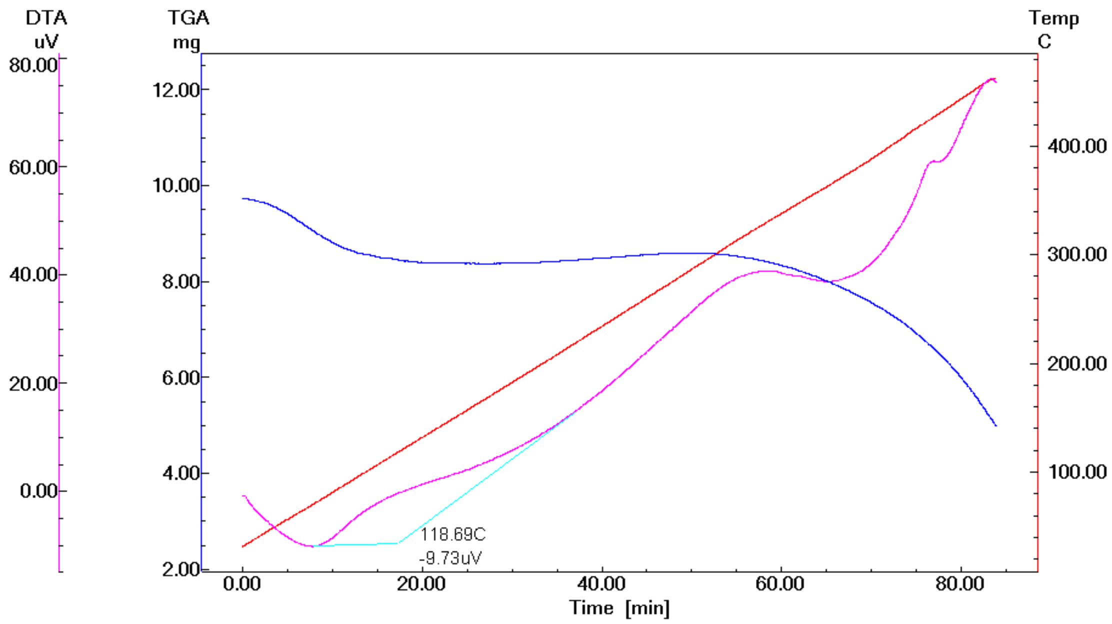

Figure A4.16 DTA thermogram of SCCL - 6 coal sample

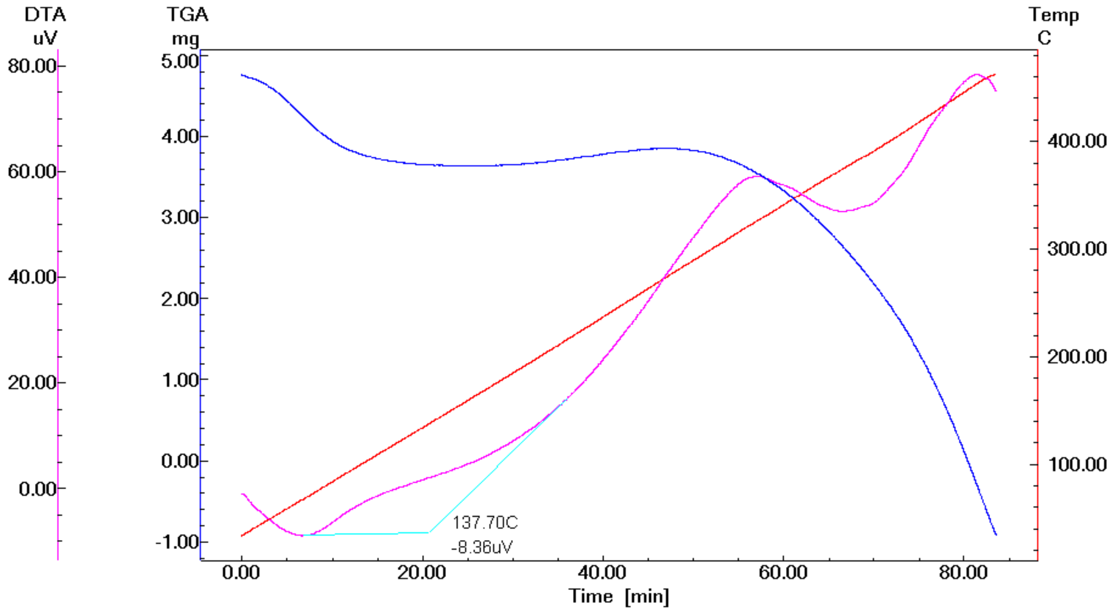

Figure A4.17 DTA thermogram of SCCL – 7 coal sample

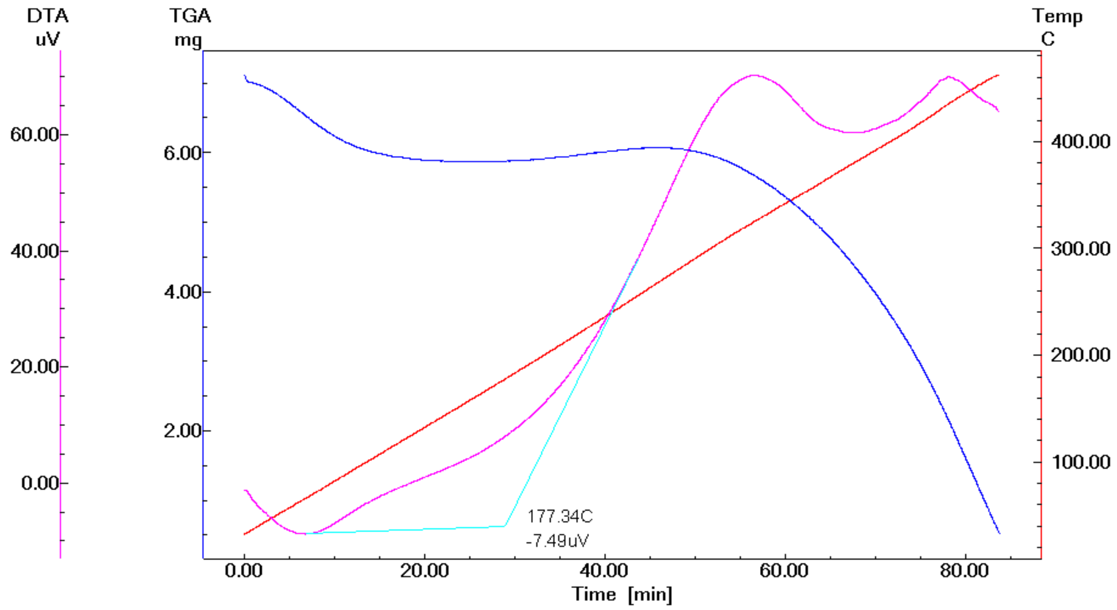

Figure A4.18 DTA thermogram of SCCL - 8 coal sample

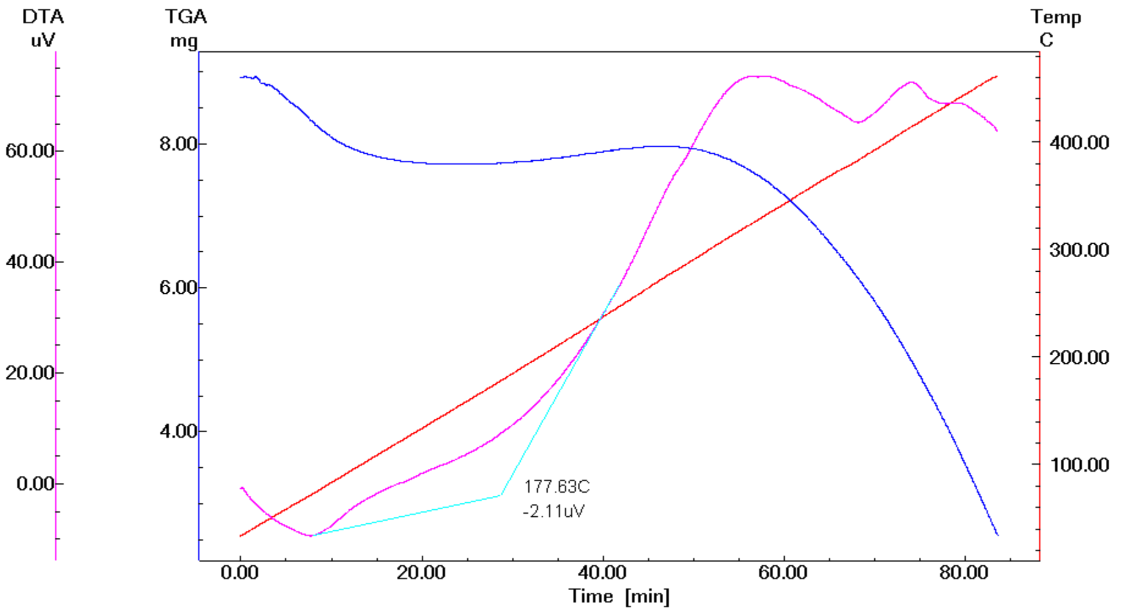

Figure A4.19 DTA thermogram of SCCL – 9 coal sample

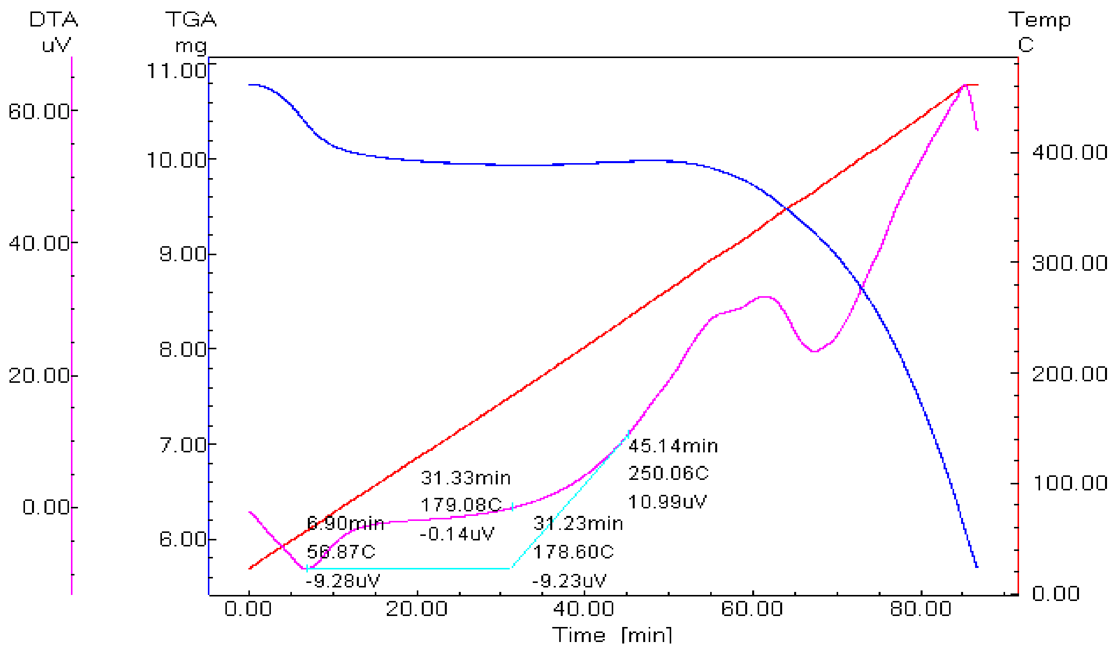

Figure A4.20 DTA thermogram of MCL-1 coal sample

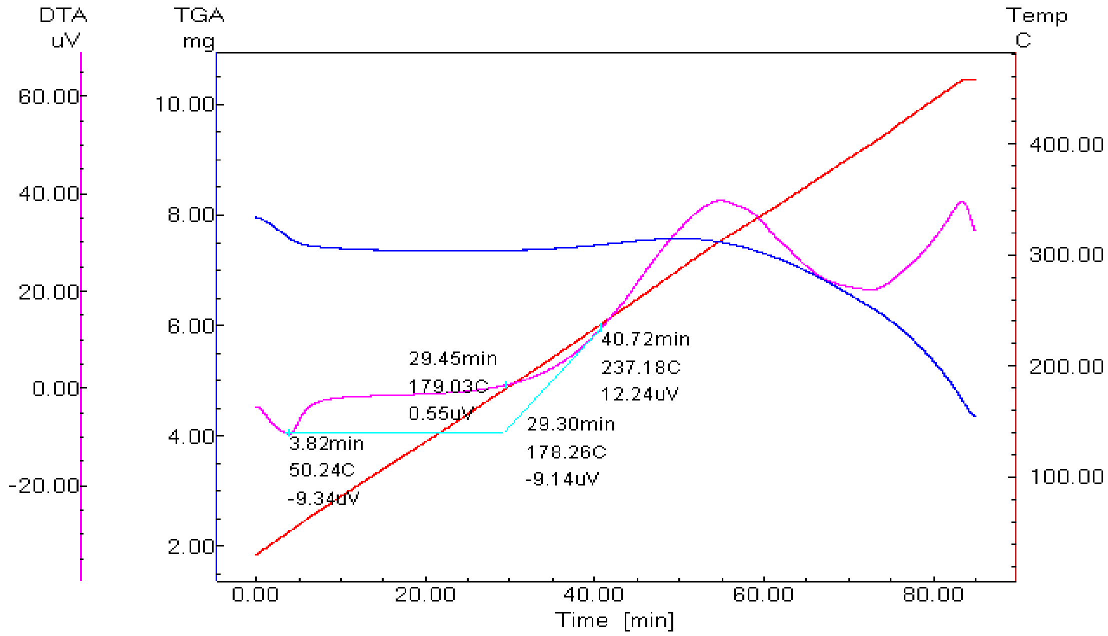

