

Permittivity Calculator: Method and Tool for Calculating the Permittivity of Oils from PVT data.

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ABSTRACT

The permittivity of oil is an important input parameter for multiphase flow meters, and it should therefore be known with high accuracy in order to ensure accurate flow rate measurements. This is especially important at low water fractions. This paper presents a method for calculating the permittivity of crude oils and condensates directly from the petroleum composition (PVT-data). The permittivity at different temperatures and pressures can be predicted from the composition, and this makes it possible to determine the permittivity at the actual multiphase conditions. The method is based on combining dielectric theory with multivariate statistical analysis. A data set consisting of 20 oils is characterized by gas chromatography (GC), density measurements, and permittivity measurements. This dataset is used to derive and validate the multivariate model. The result presented show that the permittivity can be predicted within 4 % at standard conditions.

1 INTRODUCTION

The operating principle of a multiphase flow meter (MPFM) is shown in Figure 1. In a MPFM, the volumetric flow rates of the oil, gas and water phases are determined by measuring the phase fractions and phase velocities. This is done by combining measurements from several sensors with advanced flow models. Typically, different measurement techniques are combined in order to secure high accuracy in the derived parameters and robustness towards flow variations. The multiphase flow meters also rely on knowing some input parameters such as density, salinity and permittivity in order to calculate correct flow rates. Hence, the overall accuracy of the multiphase meter will depend on the accuracy of the individual sensors, the accuracy of the flow models, and the accuracy of the input parameters. The permittivity² of the oil phase is one important input parameter to MPFM, and the aim of this paper is to present a method for calculating the oil's permittivity directly from the petroleum composition (PVT-data).

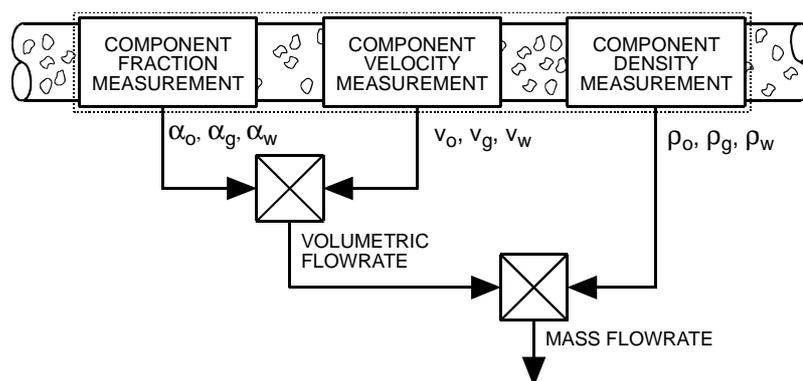


Figure 1 - Operation principle of a multi-phase flow meter [1]. Note that in typical configurations the component densities are not measured, but calculated from PVT-data.

The fraction of a given phase within a mixture is typically found by measuring the response of the mixture. If a proper model of the mixture exists and the responses of the individual phases are known, the fractions of the phases can be calculated from the measured response. Consider for example a

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² In this work the term *permittivity* will be used to mean *relative permittivity*

two phase mixture of oil and water, where the fraction of water in the mixture can be calculated from the measured mixture permittivity if the permittivity of water and oil is known. A frequently used mixture model for water-in-oil emulsions is the Bruggeman-Hanai-Boyle model [2,3,4] (hereafter referred to as Bruggeman's model). This model relates the water fraction (ϕ_w) of water-in-oil emulsion to the efficient permittivity of the mixture (ε_m)

$$\left(\frac{\varepsilon_w - \varepsilon_m}{\varepsilon_w - \varepsilon_{oil}}\right) \left(\frac{\varepsilon_{oil}}{\varepsilon_m}\right)^{\frac{1}{3}} = 1 - \phi_w \quad (1)$$

Here ε_w is the permittivity of water (dispersed phase), ε_{oil} is the permittivity of oil (continuous phase), and ϕ is the volume fraction of the dispersed phase. The permittivity is a complex parameter, and the conductivity of water (σ_w) is included by adding an imaginary term to the permittivity

$$\varepsilon_w = \varepsilon'_w - j\left(\varepsilon''_w + \frac{\sigma_w}{\omega \varepsilon_0}\right) \quad (2)$$

where ε'_w is the dielectric constant, ε''_w is the dielectric loss, $\varepsilon_0 = 8.854$ pF/m is the permittivity of vacuum and ω is the angular frequency. Note that Bruggeman's model is also applicable for oil-in-water emulsions by interchanging the subscript for water and oil.

Bruggeman's model is derived for homogeneous emulsions with spherical droplets. To improve the robustness and accuracy, MPFM manufacturers use slightly modified expressions that are derived from many years of experience. Other models must be applied to calculate the water fraction from measured permittivity for other flow regimes.

From equation (1) it is obvious that the accuracy of the estimated water fraction does not only depend on how representative the mixture model is, but also on how accurate the permittivities of oil and water are known. This is illustrated in Figure 2, which shows how a small error in the relative permittivity of a crude oil affects the estimated water-fraction of a water-in-oil emulsion. An error in crude oil permittivity of 0.15 was assumed (i.e. the error in water-fraction calculated when using 2.35 instead of 2.2 as crude oil permittivity). The figure illustrates that the effect of an oil permittivity error has largest impact for low water fractions, and decreases as the water-fraction increases. For water-fractions below 10%, the error is larger than 2 %_{abs}, which is a significant fraction of the measured value.

