Neural Network Technique to improve Carbon content of Fly Ash Measurement using a Laser Instrument

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Abstract: - The polarisation ratio of the linearly polarised light backscattered by fly ash particles is indicative of the carbon content. The determination of this parameter is useful to characterise the efficiency of coal burning furnaces. The main aim of this work is to design a single optical probe to measure the polarisation ratio.The probe has been built that can be bolted onto a furnace duct, and it has been tested on a wide range of ashes. A neural network analysis has also been explored for predicting carbon content.

Key-Words: - polirisation, carbon-in-ash, optics, Laser, TGA, Neural Networks

1 Introduction

Fly ash is a finely divided powdery substance produced in the furnaces of pulverised-coal-fired power plants. It is recovered from the flue gases leaving the furnace area by electrical precipitators or other pollution-control equipment. The main elemental component of fly ash is silicon, but it also contains several others such as aluminium, iron, calcium and magnesium. There will also be some and unburned carbon. The concentrations of the different elements are dependent on the type of coal, whereas the amount of carbon also depends on the operating conditions of the furnace. The carbon content is normally in the range 2 to 15 wt.% carbon [1]. Excessive amounts of residual carbon represent a significant loss of energy and low combustion efficiency. A high carbon content also presents difficulties with disposal of the ash.

Methods that are generally used to determine the carbon content of fly ashes may be classified into two categories: intrusive and non-intrusive. The former require collection of fly ash samples followed by subsequent analysis. Examples include Thermo-Gravimetric Analysis (TGA,) Loss On Ignition (LOI) and burn out in a furnace followed by measurement of the CO_2 evolved [2]. Measurement of the carbon content can also be accomplished; for example, by measuring the temperature differential of an excess energy absorber in the form of water before and after the fly ash is exposed to microwave radiation [3].

Another method is based on the photoacoustic effect [4]. In this, ash is sampled into a cavity and periodically heated at an acoustic frequency by absorption of a modulated laser beam. In turn heat is transferred to the gas which expands and cools at the acoustic frequency. The resulting pressure changes are monitored by a microphone, the signal being proportional to the carbon content of the ash. Finally, there are optical methods that measure the carbon content of fly ash samples based on reflectivity in the infrared [5].

Non-intrusive methods do not need a sample to be collected. They have the advantage of providing an on-line real time measurement during the combustion process, without causing significant disturbance. In early work Card and Jones [6] investigated the combustion of coal in a drop tube furnace, using light scattering to analyse the particle properties. A variable length drop tube furnace was constructed in which combustion could be pursued under plug flow conditions as a function of residence time. Particles were examined individually as they emerged from the bottom of the furnace. Horizontally polarised light from a 25 mW argon ion laser at a wavelength of 0.488 μm was scattered by the particles and collected at two angles, namely 0 and 160 degrees. The forward scatter (0^o) intensity was used to obtain particle size. The backscattered light at 160^o light was analysed by separating the vertical and horizontal polarisation states. The ratio of these two polarisations (cross-polarisation ratio) was found to provide an almost linear correlation

with the carbon content of the ash. It was further shown that this ratio was insensitive to particle size.

Bonanno et al. [7] proved a correlation between emissivity and residual carbon content for coal-fired plants. The time required for a measurement, using a FT-IR spectrometer, was a few seconds. A capacitive method has also been developed [8] in which the fly ash passes between two electrodes and the change of capacity is used as a measuring signal. It is assumed that the bulk density of the ash in the measuring chamber is approximately constant, although compensation for variation in the bulk density is possible using a weighing device.

Nuclear measurements of carbon in fly ash have also been investigated. These either employ scattering of gamma rays or of neutrons [9].

Perhaps most promisingly, a microwave resonance method has been proposed [10]. Here a microwave signal is transmitted through or reflected from the particle cloud and the attenuation and phase shift is measured. A frequency is chosen which corresponds with a particularly absorption in carbon. In this way it is claimed that unburned carbon content is obtained with good accuracy, independently of any other elements that are present.

This paper explores further development of the method of Card and Jones [6]. The principle is that non-spherical particles introduce cross-polarisation into the scattered light. In the case of fly ash this may arise from two sources: scattering from the irregular surface and multiple scattering on any internal structure, since ash is essentially glass-like. It is found that the presence of absorption reduces cross-polarisation, and this can be explained in terms of a reduction of the internal multiple scattering.

