



Development of a New Correlation for Predicting Initial Water Saturation in Carbonate Reservoirs

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Research Article

Volume 8 Issue 2

Received Date: January 24, 2024

Published Date: April 04, 2024

DOI: 10.23880/ppej-16000384

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Abstract

The Middle East, rich in oil and gas within carbonate rocks, accounts for a significant portion of global reserves, drawing extensive exploration by major oil firms. Unlike Southeast Asia's fracture and cavity-dominated carbonate reservoirs, the Middle East features thick-bedded, pore-structured reservoirs with vast reserves. These complex and varied pore structures cause reservoir inhomogeneity, challenging the technical evaluation of these unconventional reservoirs.

Characterization of carbonate reservoirs differs in terms of their mineralogical compositions and heterogenous pore systems from that of clastic reservoirs. Reservoir characterization seeks to build geological and petrophysical models for reservoir simulation. Rock types represent the most crucial characteristics of reservoirs for specialized facies modelling within specific ranges of porosity and permeability. Rock typing is an essential method routinely used by petroleum engineers for characterizing and predicting the reservoir quality of carbonate reservoirs by classifying reservoir rocks into distinct units based on similar petrophysical properties. It is imperative to predict these reservoir properties accurately and precisely. The J-function technique is considered the most effective rock typing procedure.

In this study, a new correlation for predicting initial water saturation (S_{wi}) for a reservoir producing from a Permian carbonate formation, located in the Arabian Peninsula, has been developed. The new empirical equation is an augmented Lucia model that utilizes capillary pressure (P_c), porosity (ϕ), and permeability (k), as independent variables. The coefficient of multiple R^2 , the student's t and F -tests p -value were used in the model evaluation. R^2 for the new model was about 0.92, t -test and F -test p -values were much lower than 0.05, indicating that the independent variables are significant. The model was also tested against an independent data set and yielded an R^2 of 0.88. Likewise, the new correlation was compared to Lucia's model and showed better results. The goal of the study is to use the developed correlation in the geostatistical modeling of connate water saturation for analogous formations in the region.

Keywords: Porosities; Clastic Reservoir; Carbonate Reservoir; Saturation

Introduction

Water Saturation estimation remains one of the critical correlations that help reservoir engineers quantify the

volumes of hydrocarbons contained in a reservoir. Despite the success of estimating this parameter by analyzing core samples, other engineers have resorted to using rock physics to evaluate water saturation [1]. Precise determination of

water saturation throughout every section of the reservoir is vital for accurately characterizing the reservoir and calculating the original volume of hydrocarbons present [2]. Estimating water saturation is crucial for reservoir engineers to measure the number of hydrocarbons in a reservoir accurately. Precisely identifying how water and hydrocarbons are distributed underground is vital for several practices, including enhanced oil recovery and carbon dioxide sequestration [3-10].

Carbonate reservoirs pose some of the biggest challenges in developing new technologies for exploration of hydrocarbons. In recent times, the oil and gas industry has grappled with significant challenges related to the characterization, quantification, and prediction of reservoir properties. Because of both intra and interparticle porosities, carbonate rocks have a highly complex pore structure, making characterizing carbonate rocks, gathering, and analyzing petrophysical data difficult [11,12]. Carbonate reservoirs also differ from clastic reservoirs in their surface chemical properties and inherent dual porosity systems. Analyzing reservoir rock properties to enhance understanding and boost recovery can be achieved through digital rock physics. This method employs X-ray micro-computed tomography for pore-scale modeling. Yet, implementing digital rock technology necessitates specialized skills in image analysis and numerical simulations, which can be costly and might not always be accessible within an organization [13].

The critical link between geological heterogeneity and reservoir quality is important and rock typing remains a reliable method for evaluating reservoir quality. Rock typing is an important footstep in characterizing carbonate reservoirs and building geological models for reservoir simulation. The procedure entails categorizing reservoir rocks into separate units, each deposited under comparable geological conditions and undergoing similar diagenetic changes [14]. In this study, rock samples with similar rock structural properties were grouped and distinct rock types were identified. The developed capillary pressure profiles and initial water saturation empirical model were then utilized to improve the discretization of the static model of the reservoir and reduce uncertainty in quantifying of the hydrocarbon content.

Literature Review

Combining tortuosity, cementation factor (m), formation water resistivity (R_w), effective porosity (ϕ), bulk resistivity (R_t), and saturation exponent (n), Archie came out with an equation for calculating water saturation (S_w) [15]. This expression is given by:

$$S_w = \left[\frac{a \cdot R_w}{\phi^m \cdot R_t} \right]^n \quad (1)$$

However, to use the Archie's equation, it is vital to accurately determine parameters often considered as constant values in clastic quartz reservoirs [16]. Although the parameters for predicting the water saturation using the Archie's equation can be acquired through core measurements in the laboratory and applied to logging interpretations, the reservoir heterogeneity along the longitudinal axis is overlooked by fixed parameters commonly known as "static parameters" [17]. The innate uncertainties associated with these parameters result in errors in the water saturation predictions. For instance, it is difficult to predict formation water resistivity (R_w) when there is limited production test or SP Logs and effective porosity (ϕ), when rock matrix type is unknown [3]. Given this, researchers are still advancing to find a robust correlation to predict the water saturation in complex reservoirs [18,19].