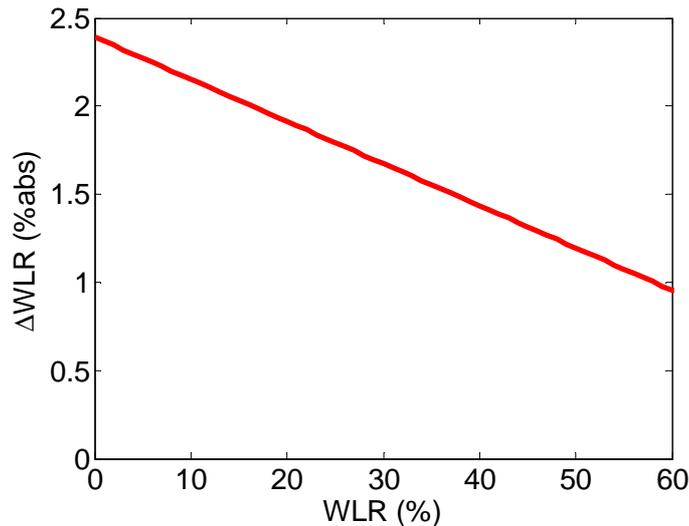


Figure 2 - Error in water-fraction (WLR water-liquid ratio) due to a small error ($\Delta\varepsilon_s = 0.15$) in oil permittivity for a water-in-oil emulsion.

In addition to oil permittivity, other typical input parameters to multiphase flow meters are phase densities and water conductivity. Temperature and pressure must also be measured so that the measured volumetric flow rates can be converted from meter conditions to standard conditions. The

required input parameters can be determined and provided to the MPFM flow computer in the following alternative ways:

- Direct input of fixed values
- Measurements provided by the MPFM itself
- Estimation from PVT-data

Typically, densities are calculated from PVT-data and water conductivity is either given as fixed input or measured by dedicated sensors in the MPFM. The permittivity of oil is usually set as a fixed value in the flow computer, or estimated from the oil density. To account for temperature and pressure dependency in the permittivity, experienced based corrections can be included. It is also possible to estimate the oil's permittivity from direct measurements within the MPFM, but this requires that measurements are done on a known mixture. Thus, there will be a rather high uncertainty in the estimated value.

The permittivity of crude oils varies from field to field, and may also change over the lifetime of a field. Further on, the permittivity changes with temperature and pressure. Ideally, oil samples should therefore be taken frequently and the sample's permittivity should be measured as a function of temperature and pressure in order to characterize the oil. This is not possible in practice, and typically the only information available is composition data for the hydrocarbon fluid. Thus, the challenge is to estimate the permittivity of an oil from the PVT data. In this paper a method for calculating the oil's permittivity directly from the petroleum composition (PVT-data) will be presented. The estimated permittivity can either be used as direct input data to the flow computer or used as redundant information to increase the robustness of the MPFM if the permittivity is estimated from direct MPFM measurements.

The permittivity calculation method to be described in this paper is based on combining dielectric theory with multivariate statistical methods (chemometrics). A data set consisting of 20 oils is characterized by gas chromatography (GC), density measurements, and permittivity measurements. A subset of this dataset is used to build a partial least squares (PLS) regression model between the composition (GC and density) and a transformed permittivity variable. The remaining oils, which are not included in the multivariate model, are used to validate the model. The GC data are grouped to be in the same order as in typical PVT-reports, and the model is also verified by predicting the permittivity of an additional oil directly from a PVT-report. The main reason for using measured GC-data to derive the multivariate model instead of data from PVT-reports is that the GC data are considered to be more representative for the oil samples studied. The GC analysis is done on samples from the same sample-bottle as the permittivity and density measurements, whereas typical PVT-reports are from well test taken before production start and the oil composition may therefore have changed before the present samplers were taken. Any changes of the oil during sampling, handling and transportation will also be reflected in the GC analysis. It should also be mentioned that PVT reports were not available for many of the oils in the study.

2 THEORY AND BACKGROUND

2.1 Permittivity model

A typical permittivity spectrum of a crude oil is shown in Figure 3. It is observed that the permittivity changes with frequency and drops from a low frequency (static) permittivity ϵ_s to a high-frequency permittivity ϵ_∞ . The multiphase flow meters from Roxar operate at frequencies below the typical dispersion region, and the relevant value for these meters is therefore the static permittivity.

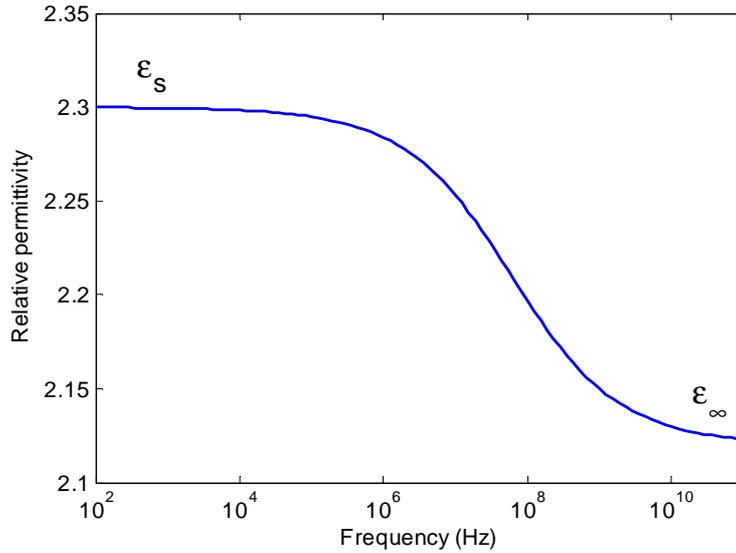


Figure 3 - Typical permittivity spectrum of a crude oil

The static permittivity ϵ_s of a liquid is estimated by Debye's equation [5]

$$\frac{\epsilon_s - 1}{\epsilon_s + 2} = K_1 \rho + K_2 \frac{\rho}{T} \quad (3)$$

