

Predicting Oil Content of Palm Fruit Based on its Electrical Properties

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ABSTRACT

The oil content of oil palm fruit is a crucial parameter that must be determined before harvest, as it directly impacts crude palm oil (CPO) quality and processing efficiency. The conventional chemical method for oil content determination is costly and time consuming. This study aims to develop a non-destructive, accurate, and rapid method for predicting oil content in oil palm fruit based on its electrical properties. Measurements of electrical properties were taken across frequencies of 50 Hz to 5 MHz. Oil content of samples were determined by chemical method. Some pre-treatments of electrical properties were carried out and the pre-treated electrical properties were calibrated with reference oil content using simple linear regression and partial least squares regression. Linear regression model showed moderate accuracy ($r = 0.61-0.81$), with RMSE values between 9.54% and 12.99%. PLS regression models using admittance ($r = 0.99$, $R^2 = 0.98$, SEP 2.20%, RPD 7.99), resistance ($r = 0.98$, $R^2 = 0.97$, SEP 2.62%, RPD 5.56), and impedance ($r = 0.98$, $R^2 = 0.95$, SEP 3.16%, RPD 4.68) produced high prediction accuracy. The results confirm that electrical properties can be used to predict oil content in oil palm fruit rapidly and non-destructively.

1. INTRODUCTION

Palm oil is a globally strategic agricultural commodity, playing a pivotal role in boosting foreign exchange earnings and supporting economic growth in producing nations. As the world's largest producer, Indonesia accounted for approximately 60% of global palm oil supply in 2023, with a plantation area of 15.9 million hectares and a total production of 51.3 million tons of crude palm oil (CPO). The commodity contributed significantly to the national economy, generating US\$29.5 billion in export revenue (BPS, 2024), with key markets including India, China, and Pakistan. The quality of oil palm fruit at harvest is crucial for improving Crude Palm Oil (CPO) quality. Accurately determining the maturity of oil palm fruit—whether under-ripe or over-ripe—is essential for maximizing oil yields and protecting the revenues of palm oil companies. The oil content of oil palm fruit is a critical quality parameter that does not increase post-harvest, making the harvesting of low-oil-content fruit detrimental to processing efficiency and profitability. Current assessment methods, such as visual inspection or indirect field measurements, lack of accuracy, while the standard Soxhlet extraction method—though reliable—is time-consuming, costly, and hazardous due to its use of n-hexane (Chin-Hashim *et al.*, 2022).

This highlights the urgent need for a non-destructive, rapid, cost-effective, and environmentally friendly alternative for oil content measurement. Several non-destructive techniques have been explored, including Near-Infrared Spectroscopy (NIRS), which is rapid and reagent-free but requires extensive calibration (Pourdarbani *et al.*, 2022);

Nuclear Magnetic Resonance (NMR), which is highly accurate but expensive and impractical for field use (Hao *et al.*, 2022); Hyperspectral Imaging, which provides detailed spatial and spectral data but involves complex processing (Phattaraworamet *et al.*, 2024); and Ultrasonic Sensing, which is portable but affected by fruit heterogeneity (Mohammed *et al.*, 2021). Among these, electrical property-based methods, such as Electrical Impedance Spectroscopy (EIS) and capacitance measurement, stand out due to their cost-effectiveness, portability, real-time analysis capability, and strong correlation with oil content (Chin-Hashim *et al.*, 2022). These methods also eliminate the need for hazardous chemicals, align with green chemistry principles, and are adaptable for both industrial and smallholder use, making them a promising solution for accurate and sustainable oil content assessment in oil palm fruit. Electrical method has also been previously studied to determine maturity in various crops, including melon, banana (Jamaludin *et al.*, 2014), mango, and citrus fruits (Juansah *et al.*, 2014). Moreover, method based on electrical properties have been assessed to determine oil and moisture content in oil palm fruit (Chin-Hashim *et al.*, 2022; Mellyana *et al.*, 2024; Misron *et al.*, 2016).

This study extended the work of previous study (Chin-Hashim *et al.*, 2022), who evaluated the water and oil content in oil palm fruits using electrical impedance spectroscopy. Their study achieved the best predictions at 100 kHz, with coefficients of determination (R^2) of 0.72 for oil content (RMSE = 5.71%) and 0.77 for moisture content (RMSE = 5.85%). Whilst these results demonstrated potential, the prediction accuracy required improvement. One possible limitation was the relatively narrow frequency range used, up to only 100 kHz. In contrast, previous studies on other fruits have shown that higher frequency ranges can enhance prediction accuracy. For instance, (Juansah *et al.*, 2013) investigated Garut citrus fruits using resistance and impedance measurements up to 5 MHz to determine fruit maturity based on sugar content (total soluble solids), firmness, and pH. They found that at 1 MHz, the correlations between electrical properties and physicochemical attributes were strongest, with R^2 values of 0.96 for resistance versus pH and 0.97 for impedance versus pH. Additionally, the correlation between resistance and firmness was $R^2 = 0.95$, and between impedance and firmness was $R^2 = 0.92$. Similarly, the study reported a strong correlation between the ratio of total soluble solids (TSS) to hydrogen ion concentration (H^+) and electrical properties. Specifically, at a frequency of 1 MHz, R^2 between impedance and TSS/ H^+ was 0.91, while between resistance and TSS/ H^+ it was 0.91.

Furthermore, (Kato, 1997) utilized capacitance measurements at frequencies above 1 MHz to assess the internal cavity status of watermelon fruits, correlating specific gravity with fruit quality. Watermelons with a specific gravity greater than 0.95 g/cm³ were classified as non-hollow, while those below this threshold were considered hollow. A correlation coefficient of $r = 0.69$ was observed between fruit weight and specific gravity. These findings suggest that employing higher frequencies can significantly improve the accuracy of nondestructive fruit quality assessments.

The objective of this research is to develop a non-destructive method for predicting the oil content of oil palm fruitlets by analyzing their electrical properties—specifically impedance, resistance, admittance, inductance, capacitance, reactance, and conductance—across frequencies ranging from 50 Hz to 5 MHz. This study is expected to offer an accurate, rapid, and non-destructive method for determining the oil content of oil palm fruit, serving as an alternative to conventional chemical analysis methods. The availability of the method will be beneficial for farmer and industries in increasing productivity and quality of CPO, reducing cost of production and increasing competitiveness of CPO industries as well.