Figure A4.21 DTA thermogram of MCL-2 coal sample

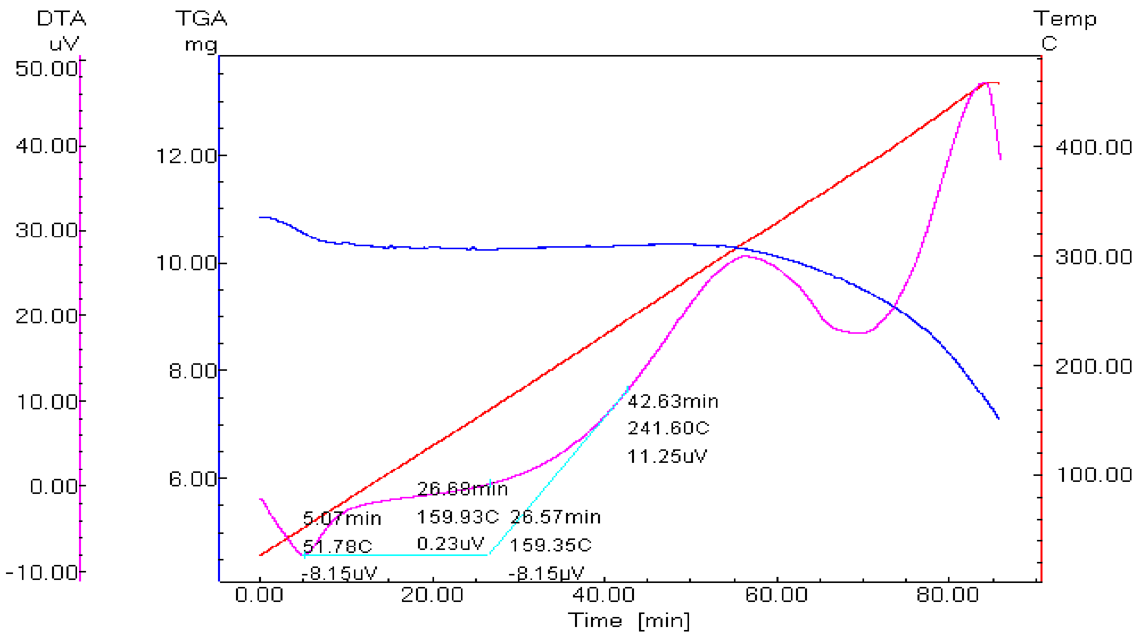

Figure A4.22 DTA thermogram of MCL-3 coal sample

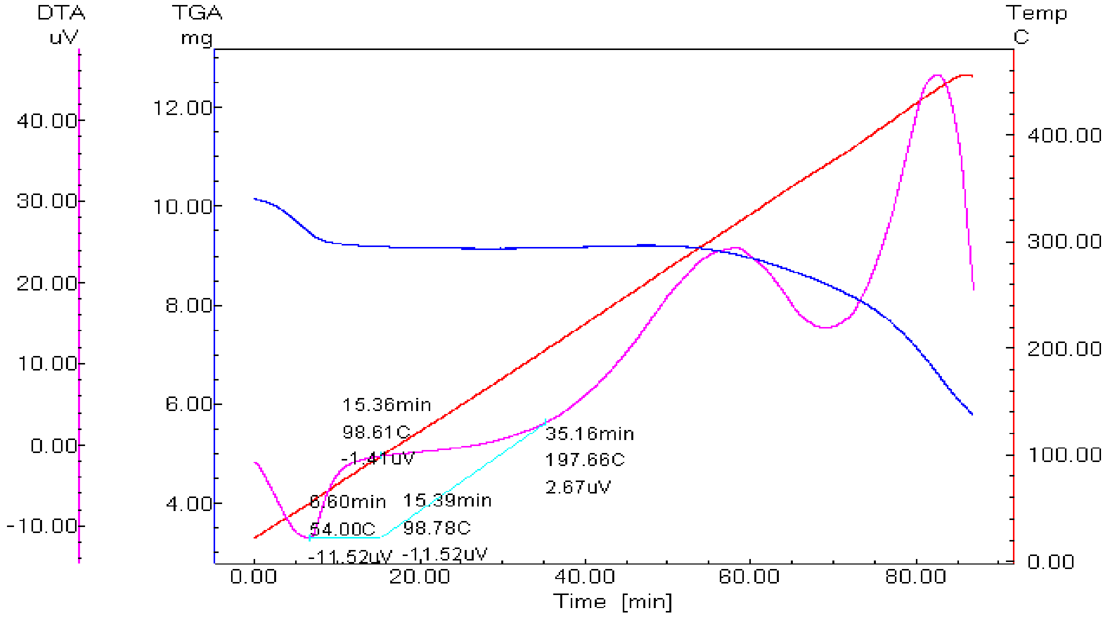

Figure A4.23 DTA thermogram of MCL-4 coal sample

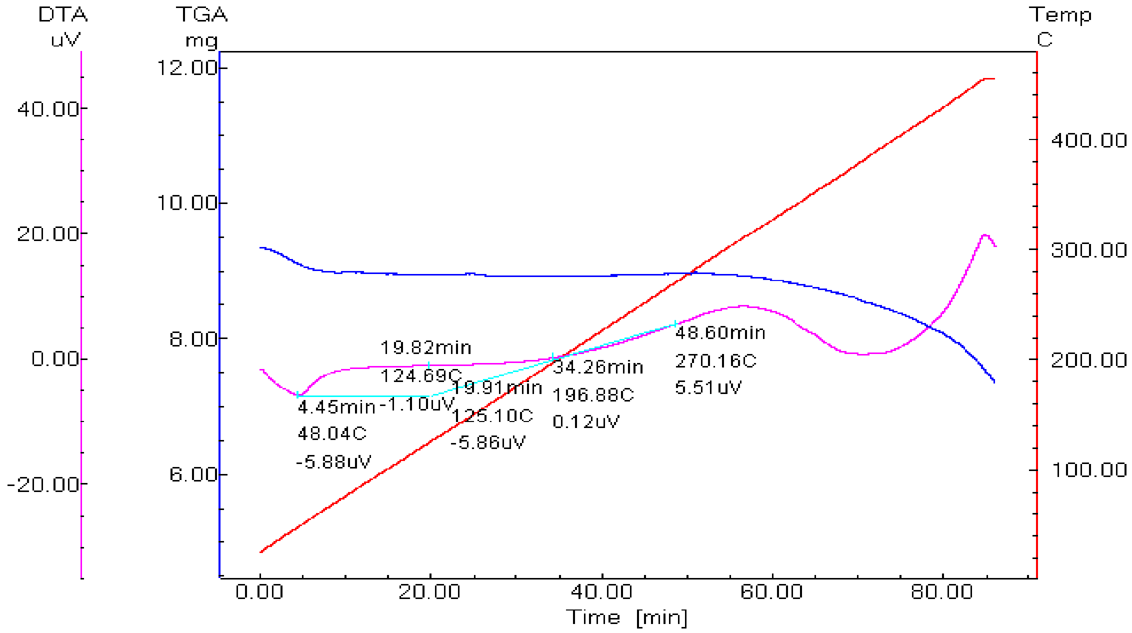

Figure A4.24 DTA thermogram of MCL-5 coal sample

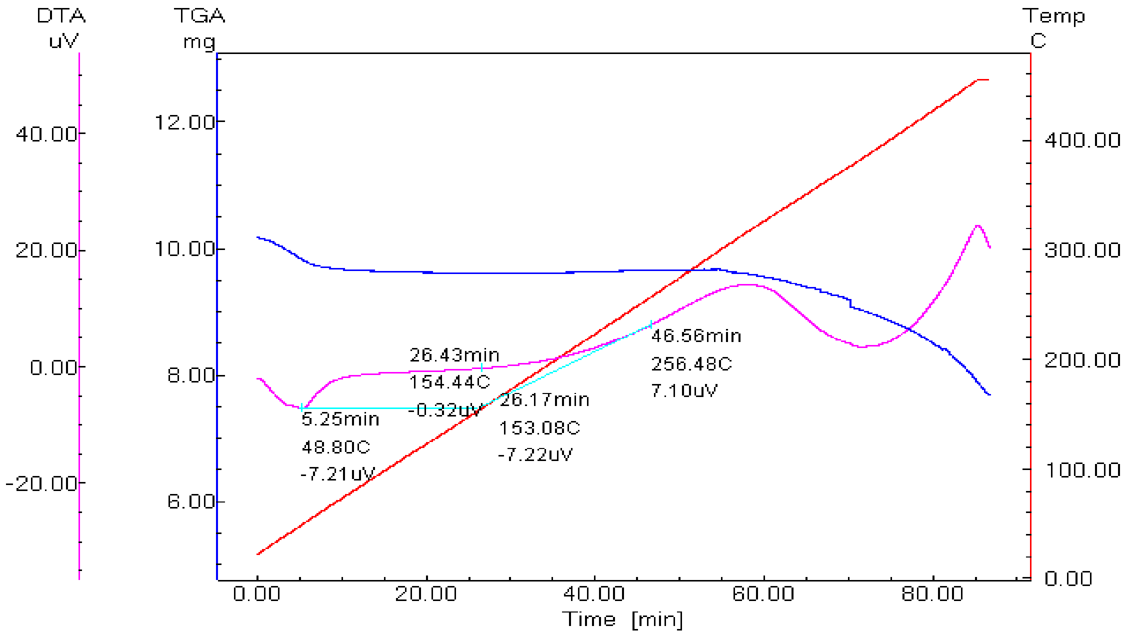

Figure A4.25 DTA thermogram of MCL-6 coal sample

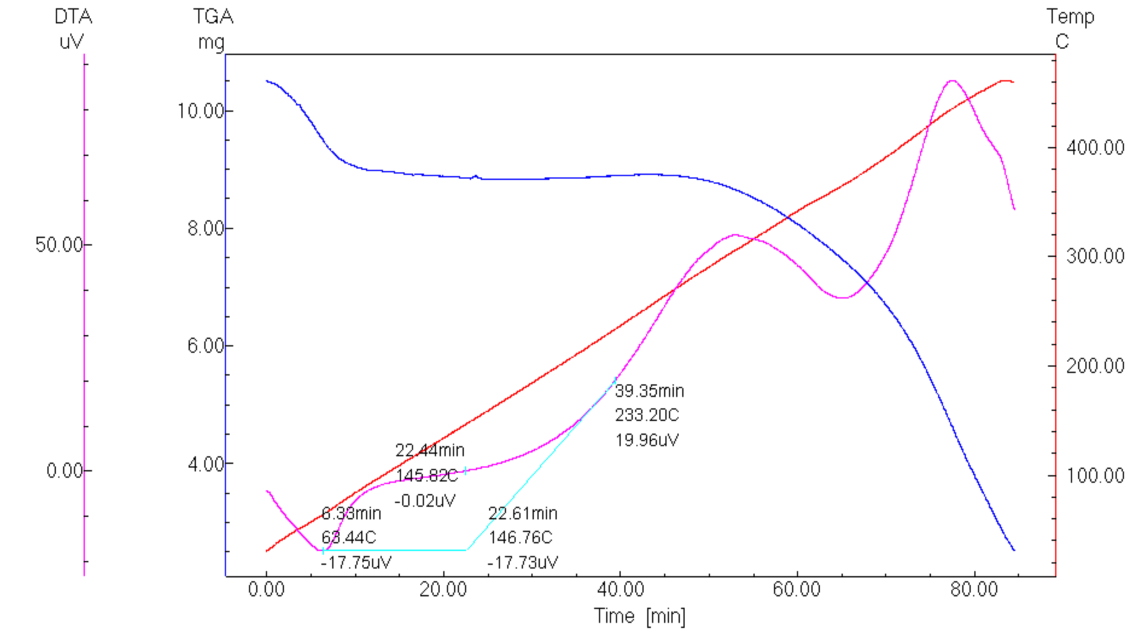

Figure A4.26 DTA thermogram of MCL-7 coal sample