Here $K_1 = \frac{N_A \alpha}{3M\epsilon_0}$ [m^3/kg], $K_2 = \frac{N_A \mu^2}{9Mk\epsilon_0}$ [m^3/kg], ρ [kg/m^3] is density, T [K] is temperature, M

[kg/mol] is the molar mass, α [Cm^2/V] is the polarizability, N_A [mol^{-1}] is Avogadro's number, ϵ_0 [F/m] is the permittivity of vacuum, k [J/K] is Boltzmann's constant and μ is the permanent dipole moment [Cm]. In this work we will refer to K_2 as the "polarity coefficient" as it is connected to the dipole moment and amount of polar molecules. Note that other and more accurate models for the static permittivity have been published (see e.g. [6].), but as the model will be combined with a multivariate prediction of K_2 the Debye equation is considered to be well suited for the present study.

At very high frequencies, the permanent dipoles do not contribute to the permittivity and equation (3) can be simplified to the Clausius-Mosotti equation

$$\frac{\epsilon_\infty - 1}{\epsilon_\infty + 2} = K_1 \rho \quad (4)$$

where ϵ_∞ is the high-frequency (optic) permittivity.

From equation (4) it is seen that the high-frequency permittivity is directly related to the density. This is illustrated for liquid alkanes in Figure 4 (permittivity values from [7]). In section 4.2. it is shown that this bilinear relation is also applicable for crude oils.

This illustrates that the high-frequency permittivity can be calculated from the density if the coefficient K_1 is known. In this work K_1 is estimated from the measured densities and high-frequency permittivities of the crude oils. This is discussed further in section 4.2.

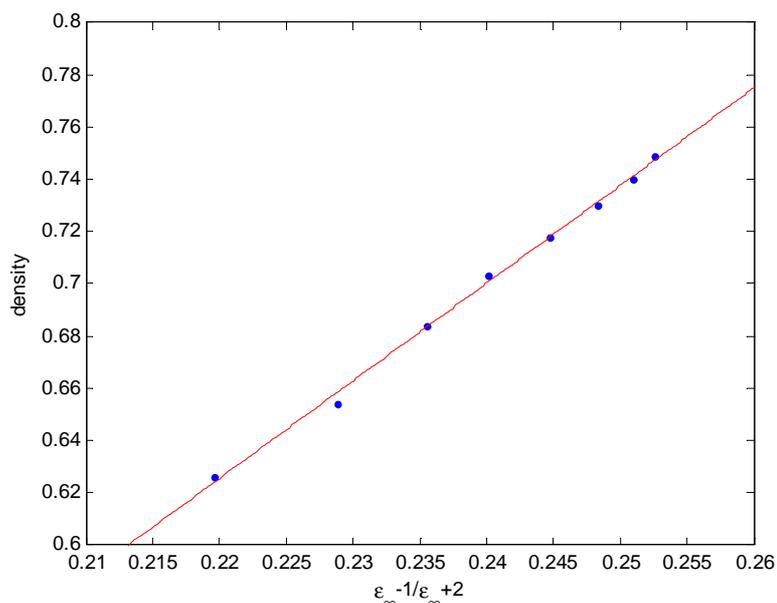


Figure 4 - Bilinear relation between high-frequency permittivity and density (g/cm³) for liquid alkanes.

In order to calculate the static permittivity with equation (3), the polarity coefficient K_2 must be known. K_2 depends strongly on the dipole moments of the oils, and thus on the amount of polar molecules within the oil. For oils with low amount of polar components K_2 will be small, and the static permittivity will be approximately equal to the high frequency permittivity. For polar oils with larger dipole moment, K_2 will be larger and the static permittivity will be larger than the high frequency permittivity. As the oil molecular distribution is given by its composition, it should be possible to predict K_2 from the composition. In the following section a multivariate model relating the oil composition and K_2 will be described.

2.2 Multivariate modelling

The relation between an oil's composition and its polarity coefficient K_2 is complex, and there are several factors that affect this coefficient. Thus, it is not possible to derive an analytical model for this relation. It is, however, possible to extract hidden relations by using advanced statistical analysis such as principal component analysis (PCA) and partial least-squares (PLS) regression. These techniques are frequently used in chemistry to extract information from chemical structures by analyzing large data-sets (see e.g. [8,9]), and are referred to as chemometrics. In this work a statistical model relating the measured polarity coefficient K_2 and the composition and density of 17 oils is established. The compositions are measured by gas chromatography, and the results grouped as in standard PVT-reports. The methodology will be described in some more detail in the following sections.

2.2.1 Data pretreatment

Data collected from an instrument is termed raw data, and in this work the raw data are the measured GC-data, densities and the polarity coefficient K_2 . Raw data can contain noise, baseline drift, scattering effects and other factors that may influence the significant information in the data set. Therefore it may be necessary to pretreat the raw data, in order to remove effects that do not represent chemical, physical, electrical or biological properties in the sample. In order to find the variation between the objects, the raw data needs to be centred. This can be done by calculating the average value for each variable, and then subtracting this from each of the original variables. By doing this, the origin of the coordinate system is placed at the centre of gravity in the data set. The centring of the data can be expressed as

$$X_{centred}(i, j) = X(i, j) - \frac{1}{N} \sum_{i=1}^N x(i, j) \quad (5)$$

where X is the data matrix, i column in matrix, j row in matrix, N is the total number of objects. The columns represent variables in the system, whereas the rows are different samples (objects).

