Application of Electric Field for Rapid Estimation of Coal Quality

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Abstract. Rapid and non-destructive evaluation of coal quality is critical for optimizing energy production and mining operations. This study investigates the application of a capacitive impedance-based approach as an alternative technique for estimating the relative dielectric properties of coal, which are key indicators in proximate analysis. Coal samples were characterized using electric field–based measurements and compared with conventional proximate analysis methods. The measurements employed a capacitive impedance system operating under low-frequency AC excitation to capture dielectric response parameters associated with moisture content. Subsequent linear and quadratic regression analyses were performed to assess the correlations between methods. The results demonstrated a positive correlation with acceptable relative deviations, supporting the feasibility of this technique for preliminary quality assessment. Furthermore, composite variables incorporating both capacitive measurements and ash content yielded significantly improved predictive performance. These findings indicate that capacitive impedance analysis offers a promising, rapid, and non-destructive alternative for estimating coal moisture content, particularly suited for field applications and early-stage quality control.

1 Introduction

Coal remains one of the primary sources of energy, especially for power generation and heavy industries. Its quality is largely determined by its physical and chemical properties, including moisture content, density, and chemical composition, all of which significantly influence combustion efficiency and environmental impact [1].

Conventional coal quality assessments, such as chemical analysis, are time-consuming, require well-equipped laboratories, and involve the use of hazardous substances. In contrast, non-destructive sensor-based methods have seen rapid development in recent years. One promising technique is capacitive impedance spectroscopy, which allows for fast and direct measurement with relatively high accuracy.

Capacitance-based sensing has been investigated as an alternative technique for determining coal moisture content since the 1960s. Capacitive sensors operate by detecting changes in capacitance between two electrodes, which are influenced by the physical properties of the material between them. Moisture and density variations alter the charge distribution, thereby affecting sensor capacitance. By applying scanning impedance techniques across a range of frequencies, changes in impedance can be monitored and correlated with coal quality metrics.

In general, materials exhibit specific electrical properties, including resistance, capacitance, and inductance. Variations in moisture content are relatively easy to detect using capacitance-based sensing methods. This approach has been widely applied to determine water content or moisture levels in various materials, such as rice [2], wood [3], tea leaves [4], and municipal solid waste [5]. The application of capacitive sensors to investigate moisture content in coal has also been extensively reported. The principle of capacitive sensing has been studied not only at the laboratory-scale reactor level but has also been implemented in sampling systems for coal loading processes in thermal power plants [6]. Previous research also demonstrated the successful application of capacitive impedance methods to monitor moisture and density in various industrial materials, including fuel analysis.

However, methods based on electrical properties present several limitations, including susceptibility to environmental factors as well as signal interference and instability. Prior to this study, our previous research has demonstrated the capability of the electrical capacitance volume tomography (ECVT) system for moisture investigation in various types of coal [7]. Based on these findings, the present study proposes the use of a simpler closed reactor with a double-insulation configuration to investigate the coal quality evaluation method based on scanning capacitive impedance. This innovation aims to

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reduce noise caused by signal interference and environmental fluctuations. The system transmits sinusoidal signals through the sensor to detect impedance changes associated with coal's physical properties. By analyzing amplitude and phase shifts in the received signal, we aim to extract moisture and density data with improved precision. This approach offers a faster, safer, and more economical alternative to traditional testing procedures [8].

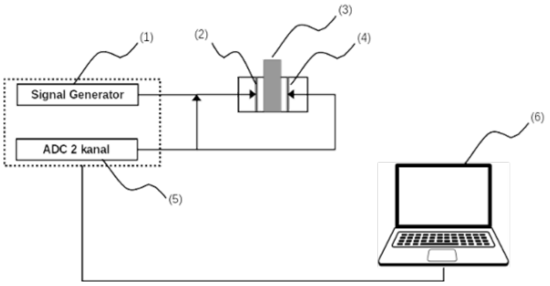
2 Materials and Methods

The coal samples utilized in this study were obtained from multiple mining locations across Sumatra and Kalimantan, Indonesia. These samples represented a range of coal ranks and compositions, reflecting the diverse physical and chemical characteristics typical of Indonesian coal deposits. To evaluate coal quality, a pair of pure copper sensor plates was employed, one serving as a transmitter and the other as a receiver. The plates were affixed to a test tube and integrated into an electronic circuit specifically designed to measure the capacitance of the coal samples.

To assess the quality of the coal samples, an electric field-based technique was employed using a capacitive sensor system. This system comprised a transmitter and a receiver, configured to detect the capacitance of materials positioned between them. Prior to measurement, each coal sample was finely ground to a uniform particle size and placed into a non-conductive plastic holder, precisely engineered to fit between the sensor plates (Fig. 1).