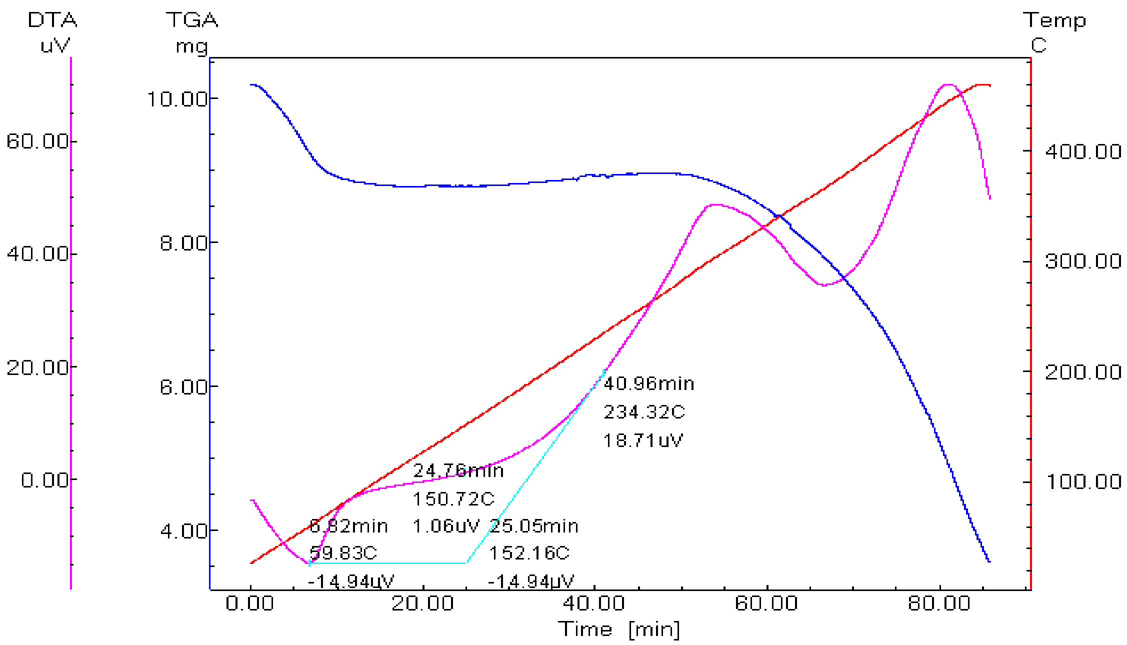

Figure A4.27 DTA thermogram of MCL-8 coal sample

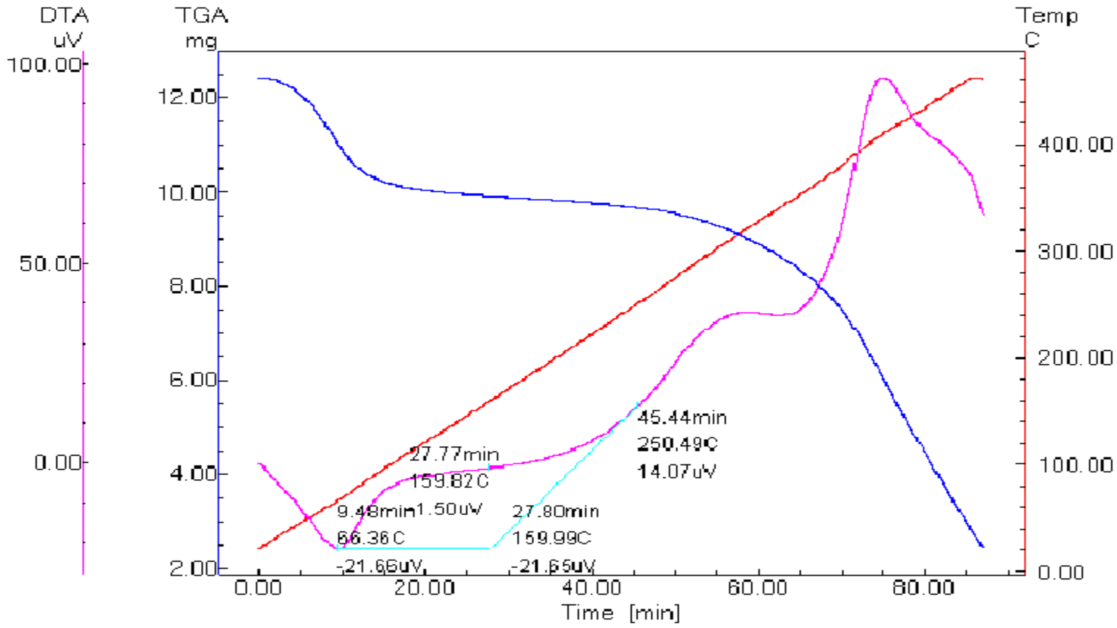

Figure A4.28 DTA thermogram of WCL-1 coal sample

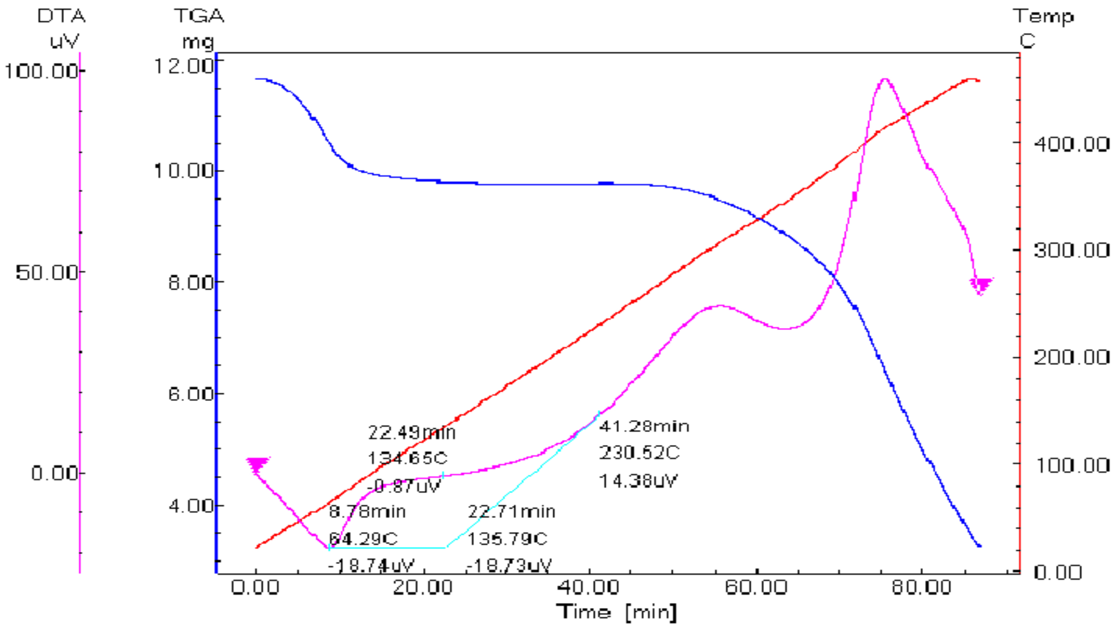

Figure A4.29 DTA thermogram of WCL-2 coal sample

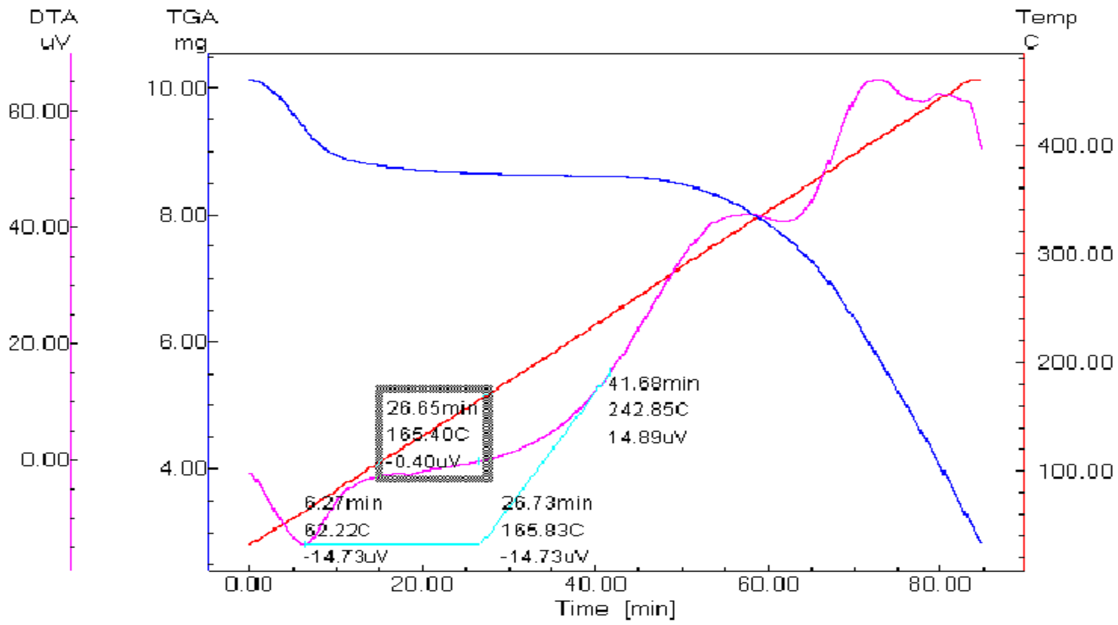

Figure A4.30 DTA thermogram of WCL-3 coal sample

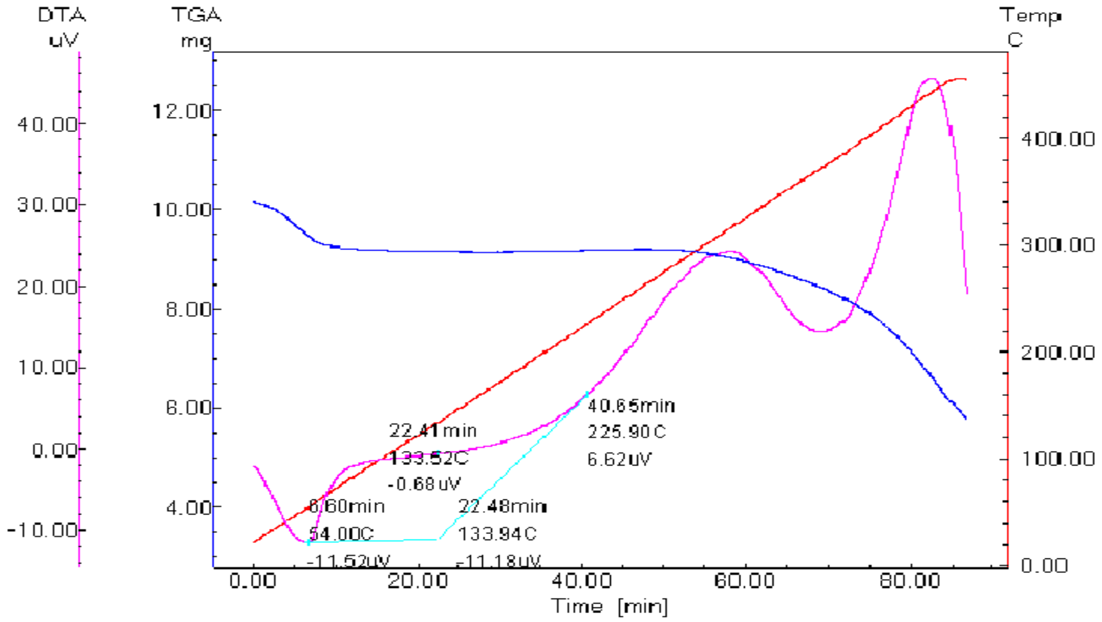

Figure A4.31 DTA thermogram of WCL-4 coal sample

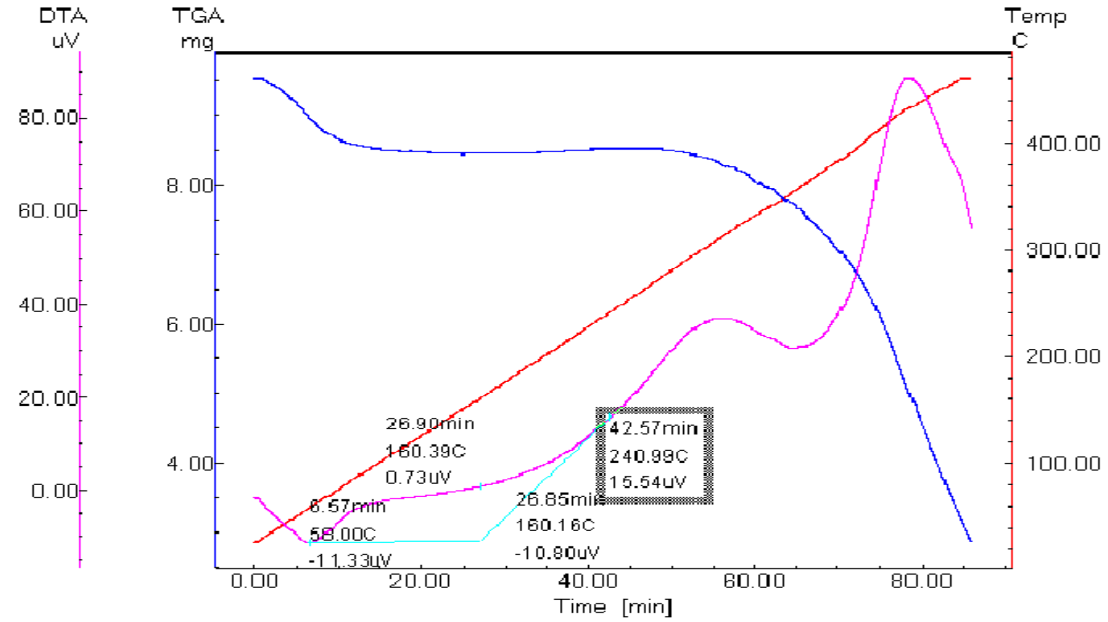