When injecting samples onto the GC column, it is not certain that the amount of sample is exactly the same in every injection. In order to eliminate any effects from this, the quantified amounts have been normalized to constant sum. This is done by dividing the selected variables of each object with the sum of the objects to obtain the relative distribution of the variables in each object. This procedure is normal for GC [10,11]. The datasets have been centred and normalized to constant sum. In addition, the polarity coefficients have been transformed logarithmically in order to reduce gaps between high and low value.

2.2.2 Partial Least Squares (PLS) Modelling

Multivariate data analysis has been performed using the SIRIUS™ programme package, version 7.0 [12]. Partial Least Squares (PLS) [13] calibration models have been built based on GC data (grouped as PVT data) and density data in order to investigate the possibility of predicting K_2 and subsequently calculating the static permittivity of a crude oil sample.

A PLS model starts with a decomposition of the input data into Principal Components (PCs), also called Latent Variables (LVs). In a PLS model the covariance between the predictors and the responses are the focus of the decomposition. The LVs are orthogonal linear combinations of the original variables with the additional property of minimising the residual covariance in a data table in a least-squares sense. The two first LVs define the window in multivariate space with maximum covariance between the independent data matrix (the analytical data) and the dependent data (the predicted properties). The regression modelling is then performed on the LVs.

A general model of PLS can be expressed by the following equations:

$$X = TP^T + E \quad (6)$$

$$Y = UQ^T + F \quad (7)$$

where X is an $n \cdot m$ matrix of predictors (i.e. pre-treated GC-data and density), Y is an $n \cdot p$ matrix of responses (i.e. pretreated polarity coefficient); T and U are $n \cdot l$ and m matrices that are, respectively, projections of X (the X score, component or factor matrix) and projections of Y (the Y scores); P and Q are, respectively, $m \cdot l$ and $p \cdot l$ orthogonal loading matrices; E and F are the error terms. The decompositions of X and Y are made so as to maximize the covariance of T and U.

The model is based on 17 of the 20 oils in the dataset. 3 oils have been omitted from the model in order to use them as validation objects. It is important to balance the number of validation objects against the total number of samples, as the model might be less robust if too many oils are omitted. The predictive quality of the models can be examined by testing the apparently unknown objects against the models. The validation objects have been chosen in order to span the entire range in which the model is valid, meaning the range from the object with the highest value to the object with the lowest value. As such, one validation objects has high value for K_2 , one validation object has low value for K_2 and one validation object has a medium value for K_2 . This is done in order to validate the predictive quality of the model, given unknown samples with high, low and medium value of the modelled variable.

When building a PLS model, the response Y (i.e. the polarity coefficient K_2) can be expressed as a function of the variables X (composition and density) as

$$Y = B_0 + B_1 \cdot X_1 + B_2 \cdot X_2 + B_3 \cdot X_3 + \dots + B_N \cdot X_N \quad (8)$$

where N is the total amount of variables in the model, B_0 is the starting point, B_1, B_2, \dots, B_N are regression coefficients, and X_1, X_2, \dots, X_N are the variables.

By evaluating the regression coefficients for a given model, it can be detected which variables have the most significant effect on the model, be it positive or negative effect, and hence see which variables are most important for the variation in the model. Nevertheless, the effect of the total amount of coefficients usually is more important than the effect of one single coefficient.

In the modelling stage, the goal was to find the model that gave as low deviation as possible for the validation objects. The number of Latent Variables (LV's) giving the lowest deviations is then chosen, but bearing in mind that if too many LV's are chosen, there is a possibility that noise is modelled as well as the significant signal, causing the model to give poor predictions for unknown samples. Also, if too few LV's are chosen, there is a possibility that some of the significant information remains unmodeled and gets categorized as noise, also causing the model to give poor predictions for unknown samples.

3 EXPERIMENTAL

The experimental results presented are based on measurements on 20 oils from various fields around the world, but with a majority of oils from the North Sea. The dataset consists of 4 condensates, which are light crude oils with a clear yellow to brown colour, while the rest of the oils are black and opaque crude oil.

All oils have prior to all measurements been placed in an oven at 60°C for 4 hours, in order to dissolve waxes that may have precipitated during storage. They have also been shaken and turned upside down multiple times, in order to homogenize the oils thoroughly.

The following measurements were made:

- Whole oil gas chromatography
- Density
- Complex permittivity spectrum

Whole oil gas chromatography (GC): The oils have been analysed on a ThermoFinnigan Trace GC equipped with a Flame Ionization Detector (FID). The stationary phase is a HP-PONA dimethylpolysiloxane column (50 m × 0.20 mm × 0.5 µm) from Agilent technologies. The mobile phase is helium. The temperature programme is as follows; 30°C for 15 min, 1.5 °C/min 60 C, 4 °C/min 320 °C, 320 C for 35 min. The injector temperature is 300 °C while the FID is kept at 350 °C. 1 µL of warm, homogenized crude oil is introduced manually into the GC system through a syringe, using split injection. The assignment of chromatographic peaks and quality assessment are based on the Norwegian Standard Oil (NSO-1) [14], in which the compounds have been identified in a GC-MS(Mass Spectroscopy), and by manual inspection the compounds in the chromatograms have been identified and quantified for all the oils, assuming a constant response factor. The quantified values for two gas chromatograms for each oil are averaged, giving the quantified values used in the modelling.