Capacitance measurements were conducted five times per sample to ensure consistency and repeatability. The system was calibrated before each measurement session using air and water, selected for their well-characterized dielectric constants.

To validate the capacitance-based results, each coal sample was also subjected to standard laboratory proximate analysis. The parameters measured included moisture content, volatile matter, fixed carbon, and ash content. These values were then compared with the corresponding capacitance measurements to evaluate the correlation and determine the feasibility of the capacitive sensor system as a rapid, non-destructive tool for assessing coal quality.



*Note:

1. Signal generator
2. Copper sensor as transmitter
3. Sample holder
4. Copper sensor as receiver
5. Electronic circuit
6. Computer

Fig. 1. Experimental setup

The capacitive impedance scanning method uses transmitted sinusoidal signals $x_{Tx}(t)$ and received signals $x_{Rx}(t)$ to monitor sensor impedance variations across multiple frequencies. These variations are used to detect changes in coal's moisture, volatile matter, fixed carbon, and ash content, thus enhancing coal quality estimation accuracy. Figure 2 illustrates the capacitive impedance-based coal quality measurement system.

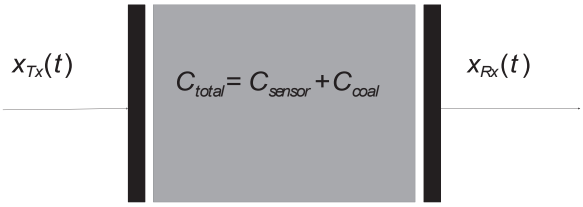


Fig. 2. Capacitive impedance-based coal quality measurement system.

The measurement system scheme is presented in Figure 2. The transmitted signal $x_{Tx}(t)$ is a sinusoidal wave with amplitude A and frequency f, described by:

$$x_{Tx}(t) = Asin(2\pi ft + \phi_{Tx}) \quad (1)$$

where A is the amplitude of the signal, f is the frequency, t is time, and ϕTx is the initial phase of transmission. As this signal interacts with the coal sample, the dielectric properties affect the capacitance of the sensor. The total sensor capacitance is given by:

$$C_{total} = C_{sensor} + C_{coal} \quad (2)$$

where C_{sensor} is the base sensor capacitance without coal, and C_{coal} is the change in capacitance due to coal presence. Impedance is calculated as:

$$Z_{total}(f) = \frac{1}{j\omega C_{total}} \quad (3)$$

Reflected signal characteristics depend on the impedance mismatch between the source (Z_{coal}) and sensor (Z_{sensor}). The reflection coefficient $R_{(f)}$ is:

$$R(f) = \left(\frac{Z_{total}(f) - Z_{coal}}{Z_{total}(f) + Z_{coal}}\right) \quad (4)$$

The received signal ($x_{Rx}(t)$), considering reflection is:

$$x_{Rx}(t) = A\big(1 + R(f)\big)sin(2\pi ft + \phi_{Rx}) \quad (5)$$

Substituting back, the final received signal becomes:

$$x_{Rx}(t) = A\left(1 + \frac{Z_{total}(f) - Z_{coal}}{Z_{total}(f) + Z_{coal}}\right)sin(2\pi ft + \phi_{Rx}) \quad (6)$$

For ideal capacitive sensors (neglecting resistance and inductance), the sensor impedance simplifies to:

$$Z_{total}(f) = \frac{1}{j\omega(C_{sensor} + C_{coal})} \quad (7)$$

Changes in C_{coal} directly affect Z_{sensor}, modifying both amplitude and phase of the received signal. A match between Z_{sensor} and Z_{coal} leads to a stronger signal, while phase shifts provide additional insight into dielectric behavior. By scanning through multiple frequencies, this system captures a wide range of impedance responses, enabling precise coal quality characterization.

In our system, coal quality estimation is based on analyzing the amplitude difference between the transmitted $x_{Tx}(t)$ and received $x_{Rx}(t)$ signals. Variations in amplitude are caused by changes in the dielectric properties of coal, which influence the capacitive impedance of the sensor. By measuring the amplitude attenuation between $x_{Tx}(t)$ and $x_{Rx}(t)$ across different frequencies, the system can infer the moisture, volatile matter, fixed carbon, and ash content of the coal sample. This amplitude-based approach enables a simplified yet effective method for non-destructive coal quality assessment.

3 Results and Discussion

The constituents of coal can be classified into calorific and non-calorific components. The calorific components include fixed carbon and volatile matter, while the non-calorific components consist of moisture and ash. Among these, water present in the moisture fraction, exhibits the highest dielectric constant, making it particularly responsive to detection via capacitive sensors.