An instrument has been built that can be bolted onto a furnace duct, and it has been tested on a wide range of ashes. A neural network scheme has also been explored for predicting carbon content.

2 Apparatus and materials

Fig. 1 is a schematic drawing of the laser probe. The vertically polarised beam from a Laser 2000 crystal laser (50 mW, 532 nm, TEM_{00}) passes to a periscope arrangement formed by the two mirrors M1, fixed at 45° to the incident beam direction, and M2. The light enters and leaves the instrument via a 75 cm diameter quartz window with a facility to blow nitrogen to prevent dust accumulation.

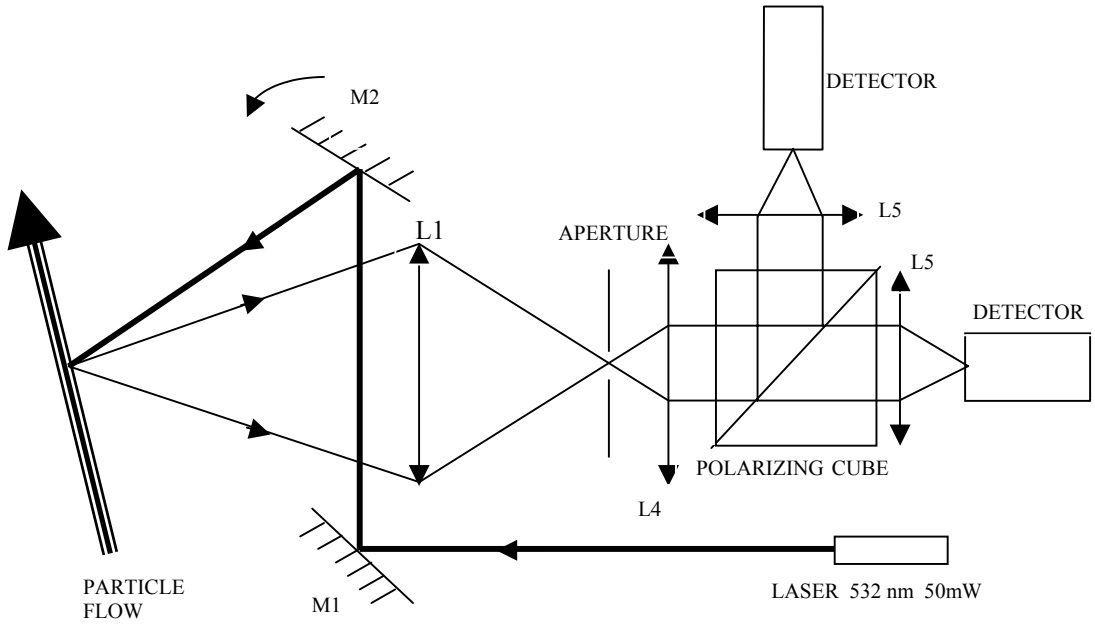

Fig.1: Experimental set-up of the probe for polarisation ratio measurements.

Light scattered by the particles crossing the beam is collected by lens L1. The lens is mounted on a microscope slide with a positioning accuracy of 10 μm, and is adjusted to focus the radiation onto a small aperture. The intersection between the laser beam and the image of the aperture defines the test volume. The mirror M2 can be rotated to vary the distance at which the laser beam and image of the aperture intersect. Distances between 0.5 m and 6 m have been explored. The size of the test space depends upon the aperture diameter and the divergence of the laser beam.

After the aperture the scattered light is collimated by lens L4 and passes to the 50:1 extinction ratio polarising beam splitter. The two polarised beams are then focused onto the two photomultipliers (EMI 9558). The polarisation ratio is defined to be

$$P = \frac{\text{Intensity of horizontally polarised light}}{\text{Intensity of vertically polarised light}} = \frac{I_H}{I_V} \quad (1)$$

The physical characteristics of the various optical elements used in the probe are listed in Table 1.