Density: The density of the oils has been measured at 20 °C using an Anton Paar K.G. DMA 60 densitometer with DMA 602 measuring cell. Air and distilled water is first measured for calibration, then the oil. 5 measurements for each oil have been averaged, and the resulting value is used in the modelling.

Permittivity: The dielectric spectra were measured at 20°C using a measurement system for complex permittivity measurements developed by Christian Michelsen Research [15]. The permittivities are obtained by curvefitting measured data to the Cole-Cole-function [16] as described in [15].

Dataset for the multivariate analysis: The densities of the crude oils are used directly as a variable in the dataset. A total of 82 compounds have been quantified from the GC analysis, all of them

compounds containing only carbon and hydrogen. These 82 compounds have been grouped together in the same order as most Pressure Volume Temperature (PVT) reports are given. This grouping is as follows; *i*-C5, *n*-C5, C6s, C7s,..., C29s, giving a total of 26 different groupings or variables. As the sensitivity of the WOGC instrument was low, the instrument was not able to detect hydrocarbons with carbon number higher than 31-32. Because of this, we were not able to apply a C30+ group as the C30+ group would only contain two or three hydrocarbons, while PVT reports normally consists of a lot more, typically up to C36+ but also C60+ and even higher. The C30+ group in our dataset would therefore not be comparable to the C30+ group in PVT reports, and is omitted from the dataset.

4 RESULTS AND DISCUSSION

4.1 Permittivity, density and GC measurements

Figure 5 shows the permittivity spectra of the 20 oils measured in this work. The static permittivity ranges from about 2.0 for the lightest condensate to about 2.7 for the most polar crude oil, whereas the high-frequency permittivity ranges from approximately 2.0 to 2.35. The shift from static permittivity ϵ_s at low frequencies to the high-frequency permittivity ϵ_∞ at high frequencies is clearly observed. Figure 6 shows the permittivity of a sub-set of the oils, and illustrates the difference between condensates and crude oils with different amount of polar molecules. It is observed that the condensate has a smaller permittivity shift with frequency than the more polar crude oils. Figure 7 shows the normalized GC measurements of the same three oils, and the different distributions between the molecular structures between the oils are clearly observed. The condensate has a higher relative concentration of molecules with low carbon number, whereas the more polar crude oils have a higher relative concentration of molecules with high carbon number.

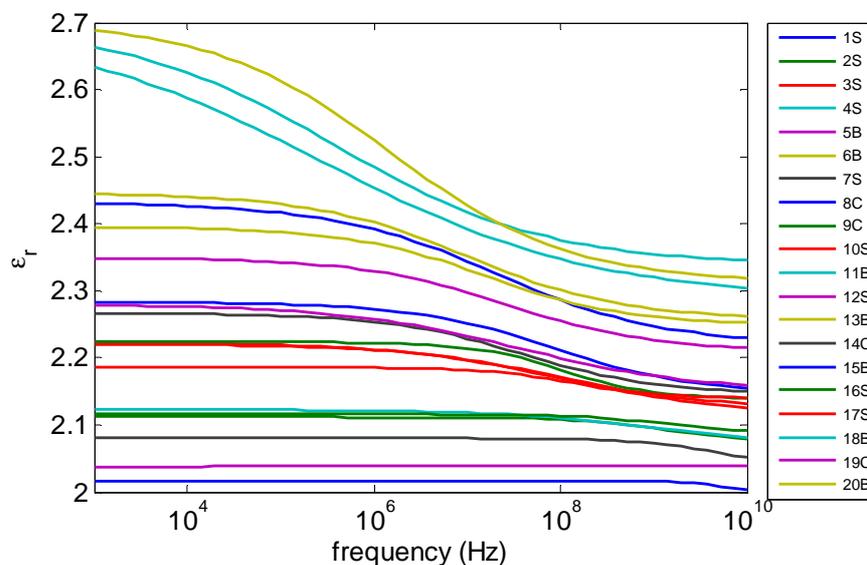


Figure 5 - Permittivity of 20 oils as a function of frequency measured at 20 °C.

Figure 5 and Figure 6 also illustrate that the shift from low frequencies to high frequencies differ between the oils, and that the static permittivity therefore cannot be extracted directly from the density (which is related to the high frequency permittivity). At frequencies in the MHz-range (the dispersion region) the permittivity will change rapid with frequency and have a value somewhere between ϵ_s and ϵ_∞ . The dispersion frequency region does, however, differ between the oils, and will also change with temperature. Thus, this makes it difficult to predict the permittivity in the MHz and low GHz range.

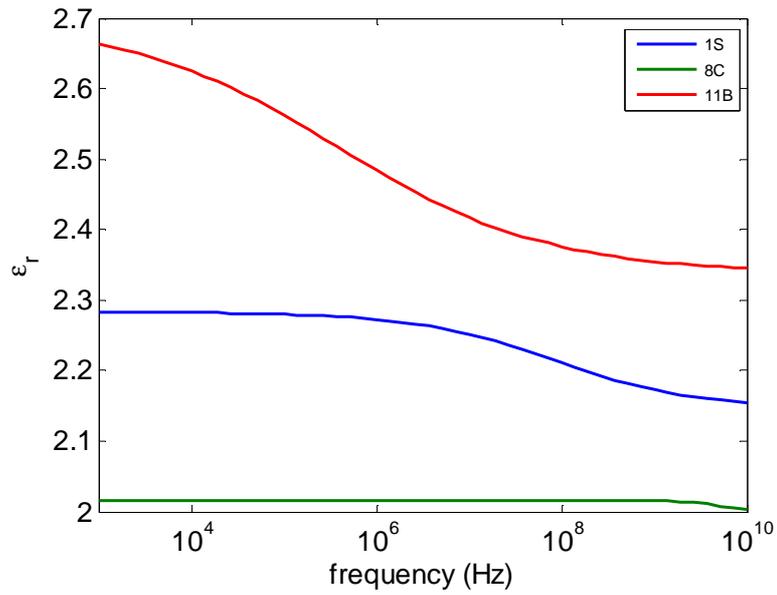


Figure 6 - Permittivity of three oils illustrating the difference between condensates and crude oils with different amount of polar molecules.