Figure A4.32 DTA thermogram of WCL-5 coal sample

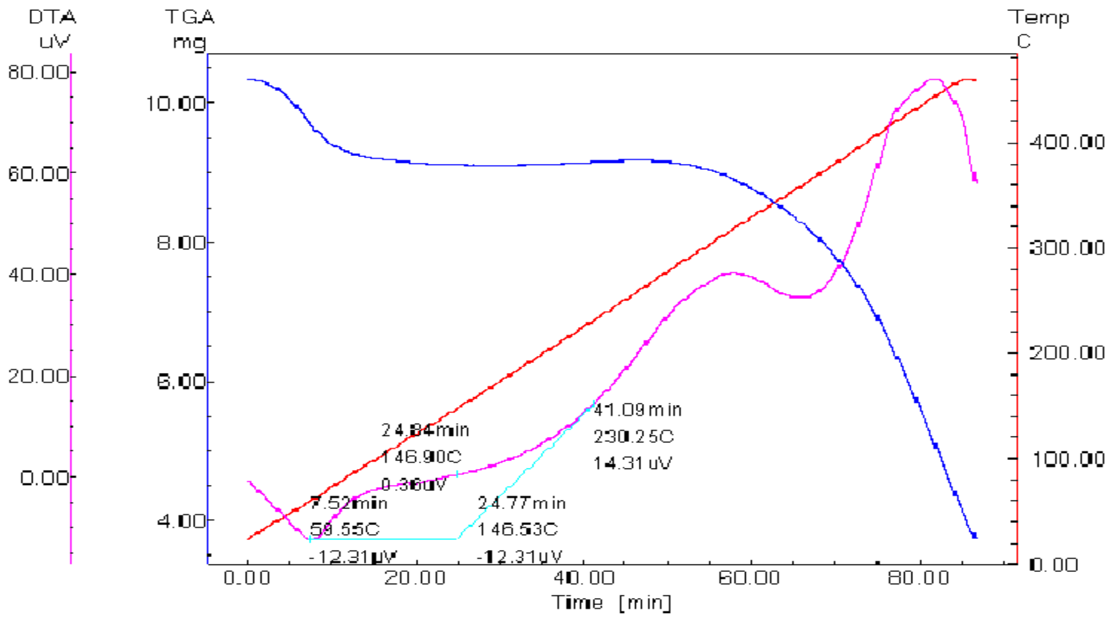

Figure A4.33 DTA thermogram of WCL-6 coal sample

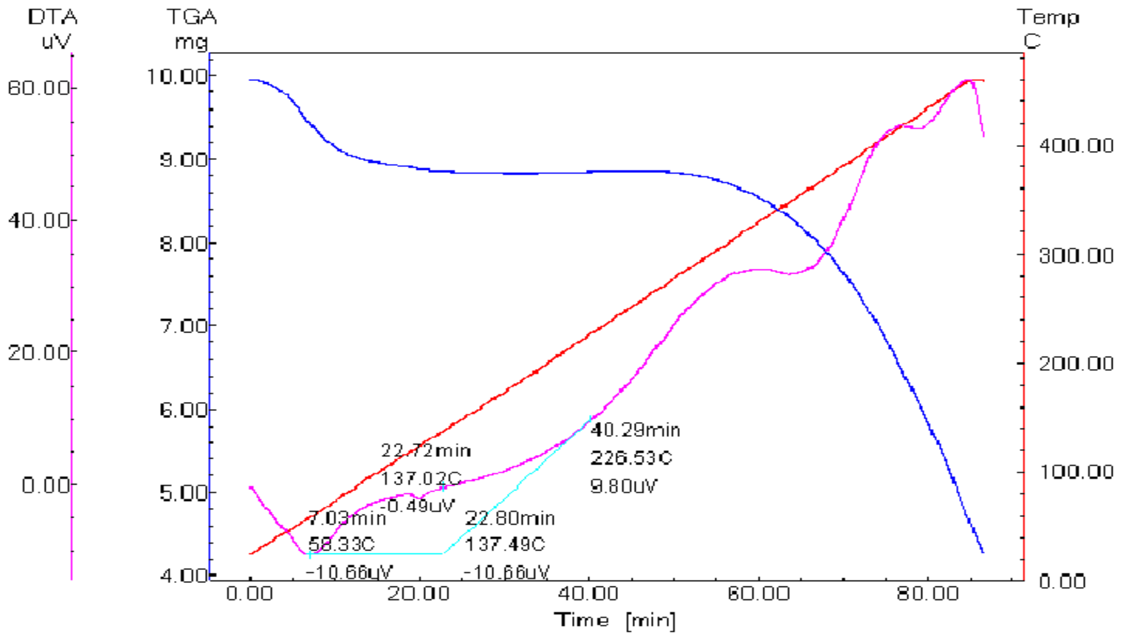

Figure A4.34 DTA thermogram of WCL-7 coal sample

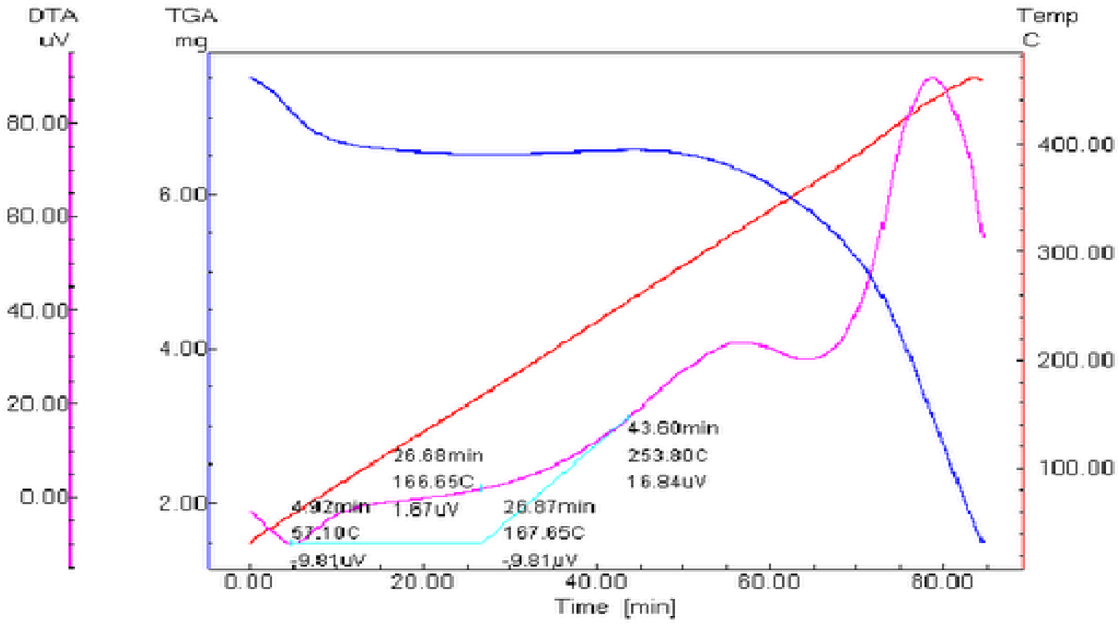

Figure A4.35 DTA thermogram of WCL-8 coal sample

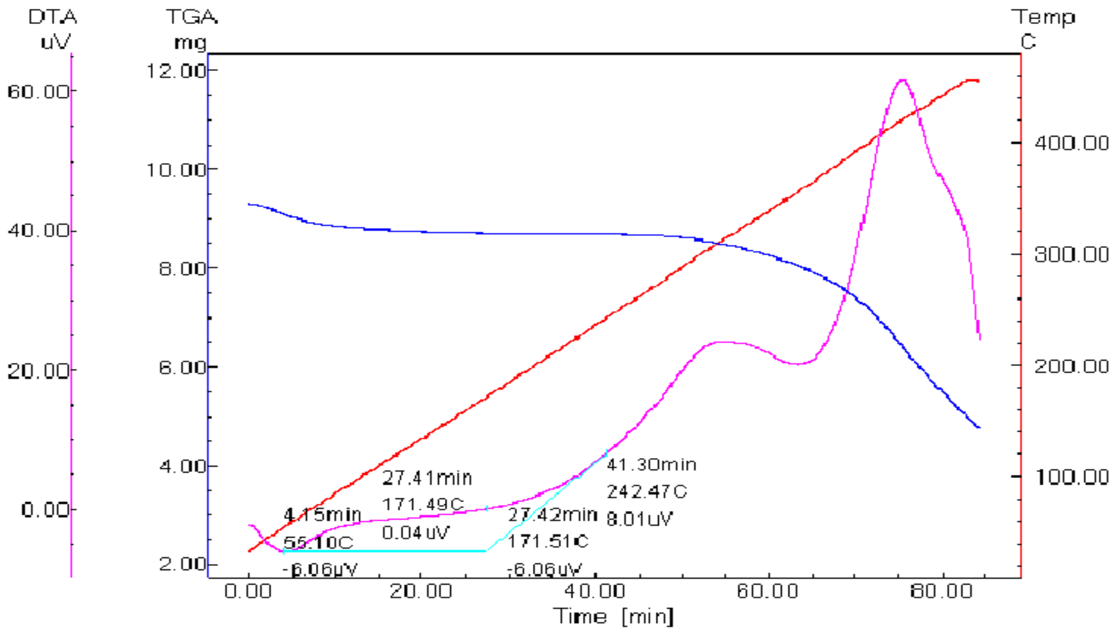

Figure A4.36 DTA thermogram of WCL-9 coal sample

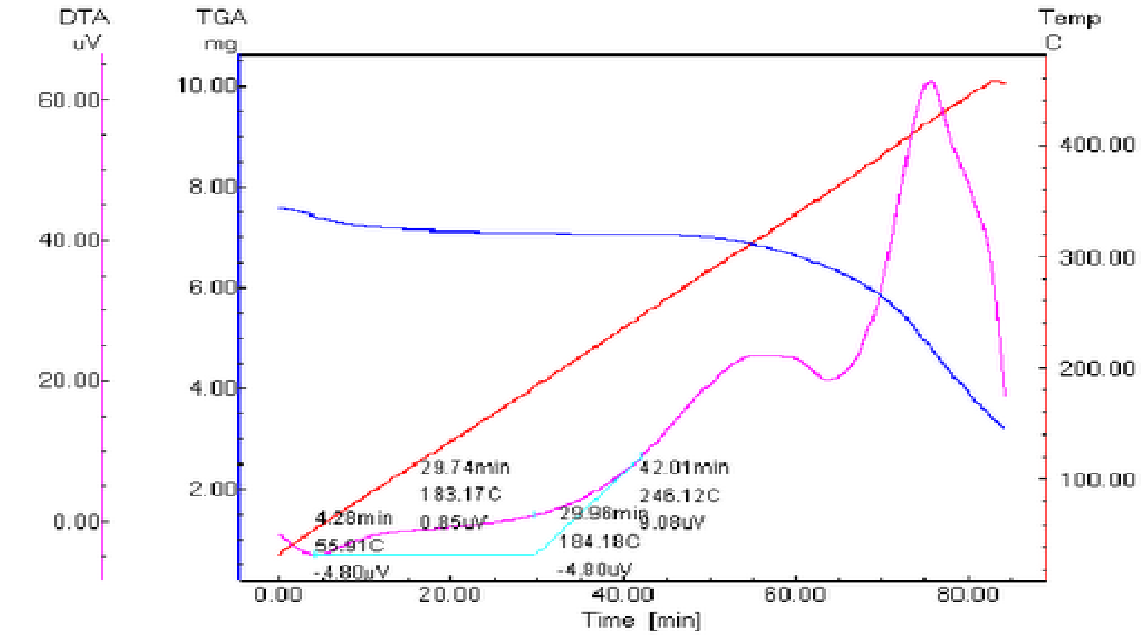