A capacitive sensor is a type of sensor that detects changes in capacitance resulting from the dielectric properties of a material. When a material interacts with an electric field, it exhibits a characteristic response depending on its dielectric nature. This response is captured as a measurable change in capacitance.

Due to the varying composition of different coal types, the dielectric properties of each sample also vary. In this context, the coal sample acts as a dielectric medium. As the composition changes, such as an increase in moisture or ash content, the relative permittivity of the sample changes accordingly. The capacitive sensor detects these changes, which can then be correlated with the quality characteristics of the coal. The proximate analysis for coal samples was carried out according to ASTM D-3172. The results from the proximate analysis and the capacitive sensor measurement were presented in Table 1.

Table 1. Proximate analysis and capacitive measurement.

Sample	GCV kcal/kg	Proximate			Capacitive	
		%M	%A	%M+ %A	$\%C_{(r)}$	$\%C_{(r)}$+ %A
1	6385	3.8	15.7	19.5	17.4	33.1
2	6080	8.5	11.5	20	28	39.5
3	5384	13.7	8.7	22.4	36.2	44.9
4	4826	4.5	30.8	35.3	20.6	51.4
5	4948	14.1	10.1	24.2	37	47.1

* GCV = Gross Calorific Value
%M = moisture measurement from proximate analysis
%A = ash measurement from proximate analysis
$\%C_{(r)}$ = relative capacitance measurement from capacitive sensing

In this study, the four proximate analysis components (%M, %A, %VM, and FC) are reformulated into two functional groups based on their contribution to calorific value (CV): the calorific phase (CP), which contributes positively to CV, and the non-calorific phase (NCP), which contributes negatively. The CP comprises volatile matter (%VM) and fixed carbon (FC), whereas the NCP consists of moisture (%M) and ash (%A). These two phases exert fundamentally different effects on the calorific performance of coal.

For capacitance-based measurements, moisture represents the dominant detectable component due to its significantly higher dielectric permittivity compared to other proximate constituents. Consequently, when a capacitive sensing approach is employed, the sensor response is primarily governed by the presence of moisture within the sample matrix.

Because moisture and ash are both classified as non-calorific constituents, the capacitance signal can be reasonably regarded as a direct representation of the NCP fraction, i.e., the combined contribution of %M and %A, rather than an independent measurement of each parameter.

Linear regression analyses were conducted to examine the relationships between %M and $\%C_{(r)}$, as well as between %M + %A and $\%C_{(r)}$ + %A, and their correlation with gross calorific value (GCV), revealing a negative gradient in all cases. This indicates a negative correlation between moisture content and calorific value. In general, it is well established that increasing moisture content leads to a reduction in coal quality due to its dilution of combustible matter.

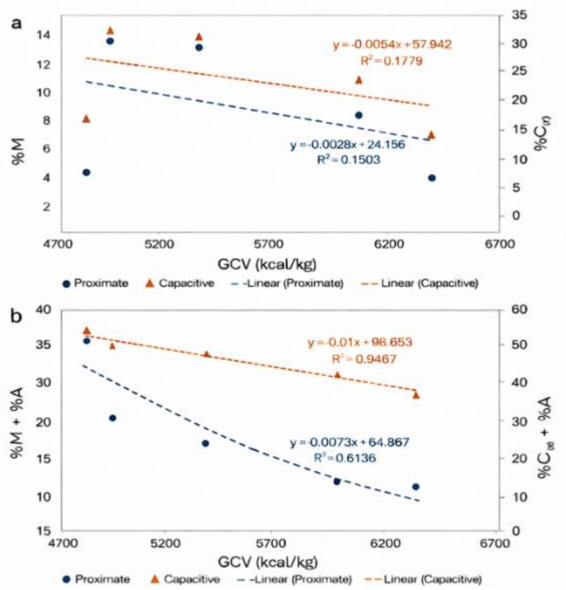


Fig. 3. Linear regression for proximate analysis and capacitive measurements on a) %M and $\%C_{(r)}$ vs GCV, and b) %M + %A and $\%C_{(r)}$ + %A vs GCV.

In the %M and $\%C_{(r)}$ vs. GCV curve (Fig. 3a), the slope from the capacitive method is steeper than that from the proximate analysis, indicating that capacitive predicts a more significant decrease in moisture content with increasing GCV. However, both methods show low coefficients of determination ($R^2 \leq 0.18$), pointing to weak predictive power; the linear model explains only about 15 – 18% of the variation observed. Therefore, although a negative trend appears, moisture content alone is not a strong predictor of GCV, regardless of the analytical approach.