2. MATERIALS AND METHODS

2.1. Oil Palm Fruit

A total of 106 Tenera oil palm fruit samples were harvested from the Cikabayan plantation, IPB University, Bogor, Indonesia. The samples were systematically classified based on their maturity stages into the following distinct categories: 12 samples at three months (3M), 12 samples at four months (4M), 12 samples at four months and one week (4M1W), 9 samples at four and a half months (4M2W), 9 samples at four and three-quarter months (4M3W), 9 samples at five months (5M), 9 samples at five and a quarter months (5M1W), 12 samples at five and a half months (5M2W), 12 samples at five and three-quarter months (5M3W), and 12 samples at six months (6M). Preliminary procedures for these samples included cleaning, weighing, and measuring their physical dimensions. Following this, the study progressed with electrical characterization and chemical analysis, both of which were integral components of the research framework.

2.2. Electrical Properties Measurements

The electrical impedance characteristics of oil palm fruit were evaluated using a custom measurement system consisting of copper elliptical electrodes (30 mm length $\times$ 20 mm width) connected to an LCR Hitester 3532-50, Hioki, Tokyo, Japan. The instrument was calibrated following the manufacturer's standard procedure (Hioki Corporation, 2015) prior to measurements. Frequency sweeps were performed across 200 points from 50 Hz to 5 MHz at room temperature ($25 \pm 1^\circ\text{C}$), with the fruit sample placed between two parallel copper plates. The following electrical properties were measured and recorded:

1. Impedance (Z): Total opposition to current flow, measured through the voltage-current phase relationship at each test frequency.
2. Resistance (R): Real component of impedance representing ohmic losses, determined via direct measurement of in-phase voltage and current.
3. Admittance (Y): Reciprocal of impedance ($1/Z$), quantifying how easily current flows through the fruit tissue.
4. Inductance (L): Minor inductive effects in the fruit tissue, computed from reactance values at lower frequencies.
5. Capacitance (C): Charge storage capacity of the fruit tissue, derived from the imaginary component of admittance.
6. Reactance (X): Imaginary component of impedance representing energy storage/release, calculated from the phase difference between voltage and current.
7. Conductance (G): Real component of admittance ($1/R$), indicating the fruit's ability to conduct electric current.

All measurements were performed using the LCR meter's automatic ranging function to ensure optimal accuracy across the wide frequency spectrum. The instrument's built-in algorithms automatically calculated derived parameters (X , Y , G) from primary measurements of Z , R , and C using standard AC circuit theory relationships. Three replicate measurements were taken for each fruit sample, with the electrodes cleaned between samples to prevent contact resistance variations.

This comprehensive characterization of multiple electrical parameters enables robust correlation analysis between electrical properties and oil content, providing multiple potential indicators for non-destructive quality assessment. The block diagram of the electrical impedance measurement setup is shown in Figure 1.

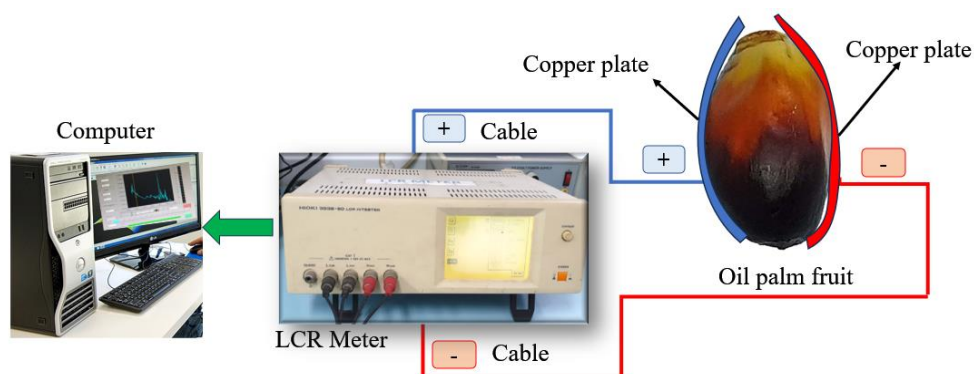


Figure 1. The block diagram of electrical impedance measurement

2.3. Oil Content Measurements

Oil extraction was performed using a Soxhlet extraction apparatus with n-hexane as the solvent. The extraction process lasted approximately four hours, during the oil was fully extracted from the samples. The oil content of each fruit was calculated using Equation (1):

$$\% \text{ Oil Content} = \left(\frac{W - W_2}{W_1} \right) \times 100 \quad (1)$$

where % oil content represents the percentage of oil, W is the weight of the flask with the oil, W_2 is the weight of the empty flask, and W_1 is the weight of the dry mesocarp sample.

2.4. Statistical Analysis

An analysis of variance (ANOVA) at a 5% significance level was used to assess the electrical variations across different frequencies and their correlation with the oil content of oil palm fruit.

2.5. Linear Regression Model

A regression analysis was performed to develop a linear regression model correlating electrical values with oil content. The model was evaluated by calculating the root-mean-square error (*RMSE*) using Equation (2):

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (y_{tn} - y_{cn})^2} \quad (2)$$

Where *N* is the number of samples in the dataset, y_{tn} is the predicted value from the regression equation, and y_{cn} is the measured value obtained through experimental procedures.

2.6. Calibration and Validation of Partial Least Square (PLS)

Partial Least Squares (PLS) is a regression-based technique designed for analyzing high-dimensional data in low-structure environments (Silalahi *et al.*, 2021; Wu *et al.*, 2023). PLS modelling uses a component-based approach to generate deterministic construct scores for predictive purposes (Shmueli *et al.*, 2016), aiming to estimate the variance of endogenous constructs and their associated manifest variables. Model validation in PLS typically involves parameter inference and testing the significance of the estimated parameters.

In this study, calibration models were developed and evaluated to examine the relationship between spectral data (x-variables) and chemical variables (y-variables) using an optimal number of PLS factors (Borràs *et al.*, 2016; Miloš *et al.*, 2022; Widyaningrum *et al.*, 2024). The spectral data, which included measurements of impedance, resistance, and admittance, along with the reference dataset, employed 3, 5, and 7 PLS factors to create the calibration model for predicting oil content. This process was facilitated by Unscramble Software 10, developed by CAMO in Norway (CAMO Software, 2014). The goal was to enhance model performance by providing a comprehensive toolbox for data processing. The software effectively managed and pre-processed both the spectral and reference data.

For model development and testing, approximately two-thirds of the samples were used to train the model, while the remaining third served to evaluate its performance. The training set was deliberately selected to include spectral extremes, ensuring the robustness and boundary sensitivity of the model. Various data pre-treatments were applied to the spectral data for different purposes. Normalization was used to reduce the effects of particle size and improve spectral values, compensating for errors caused by physical factors such as uneven data dispersion, noise, and suboptimal spectral shapes. This method minimized interference from underlying factors by dividing each row of the data matrix by its mean. The Standard Normal Variate (SNV) correction was commonly applied to improve spectral data quality by mitigating scattering effects during data acquisition (Widyaningrum *et al.*, 2024). Additionally, first-derivative data pre-treatment, such as the Savitzky-Golay filter, was used to better distinguish components within the data, leading to improved calibration outcomes.