Mirror M1	φ=12.5mm, Coating: Laser Line Max-R™ at 45° incidence, R>99%
Mirror M2	φ=12.5 mm, Coating: MAXBRITE™ for 0° to 45° incidence, R>98%
Lens L1	Aspheric glass condenser φ=75 mm, f=50 mm, ARC
Lens L4	Aspheric glass condenser φ=18 mm f=12 mm, no ARC
Lens L5	Convex lens, φ= 12 mm, f=20 mm, no ARC
Aperture	φ=500μm
Polarising cube	Broadband polarising cube beam splitter l=25.4 mm, ARC, 50:1

Table 1 Physical characteristics of the optical elements
(Key: φ - diameter; f – focal length; l – side of cube;
ARC – Anti-reflection coating; R – reflectivity)

A picture of the probe is presented in Fig. 2.

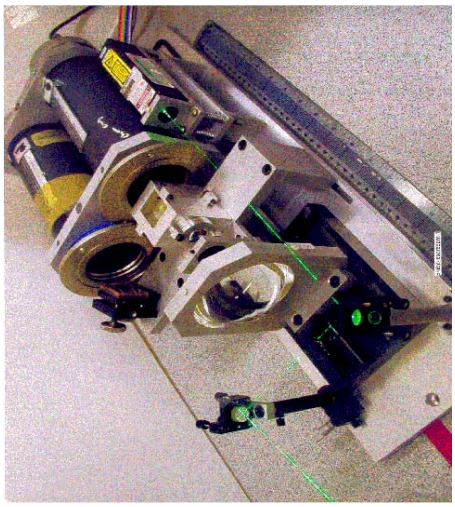

Fig. 2 a picture of the probe used for measuring carbon in ash

For the measurements, Powergen supplied samples of ashes from 12 different coals together with their proximate analyses. These samples were then partially burned to produce 63 ashes of varying carbon content and of widely different mineral content. The carbon content by mass was determined by thermo-gravimetric analysis (TGA). The properties of the ashes are given in table 2.

Ash	carb. cont.	Fe	Al	Si	Ca	Mg	Ti
BET96042	4.90%	13.70%	28%	46.40%	1.30%	1.70%	1.20%
ELC990111	9.10%	7.40%	22%	54.50%	2.20%	2.30%	1.00%
LAC980624	9.20%	7.10%	25.80%	52.60%	3.60%	1.10%	1.20%
FOR98062	10.10%	3.70%	28%	45.70%	6.90%	2.20%	1.50%
ATC981207	10.10%	3.40%	28.90%	41.80%	8.30%	2.20%	1.80%
KNP98092	12.10%	5.70%	26.10%	46.80%	3.20%	1.50%	1.20%
ELC97050	12.60%	6.80%	22.30%	51.10%	3.20%	1.60%	1%
LAJ98062	13.10%	6.10%	21.70%	50.90%	2.80%	0.70%	1%
PRO98070	16.40%	5.50%	19.80%	45.80%	4.10%	2.50%	1%
cyclone18	15.30%	5.30%	30.77%	52.75%	4.77%	1.68%	1.69%
cyclone17	14.50%	5.44%	30.25%	53.11%	4.83%	1.73%	1.66%
cyclone19	7.40%	5.37%	29.73%	53.20%	4.89%	1.80%	1.74%

Table 2 Properties of the ashes used in tests

3 Measurements

The behaviour of the probe was explored by making measurements with the test space 1 m from the lens. The photomultipliers were balanced by detecting the light from an unpolarised source and ensuring that the polarisation ratio was unity. The scattered intensity and applied voltages were sufficiently low that the photomultiplers were in the linear range.

The particles were dispersed by elutriation from a fluidised bed and crossed the test space via a small tube. The instrument observed single particle counts simultaneously on the two photomultipliers, the output voltages being displayed on an oscilloscope. The polarisation ratio was calculated for each event was calculated from the ratio of these voltages.

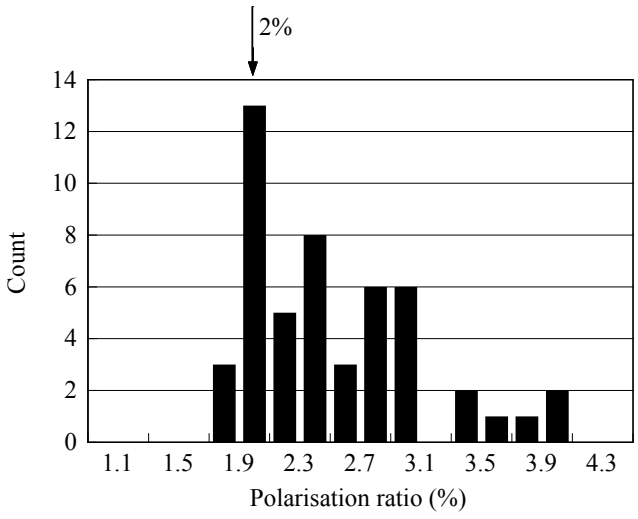

Fig. 3: Measured polarisation ratios for PMMA spheres

To test the performance of the probe initial measurements were made on spheres of PMMA (polymethylmethacrylate). For perfect spheres there should be no cross-polarisation, so the instrument

should yield a ratio of one fiftieth (2%), the extinction ratio of the prism.