By incorporating ash content (%A), the combined variable (%M + %A) and ($\%C_{(r)}$ + %A) vs. GCV curve (Fig. 3b) exhibits a substantially stronger negative correlation. This is reflected in the markedly higher R^2 values, particularly for the capacitive method (R^2 = 0.9467), signifying a strong linear relationship between

GCV and the combined moisture and ash content. In this model, the capacitive approach explains nearly 95% of the variation, demonstrating significantly improved performance. These findings indicate that the combined parameter serves as a more effective predictor of calorific value than moisture content alone. The higher the moisture and ash contents, both non-combustible fractions, the lower the energy content of the coal, consistent with the observed negative slopes. This composite variable thus provides a more accurate inverse proxy or fuel quality.

Although the capacitive system may not offer superior accuracy in predicting GCV based solely on moisture, it significantly outperforms in the combined metric. This suggests that capacitive is well-suited for integration into holistic models of coal properties. Future predictive models for GCV should include both moisture and ash content to enhance reliability. The high R^2 obtained using capacitive with composite variables highlights its potential for high-fidelity modeling in coal characterization.

To improve the interpretation of the obtained data, an alternative modeling approach was applied using quadratic regression (Fig. 4). In the %M and $\%C_{(r)}$ vs. GCV plot (Fig. 4a), a significant increase in the coefficient of determination (R^2) is observed compared to the linear regression model (Fig. 3a). This indicates that the quadratic regression model provides a considerably better fit to the data than the linear model. As in the previous analysis, the capacitive measurement yields a higher R^2 value (0.7409) compared to the proximate analysis (0.6683).

When ash content is incorporated into the model, the R^2 value for the proximate analysis further improves (Fig. 4b), reaching 0.7659. This value is notably higher than the corresponding linear regression result shown in Figure 3b, highlighting the benefit of applying a non-linear model. However, in the case of capacitive measurements, the use of quadratic regression does not result in a substantial improvement. The %M + %A and %C(r) + %A vs. GCV plot produces an R^2 of 0.9529, slightly higher than the value obtained using linear regression.

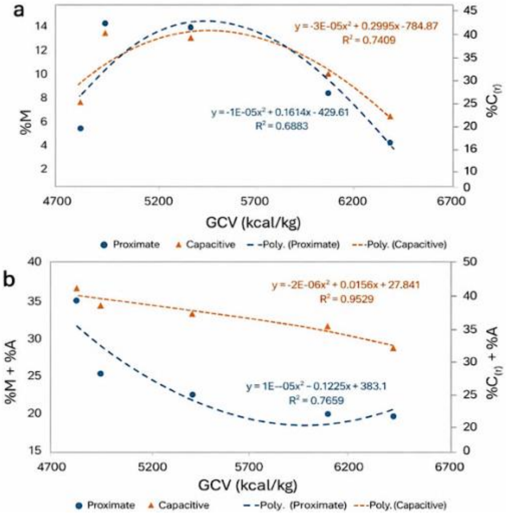


Fig. 4. Quadratic regression for proximate analysis and capacitive measurements on a) %M and $\%C_{(r)}$ vs GCV, and b) %M + %A and $\%C_{(r)}$ + %A vs GCV.

Overall, the linear regression model exhibits a consistent linear decline in GCV with increasing impurities. In contrast, the quadratic regression model provides a better fit for data that exhibits a sharper decline at lower GCV values and levels off at higher GCV values. For both data sets, the quadratic model either outperforms or performs comparably to the best model. This trend suggests a non-linear degradation behavior in fuel quality (as indicated by GCV) in response to increasing impurity levels (%M + %A and %C(r) + %A), where the impact of impurities is more pronounced at lower calorific values.

4 Conclusions

Calorific value measurements of coal derived from electric field-based techniques demonstrate a strong correlation with those obtained via standard proximate analysis, indicating comparable reliability. Moreover, the electric field approach offers the potential for enhanced efficiency through faster, non-destructive, and real-time assessment, making it a promising alternative for routine coal quality evaluation.

In this study, the relative capacity ($\%C_r$) measured from the device correlates with coal quality as indicated by GCV. This relation is even stronger when incorporating ash content (%A) from proximate analysis. From the result, it can be concluded that the developed capacitive system responded well with the non-calorific phase, i.e. moisture and ash.

The author gratefully acknowledges the financial support provided by PT CTech Labs Edwar Teknologi for this research, and extends appreciation to PT Mutiara Samawat Abadi, PT Indorama Petrochemicals, and PT Jawamanis Rafinasi for supplying the experimental samples.

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