In this study, various data pre-treatment methods were applied, including a) no pre-treatment (original), b) normalization mean (NM), c) standard normal variate (SNV), d) first derivative Savitzky-Golay (dg1), and e) a combination of normalization mean and first derivative Savitzky-Golay (NM-Dg1) (Miloš *et al.*, 2022). The calibration model for predicting oil content was evaluated using key statistical metrics, such as the correlation coefficient (*r*), standard error (*SE*), coefficient of variance (*CV*), ratio of standard deviation (*RPD*), and consistency (Williams *et al.*, 2019).

The correlation coefficient (*r*) indicates the strength and direction of the linear relationship between predicted and actual values, with higher values of *r* signifying stronger correlations, which are critical for validating the model's predictive accuracy. The standard error (*SE*) measures prediction accuracy by indicating the average deviation of observed values from the regression line; lower *SE* values suggest higher accuracy. The coefficient of variance (*CV*) assesses the relative variability by comparing the standard deviation to the mean, helping to understand data dispersion and reliability. The ratio of standard deviation (*RPD*) evaluates the model's predictive power by comparing the standard

deviation of the reference data to the standard error of prediction, with higher *RPD* values indicating a more reliable model. Lastly, consistency reflects the model's reliability across different datasets, showing that it can produce stable, repeatable results under varying conditions. These metrics were essential for assessing the calibration model's accuracy and reliability, ensuring precise measurements of oil content.

3. RESULTS AND DISCUSSION

3.1. Chemical Properties of Oil Palm Fruit

The progression of oil content, moisture content, and free fatty acid (FFA) across ten different maturity stages is shown in Figure 2a. The fruits exhibited varying characteristics, with oil content ranging from 0.16% to 53.5% (Table 1), moisture content between 27.75% and 86.39%, and FFA content from 0 to 14.87% (Mellyana *et al.*, 2024). The correlation between moisture content and oil content during fruit maturation is depicted by a linear regression line, indicating an inverse relationship (Figure 2b). The regression analysis revealed an R^2 value of 0.89, which is comparable to the R^2 value of 0.86 observed at the 12, 16, and 20 weeks after anthesis (WAA) stages (Chin-Hashim *et al.*, 2022). These findings support the notion that as oil palm fruit matures, its oil content reaches a peak while the moisture content decreases to its lowest level.

Previous studies also revealed an inverse linear relationship between moisture content and oil content in oil palm fruit, suggesting this trend can be a useful indicator of mesocarp maturity. Variations in the moisture content of oil palm fruit cause changes in electrical impedance due to the reactive nature of water molecules when exposed to alternating electric currents (Ibrahim *et al.*, 2019). Statistical analysis using ANOVA revealed significant differences in oil content across the ten maturity stages, with a *p*-value of less than 0.05 (Table 2).

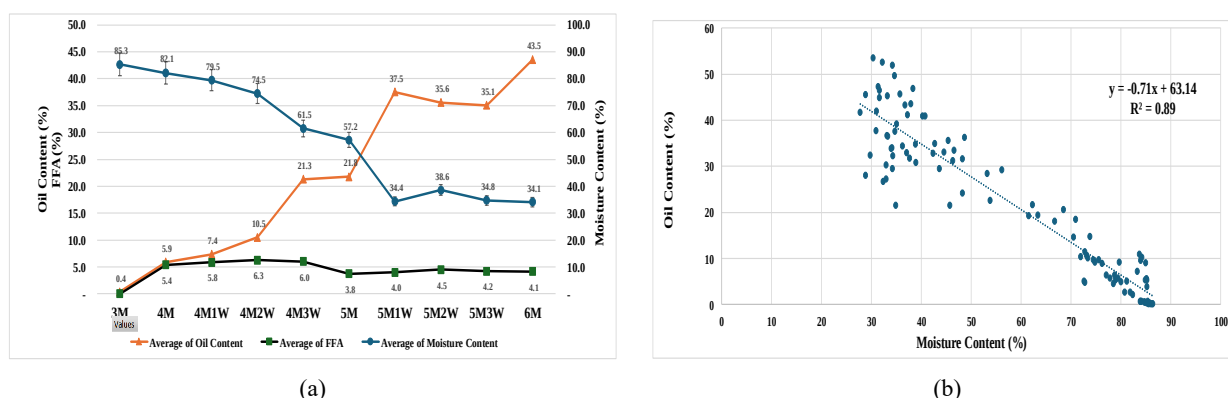


Figure 2. (a) The progression of oil content, moisture content, and FFA at ten diverse maturity stages, (b) The association between oil and moisture content in oil palm fruit.

Table 1. Reference data of Tenera oil palm fruit

Chemical properties	Stages of maturation	Average (%)	Deviation standard (%)	Minimum (%)	Maximum (%)
Oil content	3M	0.38	0.23	0.16	0.73
	4M	5.91	1.85	3.83	10.31
	4M1W	7.37	4.23	0.39	10.97
	4M2W	10.53	7.78	2.18	20.57
	4M3W	21.30	12.88	6.44	40.92
	5M	21.77	10.06	4.79	36.27
	5M1W	37.52	6.39	29.54	47.31
	5M2W	35.58	6.14	28.00	46.87
	5M3W	35.07	8.49	21.48	49.64
	6M	43.54	8.02	8.37	53.50

Table 2. ANOVA results for oil content of oil palm fruit

Mesocarp Oil Content	Sum of squares	df	Mean Squares	F	Sig
Between Groups*	23513.07	9	2612.56	50.47	0.00
Within Groups*	4969.52	96	51.77		
Total	28482.59	105			

*Groups are 3M, 4M, 4M1W, 4M2W, 4M3W, 5M, 5M1W, 5M2W, 5M3W, and 6M.

3.2. Linear Regression Model of Electrical Characteristics of Oil Palm Fruit

3.2.1. Impedance Characteristics of Oil Palm Fruit at Different Maturity Levels

In an electrical circuit, impedance is defined as the ratio of the voltage across a circuit element to the current passing through it. In oil palm fruit, electrical impedance hinders the flow of electric charge or alternating current, and its magnitude is influenced by resistance, frequency, and reactance. At low frequencies, reactance plays a significant role, resulting in higher impedance. As the frequency increases, reactance decreases, leading to a reduction in impedance. Impedance is the total resistance experienced when the fruit is subjected to alternating current. Additionally, impedance values are related to conductance and capacitance, both of which vary with frequency. Capacitive reactance is an imaginary component of impedance and is directly proportional to the product of capacitance and frequency, while conductance is inversely proportional to resistance. As frequency increases, both resistance and reactance decrease, leading to a reduction in impedance. The interaction of resistance and reactance determines the total impedance, which generally decreases with increasing frequency (Barsoukov & Macdonald, 2018).