The result of the test is seen in Fig. 3. It can be seen that the peak occurs at 2%, which is the expectation. There are a few particles with lower polarisation ratio, which is due to imperfection in the optics. There are a significant number of particles above 2%. This is expected since only perfect spheres will result in zero cross-polarisation. Even with only 1% deviation from a sphere the influence of shape becomes very significant .

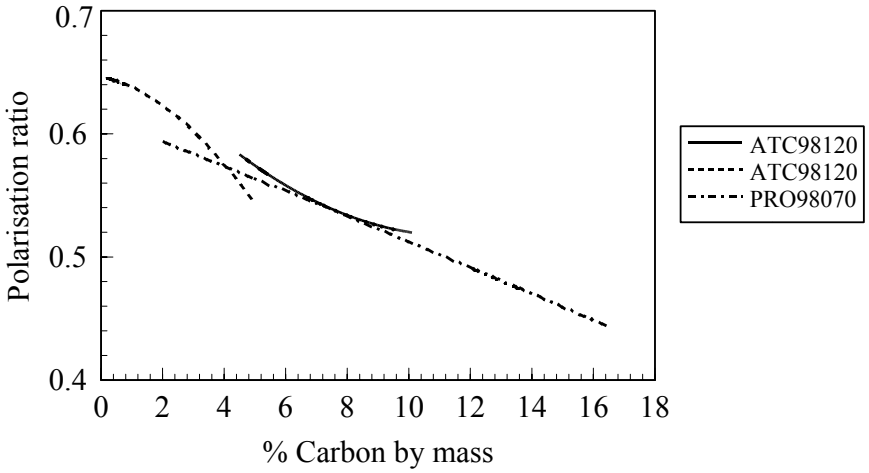

Fig. 4: Polarisation ratio against carbon mass fraction (%) for selected ashes

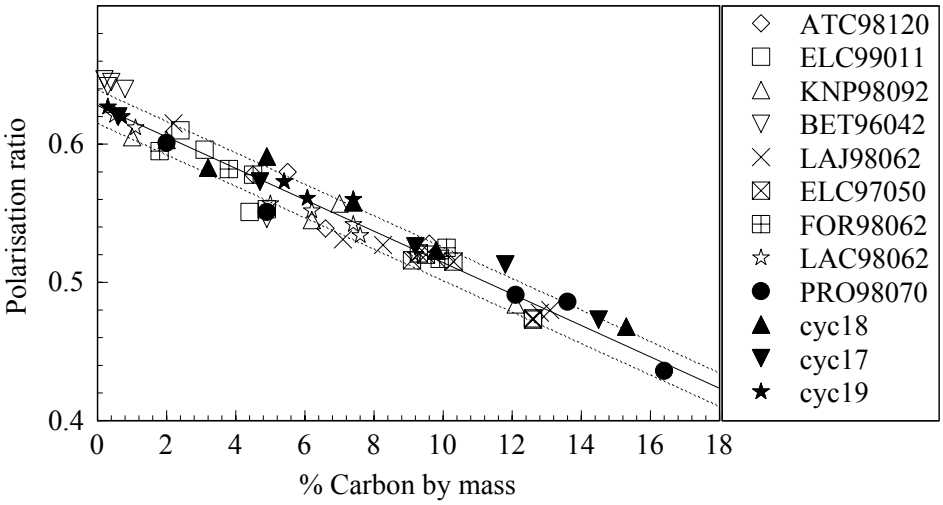

Fig. 5: Polarisation ratio against carbon mass fraction (%) for all twelve ashes

For the ashes, the actual cross-polarisation is a function of the mineral composition as well the amount of carbon. This is illustrated in Fig. 4 for a selection of the ashes used in this study. In this diagram the measured points are not represented but the data are fitted by a quadratic polynomial, simply to show the typical variation between ashes.