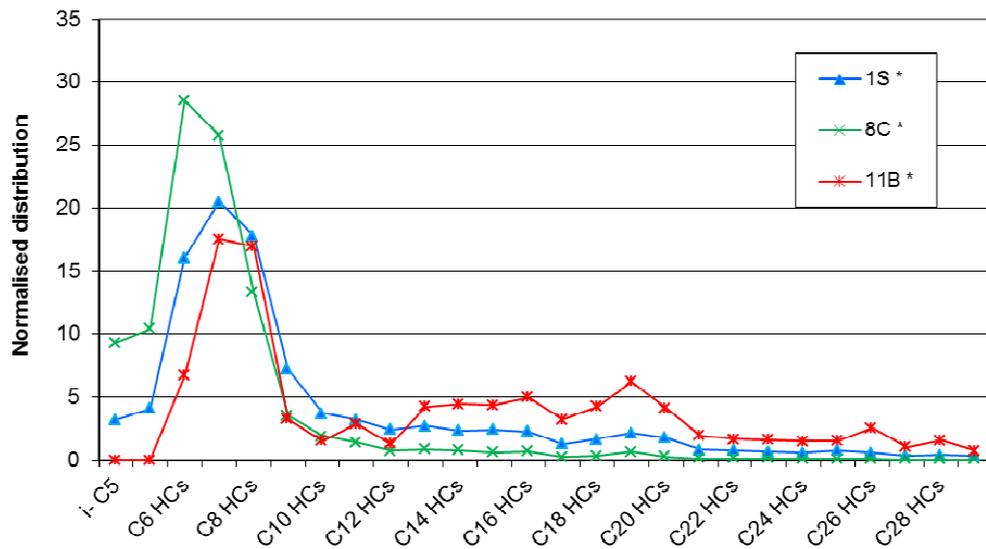


Figure 7 - Normalised GC measurements of three oils shown in Figure 6.

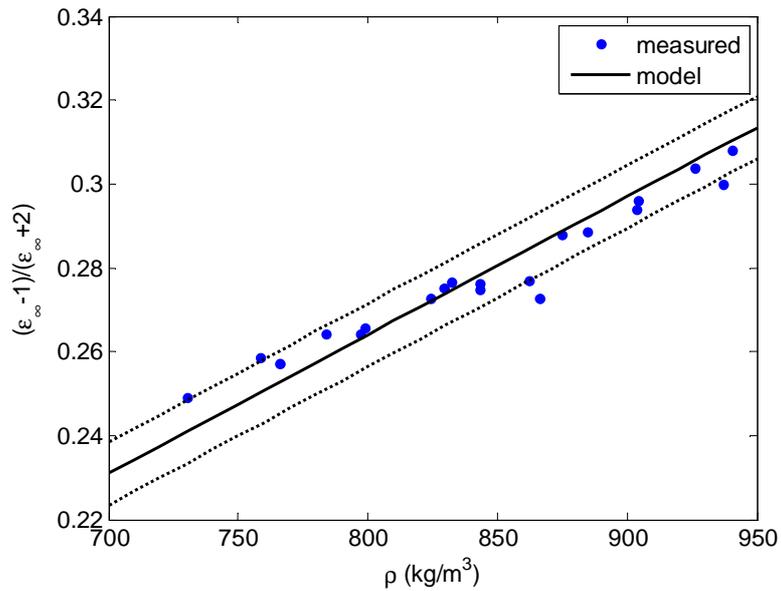


Figure 8 - Bilinear relation between permittivity and density for crude oils. The dotted line illustrates a 2% uncertainty in measured permittivity.

4.2 Density and high frequency permittivity.

In Figure 4 it was shown that liquid alkanes follows the bilinear relation between density and permittivity given by equation (4), and Figure 8 illustrates that this is also the case for crude oils. The measured data correspond well with the relation given in equation (4), and most of the data are within the experimental uncertainty in ϵ_{∞} estimated to 2% (shown as dotted lines). Thus it is possible to extract the coefficient K_1 from the measured data by linear regression.

4.3 Multivariate model

The multivariate model described in section 2.2 calculates the polarity coefficient K_2 from the hydrocarbon composition and density. Figure 9 shows the predicted values of K_2 for the 17 oils used to establish the model together with the three validation oils. The coefficient of determination R^2 is 0.895. The model, which consists of 5 LV's, explains 96.24% of the independent variance and 87.30% of the dependent variance in the dataset. The validation objects have an average deviation of 1.25 and a maximum deviation of 1.77 with K_2 values ranging from 0.75 to 17.98. Thus, the predictive quality of the multivariate model is not excellent, but as will be shown it is of sufficient quality to give good estimates of the static permittivity.