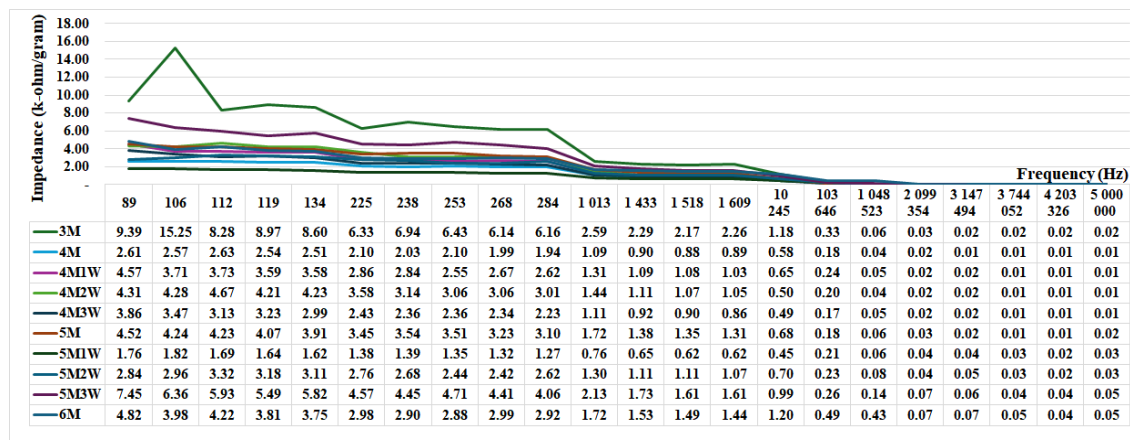


Figure 3. The impedance spectrum per unit weight at different maturity levels

In Figure 3, impedance initially increases up to a frequency of 89 Hz, then decreases at frequencies above 1 MHz. At low frequencies, the high impedance values indicate that current is restricted to the extracellular region. At higher frequencies, however, lower impedance values suggest that current can flow within the cells. The strongest correlation between impedance and oil content was observed at a frequency of 3.74 MHz, with a coefficient of determination (R^2) of 0.48 ($r = 0.70$) and the lowest $RMSE$ (11.76%) across the ten maturity levels (Table 3). In comparison, (Chin-Hashim *et al.*, 2022) reported the best results at a frequency of 100 kHz, with an R^2 of 0.72 and an $RMSE$ of 5.71% for the 12, 16, and 20 WAA stages.

3.2.2. Resistance Characteristics of Oil Palm Fruit at Different Maturity Levels

Resistance refers to an object's ability to impede the flow of electrical current. The oil content in a liquid can influence its resistance value, as dissolved oil affects the liquid's chemical properties. Liquids with higher moisture content exhibit better conductivity. This relationship is shown in Figure 4, where oil palm fruit at 3 months of maturity demonstrates high resistance, inhibiting the flow of electrical current.

Table 1. A linear regression model, coefficient of determination, correlation, and RMSE to describe the relationship between electrical characteristics and oil content at various frequencies

Electric characteristics	Frequency (MHz)	Linear Regression Models	Regression Coefficient (R ²)	Correlation (r)	RMSE (%)
Impedance	3.74	$y = 716.55x + 5.06$	0.48	0.7	11.76
	3.53	$y = 626.21x + 4.76$	0.48	0.69	11.81
	4.45	$y = 781.26x + 5.23$	0.47	0.69	11.88
	5	$y = 622.88x + 6.28$	0.47	0.69	11.92
	4.2	$y = 827.33x + 5.17$	0.46	0.68	12.05
Resistance	3.53	$y = 891.30x + 2.70$	0.53	0.73	12.16
	4.45	$y = 1146.56x + 1.70$	0.52	0.72	12.23
	3.74	$y = 1435.52x + 0.31$	0.51	0.71	12.47
	5	$y = 808.95x + 3.93$	0.49	0.7	12.55
	4.2	$y = 1239.36x + 1.83$	0.49	0.7	12.65
Admittance	5	$y = -0.030x + 41.52$	0.66	0.81	11.26
	3.74	$y = -0.028x + 41.13$	0.64	0.8	11.34
	4.2	$y = -0.026x + 41.82$	0.64	0.8	11.48
	3.97	$y = -0.027x + 42.26$	0.64	0.8	11.65
	3.53	$y = -0.034x + 41.69$	0.63	0.8	11.7
Inductance	3.74	$y = 16.78x + 9.45$	0.4	0.63	11.76
	3.97	$y = 23.50x + 9.70$	0.39	0.63	11.84
	5	$y = 26.60x + 12.93$	0.39	0.62	11.85
	4.45	$y = 26.15x + 11.19$	0.38	0.61	11.9
	3.53	$y = 17.30x + 9.014$	0.37	0.61	11.93
Capacitance	3.74	$y = -347.69x + 37.98$	0.56	0.75	9.54
	3.97	$y = -274.87x + 37.81$	0.54	0.73	9.8
	3.53	$y = -354.01x + 38.53$	0.52	0.72	9.81
	3.33	$y = -407.90x + 38.06$	0.52	0.72	9.88
	3.15	$y = -309.35x + 35.85$	0.4	0.63	9.92
Reactance	3.74	$y = 713.56x + 9.45$	0.4	0.63	12.7
	3.97	$y = 942.88x + 9.70$	0.39	0.63	12.76
	5	$y = 846.87x + 12.93$	0.39	0.62	12.8
	4.45	$y = 934.77x + 11.19$	0.38	0.61	12.93
	3.53	$y = 779.53x + 9.01$	0.37	0.61	12.99
Conductance	5	$y = -0.029x + 40.38$	0.64	0.8	9.93
	4.72	$y = -0.026x + 39.39$	0.61	0.78	10.17
	3.97	$y = -0.029x + 40.33$	0.61	0.78	10.35
	4.2	$y = -0.027x + 40.07$	0.61	0.78	10.38
	3.74	$y = -0.032x + 38.73$	0.59	0.77	10.4