Given the variation between ashes the question arises to what accuracy the carbon content could be determined if the proximate analysis were not known, as may generally be the case when burning coal. An indication of the answer is found in
Fig. 5, where the actual measurement points for all twelve ashes are shown. The solid line is a linear fit to all the data and the two broken lines represent plus and minus one standard deviation around the fit.

The implication of this plot is that if the proximate analysis is not known the carbon content can be measured to within about ±1% carbon by mass. This is promising, but it is accepted that the data set is still limited and a wider range of measurements would better set the range of accuracy.

4 Neural Network analysis

Having estimated the accuracy of carbon determination without prior knowledge of the mineral content, it is worth exploring how this improves if the proximate analysis is known. A study of the polarisation ratio over the range of the ashes did not reveal any significant tends with regard to mineral content. It was, therefore, decided to explore a neural network analysis to see to what accuracy the carbon mass fraction may be predicted for known mineral content.

In recent years the use of neural networks in the function approximation and interpolation of data has become a feasible method, because the efficiency of algorithms and computers has increased **[11]**. Of course neural networks have many more applications in other areas of data processing, in non-linear control etc.

Of the various neural network models only general regression neural network (GRNN) which is based on the radial basis function (which has its origin in techniques used for exact interpolation between data points in multidimensional spaces) has been investigated in this paper. The facilities of the neural network toolbox of the Matlab software (Matlab is a registered trademark of the MathWorks Inc.) have been used in the computation. The interpolation with radial basis functions presented in this paper have been made with a Matlab-function, which has as many hidden neurons as there are input-output pairs. This causes the interpolation function to make exact mapping.

The topology of the general regression neural network (GRNN) with two successive layers is shown below in Fig 6. It is similar to the radial basis network, but has a slightly different second layer.

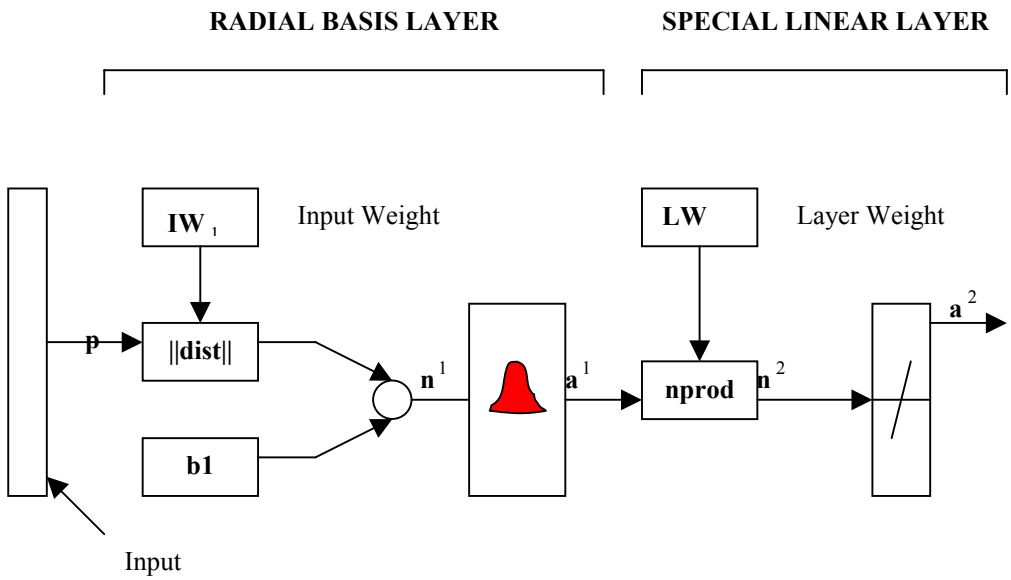

Fig. 6 Neural Network flow chart

Where a^1 is the output vector from layer 1 and is calculated as follows:

$$a^1 = \text{radbas}\,(\| IW_1 - p\|\, b1)$$

radbas is a transfer function with

$$\text{radbas}(n)=e^{-n2}$$

a^2 is the output from layer 2 which is the target (supervised learning):

$$a^2 = \text{purelin}\,(n^2)$$

with purelin being a linear transfer function.

n^1 and n^2 are neurons in layers 1 and 2, IW and LW are input weight and layer weight respectively.