Figure A4.37 DTA thermogram of WCL-10 coal sample

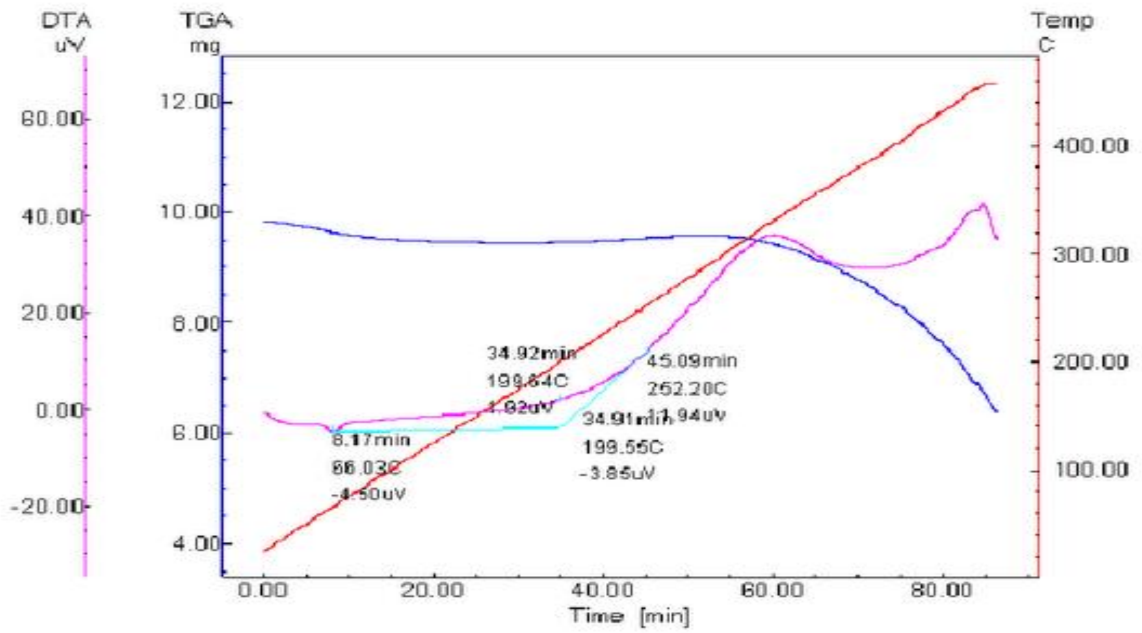

Figure A4.38 DTA thermogram of NEC-1 coal sample

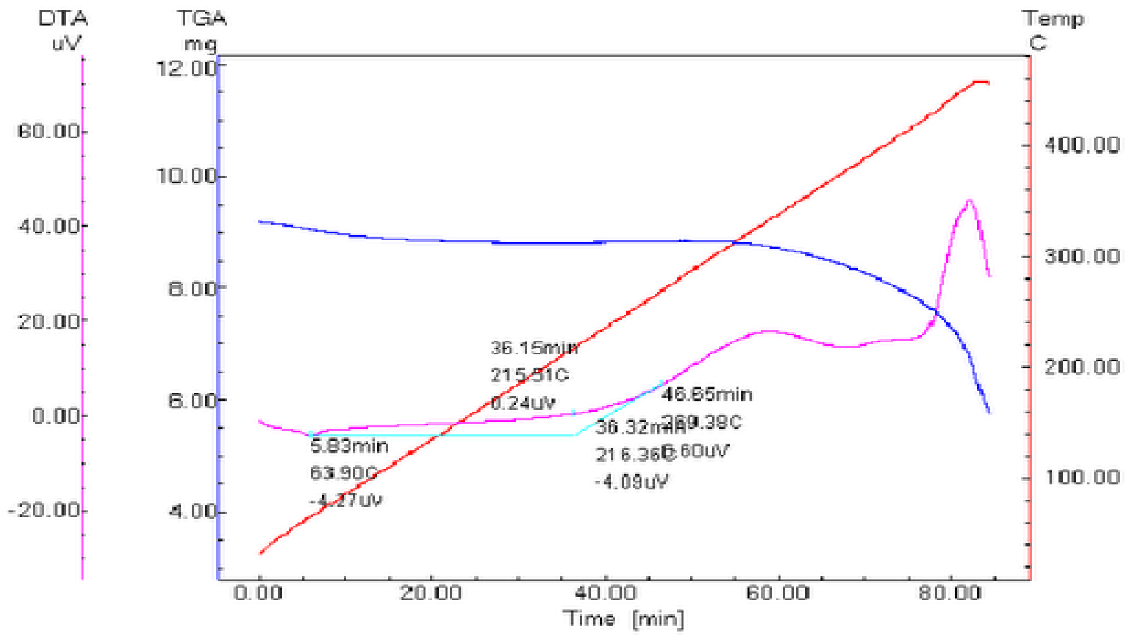

Figure A4.39 DTA thermogram of NEC-2 coal sample

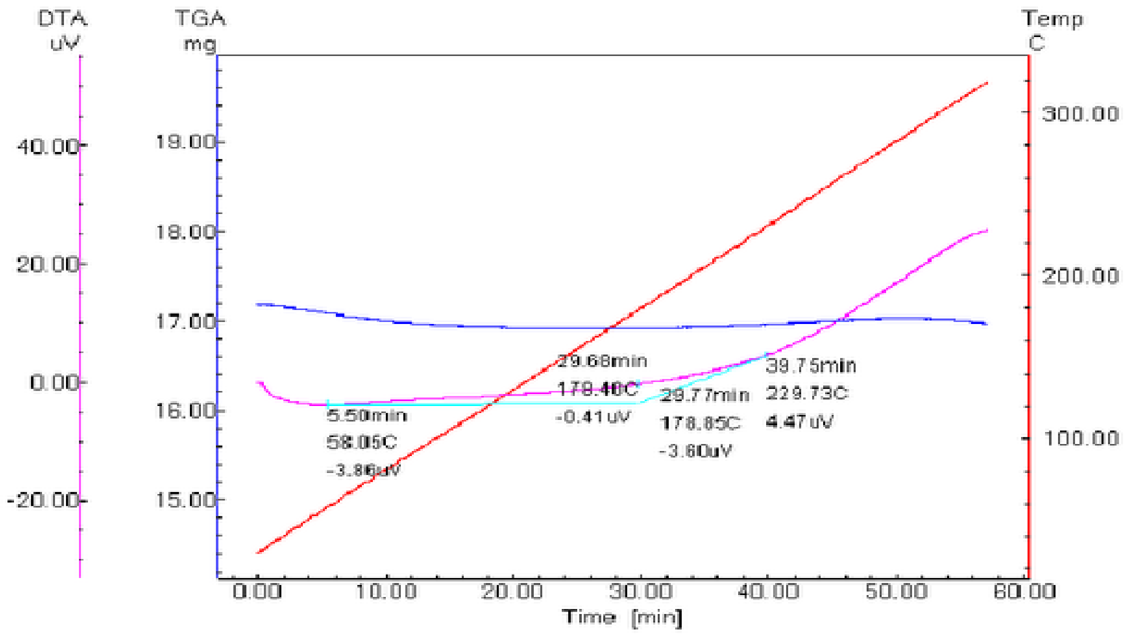

Figure A4.40 DTA thermogram of NEC-3 coal sample

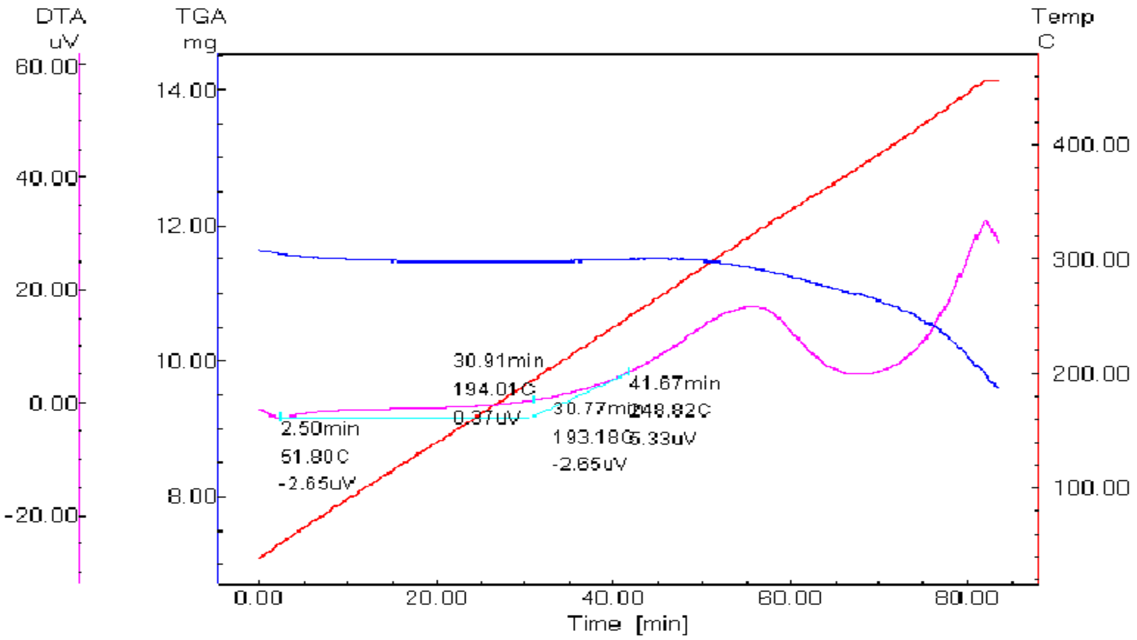

Figure A4.41 DTA thermogram of NEC-4 coal sample

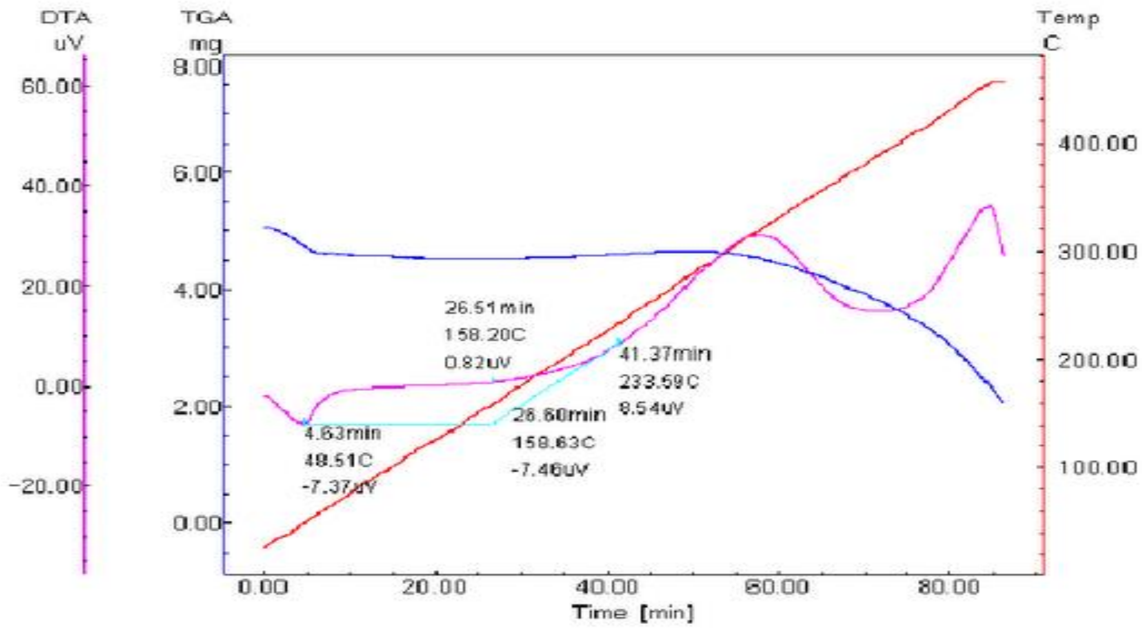

Figure A4.42 DTA thermogram of NEC-5 coal sample