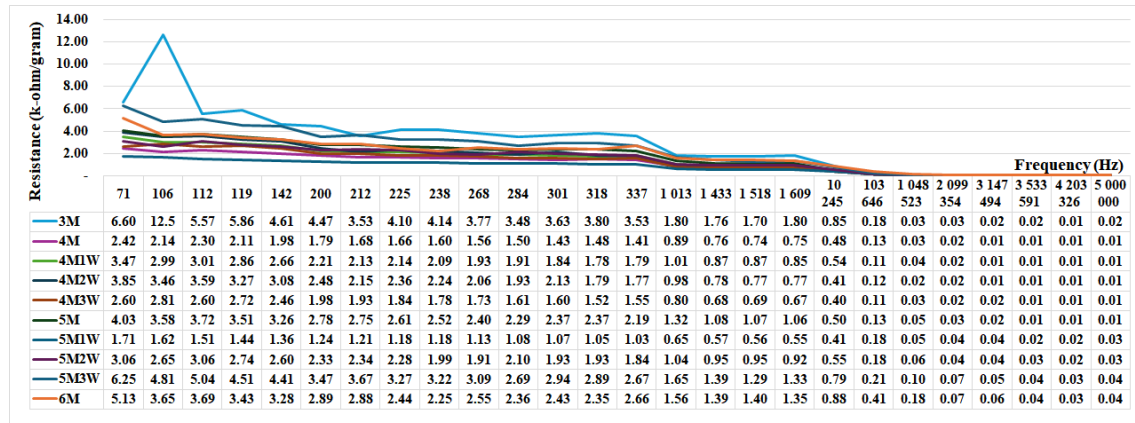


Figure 4. The resistance spectrum per unit weight at different maturity levels

Conversely, fruit at 4 months of maturity has low resistance, allowing for greater electrical current flow. As the fruit matures further, resistance decreases, which in turn reduces impedance to electrical flow. The strongest correlation between resistance and oil content occurred at a frequency of 3.53 MHz, with a coefficient of determination (R^2) of 0.53 ($r = 0.73$) and an $RMSE$ of 12.16% across the ten maturity levels (Table 3).

3.2.3. Admittance Characteristics of Oil Palm Fruit at Different Maturity Levels

Admittance, the inverse of impedance, measures a material's ability to conduct alternating current at a specific frequency. It consists of two components: conductance (the real part) and susceptance (the reactive part). In Figure 5, the admittance of oil palm fruit increases at frequencies above 1 MHz and continues rising to 5 MHz, highlighting differences between various maturity stages. The best correlation between admittance and oil content was observed at 5 MHz, with a coefficient of determination (R^2) of 0.66 ($r = 0.81$) and an $RMSE$ of 11.26% across the ten maturity levels (Table 3).

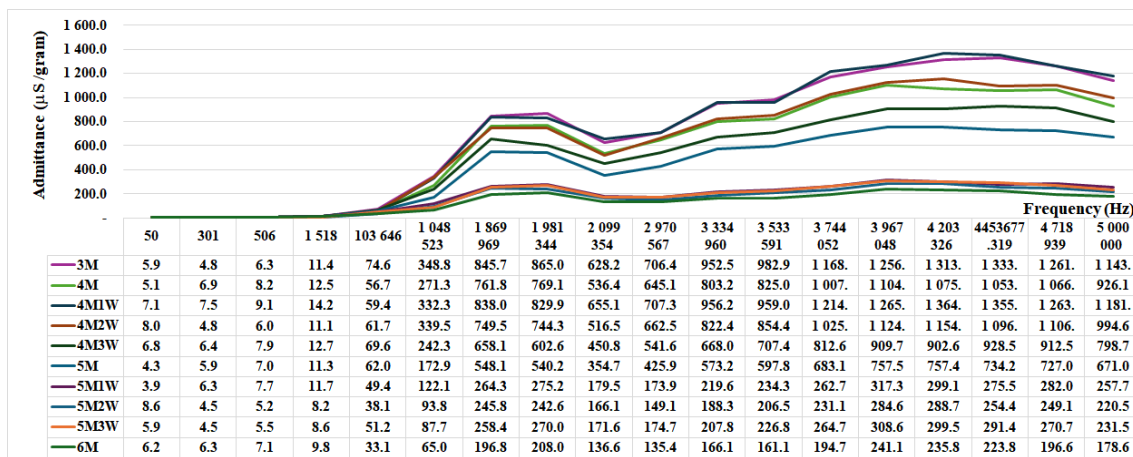


Figure 5. The admittance spectrum per unit weight at different maturity levels

3.2.4. Inductance Characteristics of Oil Palm Fruit at Different Maturity Levels

Inductance is the property of an electrical circuit that enables it to store energy in a magnetic field when an electric current flows through it. Measured in Henrys (H), inductance depends on factors like core material, number of windings, spacing, and coil diameter (Fowler & Schultz, 2022).

The strongest correlation between inductance and oil content was found at a frequency of 3.74 MHz, with a coefficient of determination (R^2) of 0.40 ($r = 0.63$) and an $RMSE$ of 11.76% across the ten maturity levels (table 3). Previous research on inductive sensors, such as capacitance inductive sensors (Harun *et al.*, 2014) and triple flat-type inductive sensors (Aliteh *et al.*, 2018), has focused on measuring moisture content. These sensors also detect oil palm fruit maturity at resonance frequencies between 270–500 Hz, with $RMSE$ values of 13.45% (Sinambela *et al.*, 2020). Flat-type oil sensors (Mison *et al.*, 2016) have similarly been used to assess both raw and ripe oil palm fruit at resonance frequencies. One study indicated that fruit ready for harvest showed a frequency of 9.8 MHz at week 18, but inductance values overlapped at 8.5 MHz during week 10. This overlap may be due to changes in moisture content as the fruit matures.

3.2.5. Capacitance Characteristics of Oil Palm Fruit at Different Maturity Levels

Capacitance refers to a capacitor's ability to store electrical energy. The presence of a dielectric material increases capacitance. In Figure 6, capacitance in oil palm fruit fluctuates at frequencies above 2 MHz, continuing up to 5 MHz. The strongest correlation between capacitance and oil content was observed at 3.74 MHz, with a coefficient of determination (R^2) of 0.56 ($r = 0.75$) and an $RMSE$ of 9.54% across the ten maturity levels (Table 3).