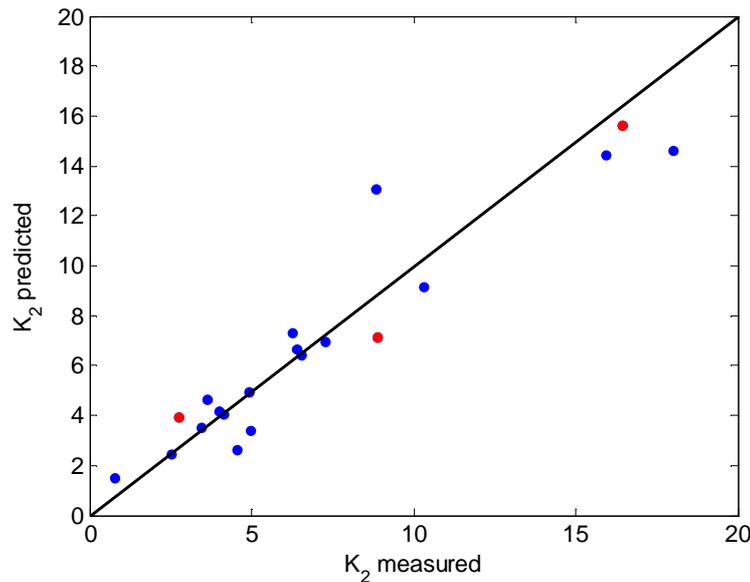


Figure 9 - Predicted polarity coefficient K_2 versus K_2 calculated from measurements. The blue circles represent model objects and the red circles are validation objects.

4.4 Predicted static permittivity

In previous section it was shown that the polarity coefficient K_2 can be calculated from the oil composition and density with reasonable accuracy. The next step is to verify that the static permittivity can be calculated using the permittivity model (equation (3)). Figure 10 shows the predicted static permittivities versus the measured static permittivities for the 17 model oils and the 3 validation oils. The relative and absolute error in the predicted permittivities are shown in Figure 11 and Figure 12 respectively, and it is observed that the validation oils are predicted within 0.035 (1.5 %). By also considering the model objects, it is seen that the largest error is about 0.09 (4 %). Thus, this shows that the static permittivity can be predicted with good accuracy.

A thorough uncertainty analysis of the measurement systems has not been conducted, but it is reasonable to assume that a significant part of the prediction error can be explained by uncertainty in the measurements. Some factors that affect the uncertainty are the handling of the oil samples used for GC, density and permittivity measurements, uncertainty due to calibration and cleaning of test cells, and measurement equipment uncertainty.

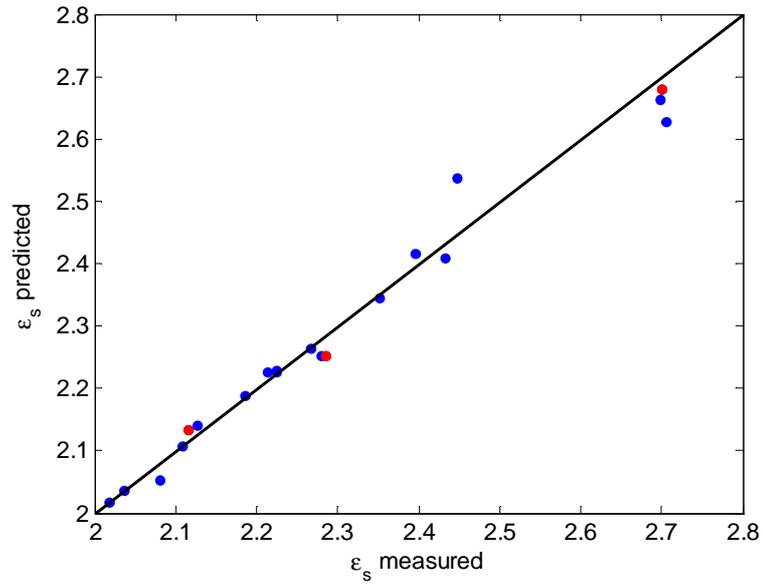


Figure 10 - Predicted static permittivity versus measured static permittivity. The permittivity is predicted using equation (3). The blue circles represent model objects and the red circles are validation objects.

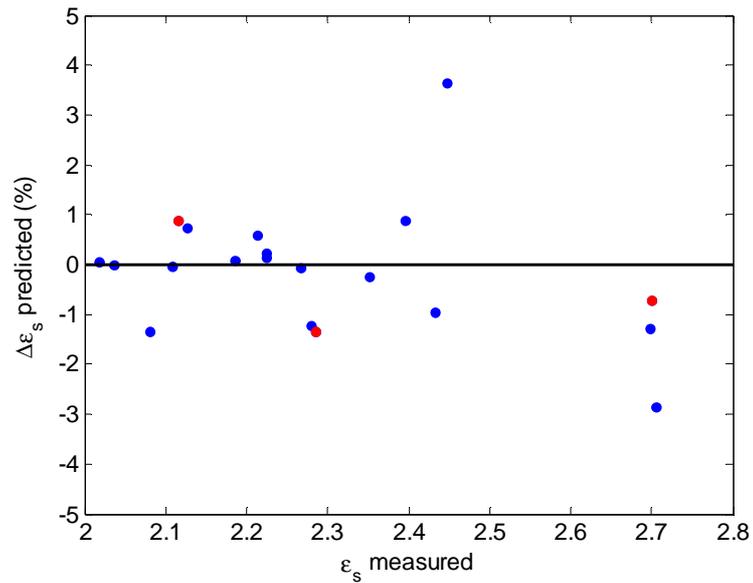


Figure 11 - Relative error in predicted static permittivity versus measured static permittivity. The permittivity is predicted using equation (3). The blue circles represent model objects and the red circles are validation objects.