Petrophysical rock types are classified according to their fluid behavior within the rock, as they are calibrated from core and dynamic data as well as from wireline logs. Facies is another term used interchangeably with rock types and refers to all the characteristics of a rock unit. Carbonates occur naturally as economically essential mineral deposits and are placed as sediments and reefs in ancient rocks, tropical, and temperate oceans. Carbonates are grouped into families known by the crystal system in which they form, such as monoclinic, orthorhombic, and crystallographic system [20]. Carbonates exist mostly as hexagonal systems and consist of two types of rocks: limestones and dolomites.

Published correlations that are based on rock texture yield good quality porosity data and a more accurate estimation of the connate water saturation of a reservoir. Rock fabrics' facies are basic elements for characterizing a carbonate reservoir [21,22]. The rock-fabric method of petrophysical characterization is done based on relationships that exist between sorting, pore type, particle, and pore size. Dunham [23] classified carbonate rocks by distinguishing between sediments deposited in agitated water and sediments deposited in calm water to gain fundamental understanding of the depositional environment. He identified the basic carbonate rocks based on three textural features, namely:

- Abundance of grains
- Abundance of mud and
- Signs of binding

Various authors tried to classify carbonates based on rock textures and compositions. Important contributions were by Choquette, et al. [24,25]. The former categorized carbonates based on fabric selective and non-fabric selective pore types while the latter revealed that the most practical division of pore types was between pore space, located amongst grains or crystals named interparticle porosity and other pore space called vuggy porosity.

Diagenesis triggers variations in size, shape, volume, chemical composition, or crystalline shape of a sedimentary rock after its detrital, biogenic, or crystalline elements have been deposited [20]. When a reservoir rock is subjected to substantial diagenesis, the existing rock properties will be quite distinct from the original rock properties present at the time of deposition [26].

Furthermore, there are different methods of rock typing. The three leading methods are Winland's R35 method Pittman [27], Flow Zone Indicator method Amaefule, et al. [28] and the Leverett J-function method [29-31]. Winland built an empirical relationship among porosity, permeability, and pore throat radius of reservoir rocks using mercury injection - capillary pressure. This relationship was published by Kolodzie [32]. Pittman examined the rocks that Winland used and discovered that the net height of sandstone having an R35 value lower than $0.5\mu\text{m}$ was useful to ascertain the point at which hydrocarbon trapping would follow Pittman [27].

According to Amaefule, et al. [28], the Flow Zone Indicator (FZI) method is a conventional method used to define hydraulic flow units (HU) in porous media, where FZI is defined as the ratio of Reservoir Quality Index (RQI) to normalized porosity, f_z :

$$FZI = \frac{RQI}{\phi_z} \quad (2)$$

$$\text{where, } RQI = 0.0314 \sqrt{\frac{k}{\phi}}$$

k is permeability (md), ϕ is total porosity (fraction), and

$$\phi_z = \left(\frac{\phi}{1-\phi} \right)$$

RQI is normally plotted against ϕ_z on a log-log scale. Data points falling on the same lines have the same characteristics and form distinct flow units. Nevertheless, Amaefule, et al. [28] indicated that this method requires a large routine core analysis (RCAL) dataset.

Moreover, the Leverett J-function is a dimensionless variable that interrelates rock and fluid properties. According to Leverett [29], the J-function is defined as:

$$J = \frac{0.216P_c}{\sigma \cos\theta} \sqrt{\frac{k}{\phi}} \quad (3)$$

where, P_c is capillary pressure in psia, σ is interfacial

tension in dynes/cm, and θ is a contact angle measured through the rock wetting (denser) phase in degrees.

According to Amaefule, et al. [28], Equation (2) can be rewritten as a function of RQI:

$$J = \frac{6.88P_c}{\sigma \cos\theta} RQI \quad (4)$$

In addition, Archie [15] defined formation resistivity factor, FR, as:

$$F_R = \frac{R_o}{R_w} \quad (5)$$

where, R_o is the resistivity of the rock, fully saturated with formation water in Ohmmeters, and R_w is the water resistivity also in Ohmmeters.

According to Archie [15], the value of R_o is important to ascertain true water saturation. FR is related to porosity as follows:

$$F_R = \frac{a}{\phi^m} \quad (6)$$

Furthermore, Archie [15] expressed resistivity to formation water saturation using the resistivity index, IR:

$$I_R = \frac{R_t}{R_o} = S_w^{-n} \quad (7)$$

Equations 5 and 6 are combined to yield the following:

$$S_w = \left(\frac{a}{\phi^m} \frac{R_w}{R_t} \right)^{1/n} \quad (8)$$

where, R_t is the true resistivity in Ohmmeters, and a is the cementation constant and the intercept of a logarithmic plot of F_R versus ϕ .