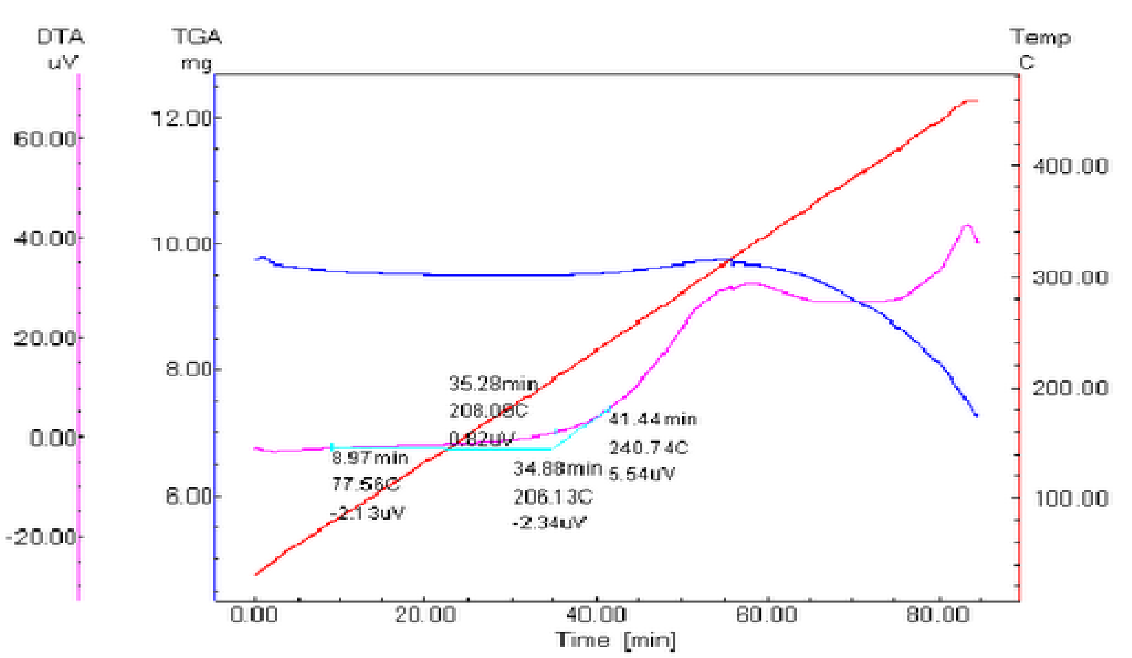

Figure A4.43 DTA thermogram of NEC-6 coal sample

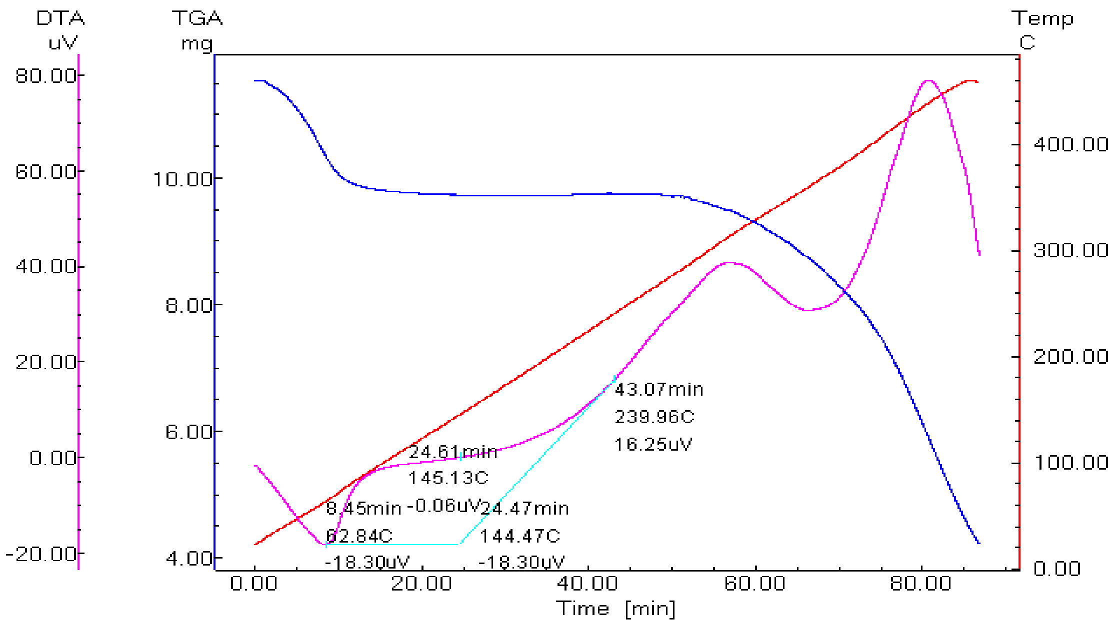

Figure A4.44 DTA thermogram of NCL-1 coal sample

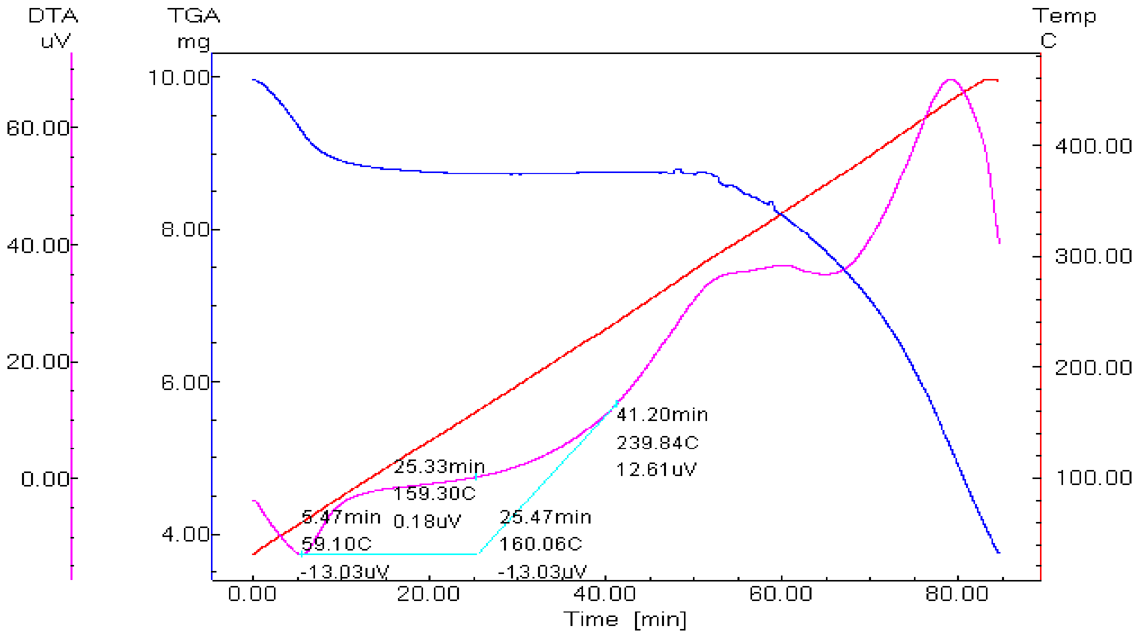

Figure A4.45 DTA thermogram of NCL-2 coal sample

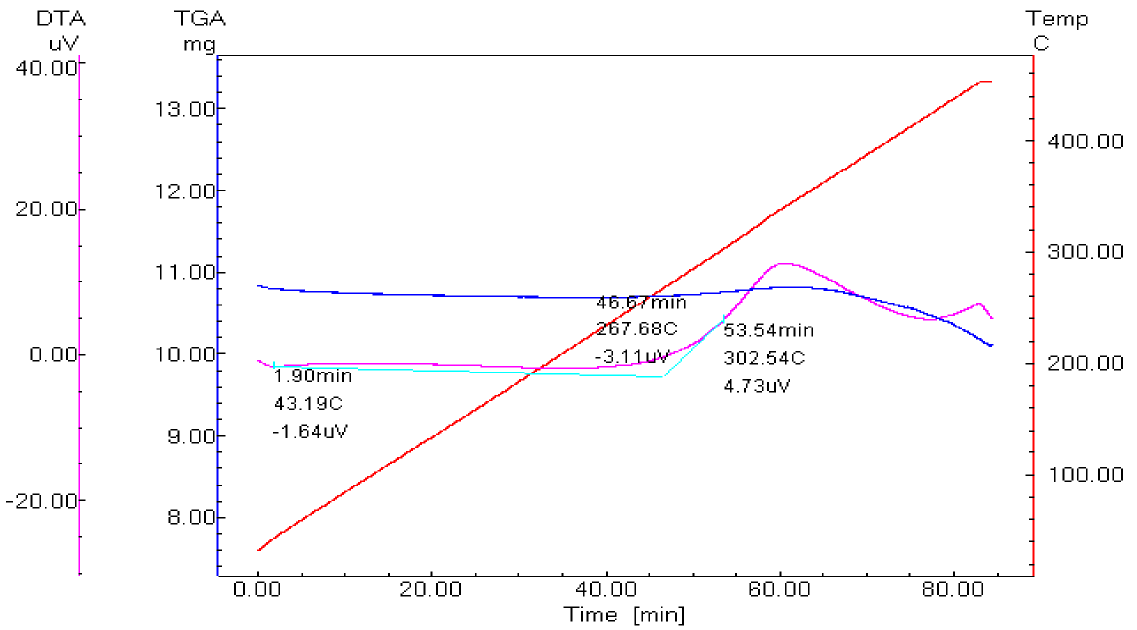

Figure A4.46 DTA thermogram of IISCO-1 coal sample

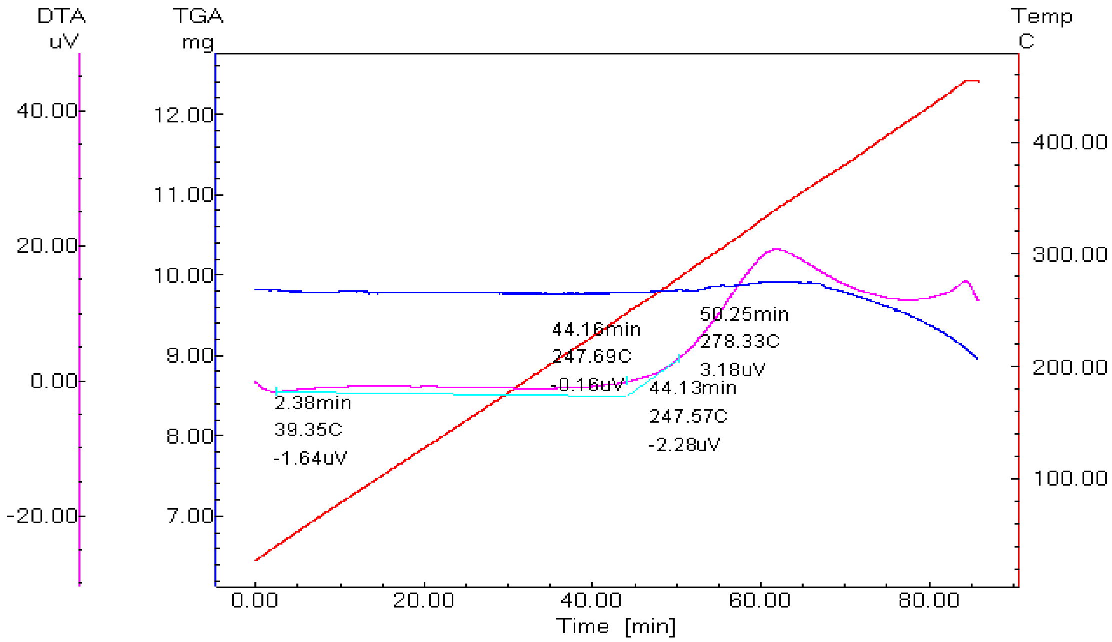

Figure A4.47 DTA thermogram of IISCO-2 coal sample

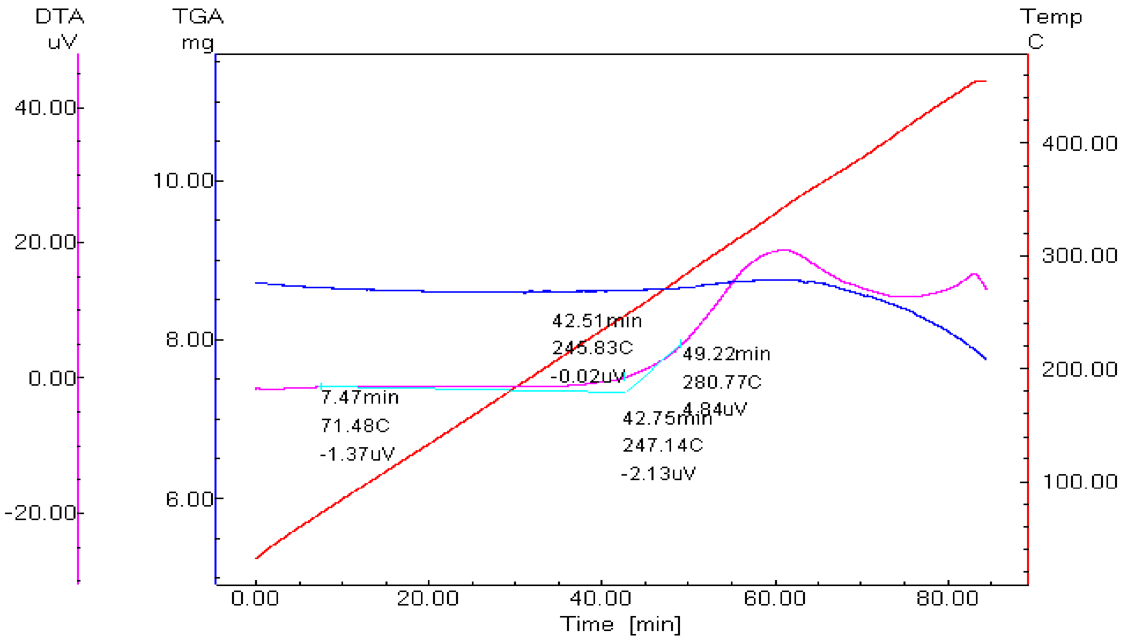