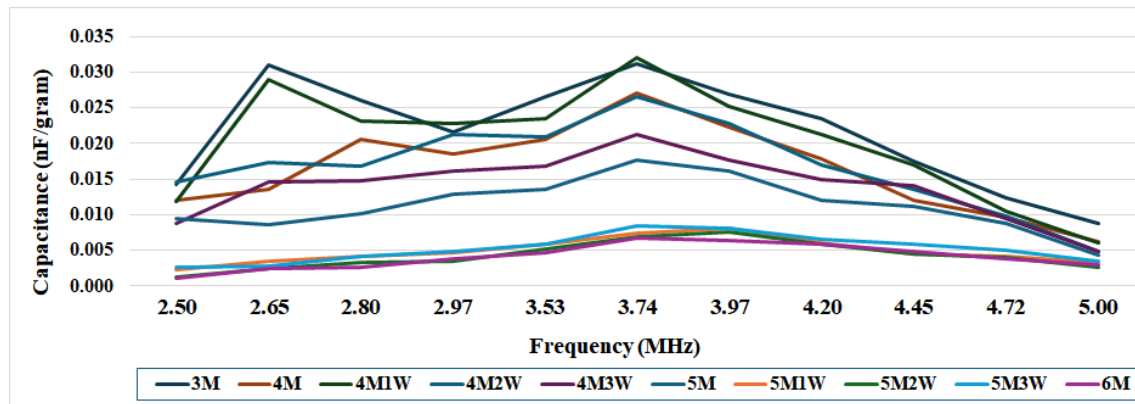


Figure 6. The capacitance spectrum per unit weight at different maturity levels

At low frequencies, capacitance can be influenced by moisture content and electrode polarization. Frequency changes also affect ion movement within the material. As frequency increases, dipole reorientation occurs more rapidly, shortening the time available for polarization events, and resulting in reduced overall polarization. Polarization within oil palm fruit is affected by moisture content and its chemical composition (Juansah *et al.*, 2014).

3.2.6. Reactance Characteristics of Oil Palm Fruit at Different Maturity Levels

Reactance can be defined as the resistance caused by the capacitive and inductive phenomena of materials when subjected to alternating current (AC). Hence, this reactance can be analogized as resistance. Reactance arises because of circuit elements such as capacitors and inductors. Reactance is a crucial concept in the analysis of AC circuits as it affects the flow of current within the circuit and the associated voltage. Reactance, together with resistive resistance, in a circuit forms impedance, which characterizes the overall resistance to AC current. In Figure 7, the reactance of oil palm fruit at various stages of maturity experiences fluctuations at frequencies above 2 MHz, continuing up to 5 MHz. The strongest correlation between reactance and oil content was observed at 3.74 MHz, with a coefficient of determination (R^2) of 0.40 ($r = 0.63$) and an RMSE of 12.70 % across the ten maturity levels (Table 3).

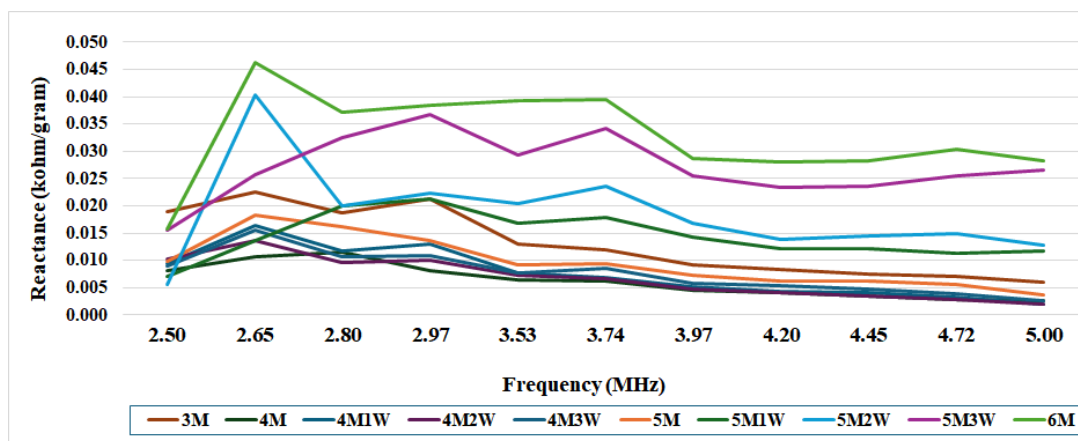


Figure 7. The reactance spectrum per unit weight at different maturity levels

3.2.7. Conductance Characteristics of Oil Palm Fruit at Different Maturity Levels

Conductance is the ability of a material to conduct electricity. Conductance is influenced by the concentration of ions and the mobility of ions that can conduct electricity within the material. The greater the number of ions and the higher the ion mobility, the larger the value of conductance. Conductance is inversely proportional to resistance, where the

greater the resistance of oil palm fruit, the smaller its conductance. In Figure 8, the conductance of oil palm fruit at various stages of maturity exhibits fluctuations at frequencies above 2 MHz continuing up to 5 MHz. The best correlation between conductance and oil content was observed at 5 MHz, with a coefficient of determination (R^2) of 0.64 ($r = 0.80$) and an RMSE of 9.93% across the ten maturity levels (Table 3).

The most favorable results for distinguishing between the stages of maturity across ten different harvest periods (ranging from 3 to 6 months) included: impedance (3.74 MHz, $r = 0.70$, RMSE = 11.76%), resistance (3.53 MHz, $r = 0.73$, RMSE = 12.16%), admittance (5 MHz, $r = 0.81$, RMSE = 11.26%), inductance (3.74 MHz, $r = 0.63$, RMSE = 11.76%), capacitance (3.74 MHz, $r = 0.75$, RMSE = 9.548%), reactance (3.74 MHz, $r = 0.63$, RMSE = 12.70%), and conductance (5 MHz, $r = 0.80$, RMSE = 9.93%). Additional data processing is required for each electrical measurement to develop an accurate calibration model for predicting oil content.

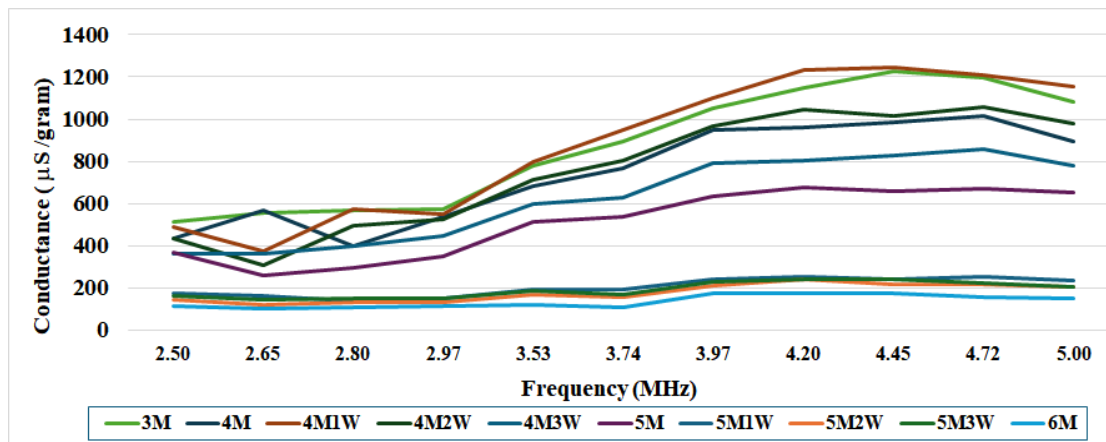


Figure 8. The conductance spectrum per unit weight at different maturity levels

3.3. PLS Calibration Model for Estimating Oil Content

Pre-processed Partial Least Squares (PLS) data formed the basis for developing a predictive model for estimating oil content in oil palm fruit. Table 4 outlines the descriptive statistics for oil content across reference, calibration, and validation datasets. The data exhibited a wide range of oil content values, varying from minimum 0.16% to maximum 53.50%. Importantly, the distribution of data within the calibration and validation samples showed high consistency, ensuring robust model performance.