The ||dist|| box in this figure accepts the input vector p and the input weight matrix IW^{11}, and produces a vector having S^1 elements. The elements are the distances between the input vector and vectors IW_1 formed from the rows of the input weight matrix. The bias vector b and the output of ||dist|| are combined with the MATLAB operation .*, which does element by element multiplication.

Here nprod box shown above (code function) produces S^2 elements in vector n^2. each element is the dot product of a row of LW and the input vector a^1, all normalised by the sum of the elements of a^1 .

The question is How does this network behave following an input p through the network to the output a^2. If we present an input vector to such a network each neuron in the radial basis layer will output a value according to how close the input vector is to each neuron's weight vector. Thus, radial basis neurons with weight vectors quite different from the input vector p will have outputs near zero. These small outputs will have only a negligible effect on the linear output neurons. In contrast a radial basis neurons with a weight vectors IWclose to the input vector p will produce a value near 1. If a neuron has an output of 1 its output weights in the second layer pass their values to the linear neurons in the second layer.
Suppose we have an input vector p close to p_i one of the input vectors among vector/target pairs used in designing layer one weights. This input p produces a layer a_i ouput close to 1. This leads to a layer 2 output close to t_i , one of the targets used for designing layer 2 weight (LW).

In this particular application we are dealing with a supervised learning, where the input vectors include {P, FeO2, Al, Si, Ca, Mg, Ti, K, P} and the target being the carbon in ash {C}. P is cross-polarisation ratio measured in the laboratory environment at Imperial College, the carbon content was measured using TGA technique and the rest of the above elements were calculated from proximate analysis method performed within Powergen environment.
The neural network results were achieved within a maximum training periods (epochs) of 1000. The network was trained with 50 of the 62 ashes, the remaining 12 being set aside for validation. The result is shown in Fig. 7. This would suggest that the neural network analysis could yield an accuracy of ±0.05% of carbon by mass.

5 Conclusions

From measurements of the polarisation ratio in the light scattered by fly ash particles from a wide range of coals, it was predicted that the carbon mass fraction could be determined to within ±1% of the carbon content even in the absence of any information on the mineral content of the original coal. If a proximate analysis was performed on the coal this could be improved to ±0.05% by the use of neural analysis.

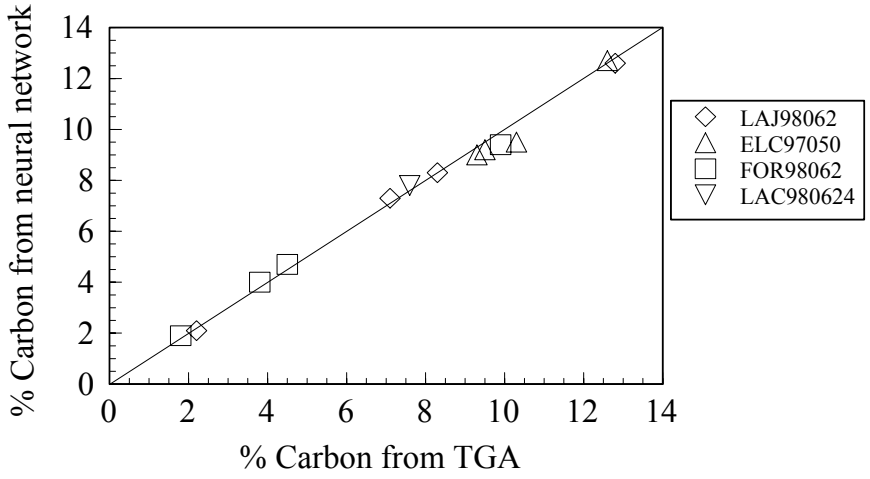

Fig. 7: Comparison of the carbon in ash predicted by the neural network calculation against the known value obtained by thermo-gravimetric analysis.

This does represent an improvement. However, it is doubtful whether it is significantly better to make it worthwhile performing a proximate analysis solely for this purpose.

A reasonably wide range of ashes was studied in view of the time consuming nature of the measurements. The range carbon contents of the ashes covered that usually achieved in power station combustion. However, while these results provide good guidance to the potential accuracy of the method, a much wider study would be valuable. To achieve this, ashes from more coals with a wider range of carbon contents would need to be prepared and the data collection system would need to be fully automated.

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