Figure A4.48 DTA thermogram of BCCL-1 coal sample

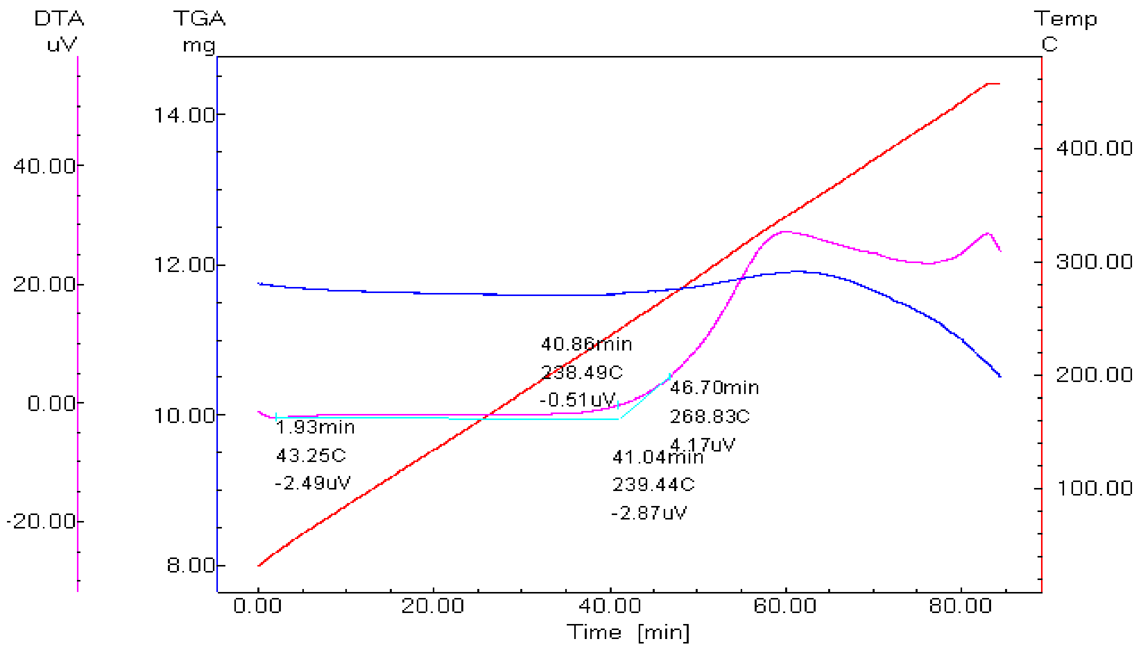

Figure A4.49 DTA thermogram of TISCO-1 coal sample

LIST OF PUBLICATIONS

1. **Nimaje D. S.**, Tripathy D. P. and Nanda S. K., "Development of regression models for assessing fire risk of some Indian coals", International Journal of Intelligent Systems and Application, 02, pp. 52-58, 2013.
2. **Nimaje D. S.** and Tripathy D. P., "Assessment of fire risk of Indian coals using artificial neural network techniques", American Journal of Mining & Metallurgy, vol. 3, no. 2, pp. 43-53, 2015.
3. **Nimaje D. S.** and Tripathy D. P., "Characterization of some Indian coals to assess their liability to spontaneous combustion", Fuel, 163, pp. 139-147, 2016.
4. **Nimaje D. S.** and Tripathy D. P., "Fire risk assessment of some Indian coals using radial basis function (RBF) technique", Journal of The Institution of Engineers (India): Series D (Under Review).

RESUME

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