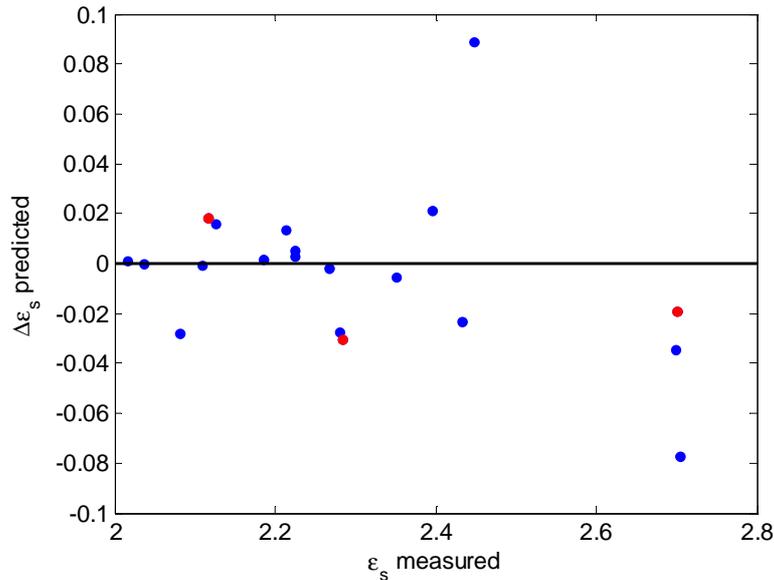


Figure 12 - Absolute error in predicted static permittivity versus measured static permittivity. The permittivity is predicted using equation (3). The blue circles represent model objects and the red circles are validation objects.

4.5 Temperature and pressure dependency

From equation (3) it is observed that changes in temperature and pressure will affect the permittivity directly and through a change in density. In addition, the composition will also change with temperature and pressure and may therefore affect the coefficients K_1 and K_2 . K_1 is a function of the average molar mass and the polarizability, and it is reasonable to assume that K_1 is independent of temperature and pressure [17] as the average molar mass of an oil does not change much with temperature or pressure even if light molecules vaporize or condense.

The polarity coefficient K_2 depends on the average dipole moment, which is dominated by heavier molecules. These heavy molecules are present in liquid phase at most temperature and pressure conditions while the lighter molecules vaporize or condense with temperature and pressure changes. Thus, both K_1 and K_2 can be considered to be independent of temperature and pressure. Note that even though the effect that temperature and pressure changes will have on K_2 will be low, the effects can be taken into account by calculating K_2 from the composition at the actual line conditions.

Given that K_1 is independent of temperature and pressure and that the temperature and pressure dependency of K_2 can be calculated from the liquid composition, the permittivity model in equation (3) can be used to calculate the permittivity of oils also at other operating conditions. To check this, the permittivities of two oils were estimated from composition data and densities at elevated temperatures using the multivariate model. The predicted values were then compared with measured permittivities at the test temperatures. Due to limitation in the experimental set-up for measuring permittivity, the upper temperature was limited to 60°C. The oil composition did not change significantly over this limited temperature range and there was only a minor change in density. The predicted changes of the test oils were estimated to approximately 0.02, and a similar change was also observed in the measured permittivities. It should however be noted that this change is in the same order of magnitude as the uncertainty in the measured permittivities at elevated temperatures, and additional measurements should therefore be conducted to further verify the findings.

4.6 Prediction from PVT-data

As an example of usage of the prediction model, PVT data for various pressure and temperature conditions were computed using Emerson Tempest PVTx [18]. The resulting liquid phase compositions and densities were put into the model, K_2 was calculated, and the static permittivities given in Table 1 were derived. In this table the predicted permittivities using K_2 calculated at standard conditions are also shown. Thus, it is assumed that the composition at elevated temperatures and pressures are the same as at standard conditions. This is obviously not the case, but it is seen that the effect on the predicted permittivity is low. The difference in predicted permittivities between the two methods are within 0.02 (i.e. about 2%), indicating that a good estimate of the permittivity change with temperature and pressure can be provided using equation (3) with K_2 calculated at standard conditions (i.e. neglect the change in liquid composition with temperature and pressure).

Table 1 Predicted permittivity at different temperature and pressure conditions

P (bara)	T (°C)	ϵ_s predicted	ϵ_s predicted (constant K_2)	$\Delta\epsilon_s$ predicted
1	15	2.23	2.23	0.00
1	65	2.19	2.21	-0.02
25	30	2.15	2.15	0.00
25	100	2.10	2.11	-0.01
100	30	2.07	2.08	-0.01
100	100	2.02	2.04	-0.01

4.7 Permittivity calculator tool

The method described in this paper has been implemented as a software tool. Input parameters to the tool are the composition and densities calculated using a PVT package [18] and temperature. The tool applies equation (3) and the PLS regression model to calculate the static permittivity.

5 CONCLUSION

In this paper a method for calculating the relative permittivity of crude oils and condensates from PVT-data has been presented. The method is based on combining dielectric theory with partial least squares (PLS) regression. The multivariate model was derived from gas chromatography, density and permittivity measurements of 17 oils, and the model was verified by comparing predicted and measured permittivities for 3 additional oils. The permittivities of the validation oils were estimated within 1.5 %, and the model oils are all within 4 %. The presented method is also applicable for estimating the permittivity change of oils with temperature and pressure if accurate PVT data is available.

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