Table 2. Compositional analysis of oil content and calibration oil palm fruit

Chemical composition	Research phase	Number of samples	Average (%)	Deviation standard (%)	Minimum (%)	Maximum (%)
Oil content (%)	References	106	21.39	16.47	0.16	53.50
	Calibration	74	23.02	16.39	0.16	53.50
	Validation	32	17.62	16.28	0.16	51.92

Based on the impedance, resistance, admittance, inductance, capacitance, reactance and conductance data (Table 3), the highest correlation values ranged from 0.61 to 0.81, with RMSE values between 9.54% and 12.99%. Although these results show a moderate level of accuracy, further calibration is necessary to improve the precision of oil content predictions. In the next phase, calibration could be refined using impedance, resistance, or admittance spectra, depending on the selected approach.

The calibration results for the impedance spectra (Table 5, Figure 9) revealed that using NM-Dg1-7 factor produced values of $r = 0.98$, $R^2 = 0.95$, $SEC = 3.51\%$, $SEP = 3.16\%$, $CV = 15.23\%$, and an RPD of 4.68. An RPD value above 4.1 signifies that this model is excellently categorized and can be applied to a variety of applications involving this type of material. (Williams, 2014).

Table 3. Calibration results for oil content using impedance, resistance, and admittance

Electrical properties	Treatment (PLS-factor)	R ²	<i>r</i>	SEC (%)	SEP (%)	CV (%)	RPD	Bias	Consistency
Impedance	Original /3	0.74	0.86	8.33	6.23	36.20	1.97	1.30	133.77
	Original /5	0.84	0.92	6.56	5.70	28.52	2.50	0.59	115.10
	Original /7 ^a	0.93	0.96	4.46	4.90	19.38	3.67	0.11	90.96
	NM /3	0.71	0.84	8.83	7.02	38.37	1.86	0.40	125.88
	NM /5	0.86	0.93	6.12	5.97	26.60	2.68	0.18	102.63
	NM /7 ^a	0.93	0.96	4.34	3.67	18.86	3.78	-0.15	118.14
	SNV /3	0.44	0.66	12.31	10.74	53.47	1.33	1.01	114.60
	SNV /5	0.78	0.88	7.79	7.92	33.85	2.10	0.89	98.42
	SNV /7	0.87	0.93	5.96	5.53	25.87	2.75	0.39	107.68
	Dg1 /3	0.64	0.80	9.90	7.50	43.02	1.66	1.55	131.98
	Dg1 /5	0.77	0.88	7.79	6.05	33.86	2.10	1.10	128.75
	Dg1 /7	0.87	0.93	6.01	5.34	26.12	2.73	0.91	112.64
	NM-Dg1 /7 ^b	0.95	0.98	3.51	3.16	15.23	4.68	0.02	110.97
Resistance	Original /3	0.78	0.88	7.77	6.07	33.75	2.11	0.90	127.98
	Original /5	0.85	0.92	6.40	4.40	27.82	2.56	0.29	145.38
	Original /7 ^a	0.90	0.95	5.10	3.15	22.17	3.21	0.05	161.81
	NM /3	0.61	0.78	10.25	6.49	44.54	1.60	0.41	158.06
	NM /5	0.84	0.92	6.54	5.40	28.40	2.51	0.25	121.00
	NM /7 ^a	0.94	0.97	3.90	3.20	16.95	4.20	-0.08	122.12
	SNV /3	0.47	0.69	11.94	8.35	51.86	1.37	1.04	142.94
	SNV /5	0.78	0.88	7.86	6.72	34.15	2.09	0.38	117.04
	SNV /7	0.88	0.94	5.69	4.82	24.72	2.88	0.17	118.16
	Dg1 /3	0.66	0.81	9.52	6.99	41.37	1.72	1.10	136.14
	Dg1 /5	0.77	0.88	7.92	5.74	34.42	2.07	0.94	138.00
	Dg1 /7	0.85	0.92	6.29	4.38	27.31	2.61	0.65	143.61
	NM-Dg1 /7 ^b	0.97	0.98	2.95	2.62	12.80	5.56	-0.19	112.45
Admittance	Original /3	0.71	0.84	8.90	7.57	38.65	1.84	-0.43	117.58
	Original /5	0.83	0.91	6.83	6.48	29.68	2.40	0.04	105.40
	Original /7	0.89	0.94	5.57	5.54	24.20	2.94	0.12	100.48
	NM /3	0.84	0.92	6.55	6.70	28.44	2.50	0.21	97.78
	NM /5 ^a	0.91	0.95	4.95	4.97	21.51	3.31	0.26	99.60
	NM /7 ^a	0.95	0.98	3.57	3.81	15.49	4.60	0.29	93.64
	SNV /3	0.86	0.93	6.08	6.98	26.40	2.70	0.37	87.07
	SNV /5 ^a	0.93	0.96	4.42	4.43	19.18	3.71	0.12	99.77
	SNV /7 ^a	0.96	0.98	3.42	2.89	14.86	4.79	0.17	118.34
	Dg1 /3	0.87	0.93	5.93	6.51	25.77	2.76	-0.01	91.16
	Dg1 /5 ^a	0.93	0.96	4.32	3.52	18.78	3.79	0.64	122.84
	Dg1 /7 ^a	0.97	0.98	2.94	2.58	12.77	5.58	0.22	113.76
	NM-Dg1 /7 ^b	0.98	0.99	2.05	2.20	8.91	7.99	0.02	93.46

Original: no data pre-treatment; NM: Normalization Mean (NM); SNV: Standard Normal Variate (SNV); Dg1: First derivative Savitzky-golay; NM-Dg1: the combination of normalization mean-first derivative Savitzky-golay. ^a R²>0.90; ^bR²>0.90 and the best model.

For the resistance spectra (Table 5, Figure 10), the best calibration results were obtained using the NM-Dg1-7 factor, yielding $r = 0.98$, $R^2 = 0.97$, $SEC = 2.95\%$, $SEP = 2.62\%$, $CV = 12.80\%$, and an RPD of 5.56. An RPD value above 4.1 signifies that this model is excellently categorized and can be applied to a variety of applications involving this type of material (Williams, 2014). The optimal calibration results for the admittance spectra (Table 5, Figure 11) were achieved using the NM-Dg1-7 factor, with $r = 0.99$, $R^2 = 0.98$, $SEC = 2.05\%$, $SEP = 2.20\%$, $CV = 8.91\%$, and an RPD of 7.99. An RPD value exceeding 4.1 indicates that this model is superbly classified and highly applicable across a wide range of materials.

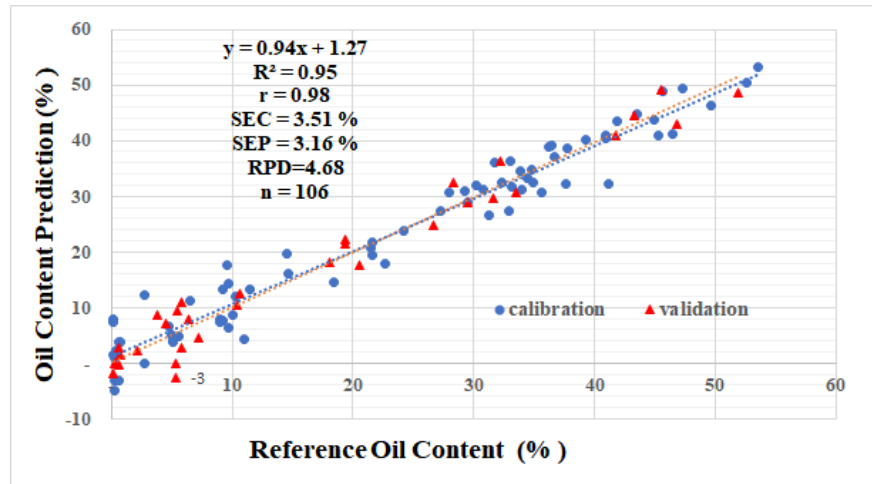


Figure 9. Plot of reference versus predicted oil content of the calibration data set based on impedance

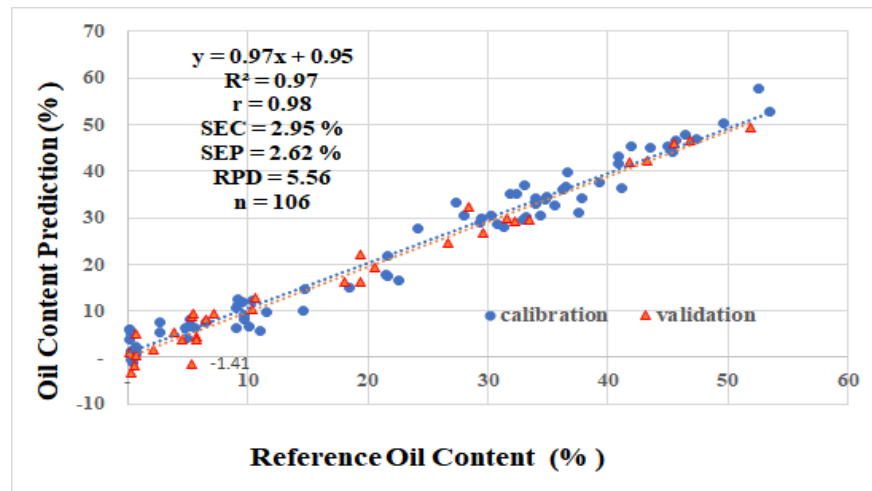


Figure 10. Plot of reference versus predicted oil content of the calibration data set based on resistance

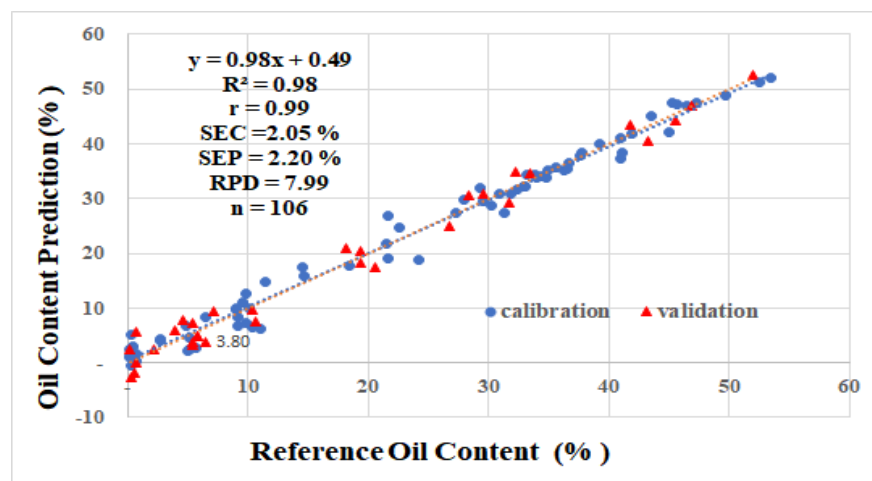


Figure 11. Plot of reference versus predicted oil content of the calibration data set based on admittance

4. CONCLUSION

The findings of this study demonstrate that linear regression models based on electrical properties—such as impedance, resistance, admittance, inductance, capacitance, reactance, and conductance—measured at specific frequencies, possess considerable potential for estimating oil content in oil palm fruit. These models yielded correlation coefficients (r) ranging from 0.61 to 0.81, with root mean square errors ($RMSE$) between 9.54% and 12.99%, indicating a moderate predictive accuracy. However, these results also suggest that further refinement of the calibration process is needed to enhance prediction precision. Future efforts may focus on optimizing spectral calibration using impedance, resistance, or admittance data, depending on the selected modelling approach.

Notably, the application of spectral pre-treatment techniques and Partial Least Squares (PLS) calibration significantly improved prediction performance. The most accurate results were obtained using the following models:

- Impedance using NM-Dg1/7 (a combination of Normalization Mean and First Derivative Savitzky-Golay, 7 factors) with $r = 0.98$, $R^2 = 0.95$, $SEC = 3.51\%$, $SEP = 3.16\%$, $CV = 15.23\%$, and $RPD = 4.68$.
- Resistance using NM-Dg1/7 with $r = 0.98$, $R^2 = 0.97$, $SEC = 2.95\%$, $SEP = 2.62\%$, $CV = 12.80\%$, and $RPD = 5.56$.
- Admittance using NM-Dg1/7 with $r = 0.99$, $R^2 = 0.98$, $SEC = 2.05\%$, $SEP = 2.20\%$, $CV = 8.91\%$, and $RPD = 7.99$.

These results underscore the high potential of utilizing electrical property-based measurements, in conjunction with advanced calibration techniques, as a reliable, accurate, and non-destructive method for determining oil content in oil palm fruit.

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