The cementation factor (m) and saturation exponent (n) values are crucial in the estimation of water saturation S_w and hydrocarbon reserves [33].

The cementation factor value (m) is estimated from the slope of a log-log formation resistivity factor (FR) and porosity plot (Figure 1). In this work, average cementation factor for the tested samples was 1.8 which is lower than 2.0 and indicates that the carbonate reservoir is naturally fractured [34].

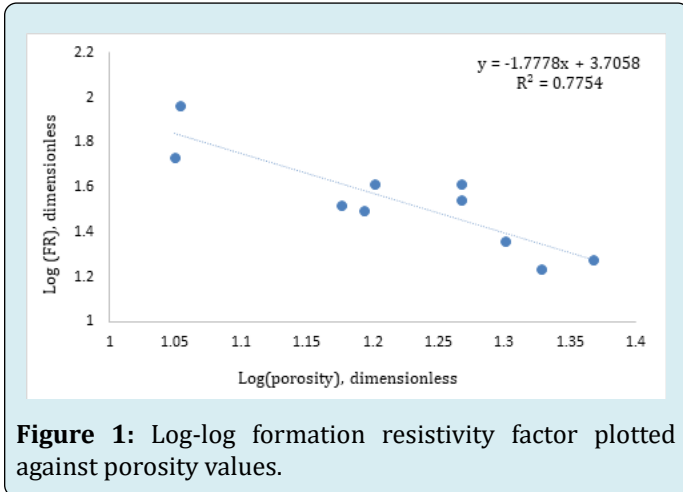


Figure 1: Log-log formation resistivity factor plotted against porosity values.

Irreducible water saturation is prone to confusion with initial or connate water saturation. The latter signifies the water saturation distribution in the reservoir during its discovery, whereas the former is commonly derived from primary drainage capillary pressure experiments in the laboratory. Nevertheless, Doveton (2014) recommended the term “immobile water saturation” over irreducible water saturation. This preference stems from mercury injection tests demonstrating that saturations at this level can ultimately be reduced to zero under sufficiently high pressures [35].

Experimental Procedure

Tested rock samples were collected from a carbonate reservoir in the Arabian Peninsula. Core samples were taken from a Permian formation made up of limestone and dolostone. The formation has been impacted by various diagenetic processes triggering abundant interparticle and moldic porosity.

Core electrical measurements were performed on 10 core samples. The samples were cored out from the crest of the structure where porosity was higher than in the flanks. It was evident that packstone with oolitic and skeletal grainstones populate the formation, composed mainly of a cyclic dolomitic shelf that was deposited during the Permian period. The Permian formation has been affected by various diagenetic processes including dolomitization, cementation, leaching, recrystallization, compaction, and fracturing. Interparticle and moldic porosity are also abundant in the region. Inter-crystalline and micro-porosity are common in limestone and dolomite lithologies [36].

The samples were cleaned in a Soxhlet™ extractor by circulating toluene and alcohol. Samples were then dried for 24 hours and weighed. The porosity of each core plug was measured using a helium porosimeter.

Absolute permeability to gas was determined using a Hassler core holder. In measuring permeability, gas is usually preferred over liquids since gas acts as a non-wetting phase and hardly alters the original state of the tested core samples. Measurements can also be repeated.

A porous plate was utilized to determine the initial water saturation for each core plug, and saturations were measured using a resistivity meter. Temperature, brine displacement, confining and pore pressures were monitored continuously. The interfacial tension and wetting angle were measured to be 29 dynes/cm and 120 degrees, respectively. The liquid surface/interfacial tension was measured using the Pendant Drop method. The contact angle was determined using a Du Noüy ring.

Study Methodology

The primary goal of reservoir characterization is to develop an initial water saturation model. The developed static model can be used to assess hydrocarbon reserves better and reduce uncertainty. In the laboratory, one can mimic/reproduce initial (connate) water saturation levels by desaturation of core plugs to amounts where water saturations become irreducible. Conventionally, irreducible water saturation is established by displacing the water present in core plugs with oil or gas using a centrifuge. In this work, we used a porous plate, and air as the non-wetting phase to establish irreducible water saturation and reproduce drainage/desaturation capillary pressure curves.

Moreover, rock typing is also carried out by grouping rock samples based on porosity values. The corresponding J-function for each rock type is calculated and plotted against normalized water saturation (S_w^*) values. S_w^* is expressed as a function of water saturation S_w and initial water saturation, S_{wi} (Lucia, 1995) as follows:

$$S_w = \frac{S_w - S_{wi}}{1 - S_{wi}} \quad (9)$$

The logarithmic plot of the J-function against S_w^* identifies the different prevalent rock types. The following relationship is utilized in the identification of the distinct types:

$$J = a(S_w^*)^b \quad (10)$$

The permeability values for each rock type form a cluster along a straight line. Permeabilities of uncored intervals in the reservoir are interpolated using the linear trendline developed for each rock type.

Furthermore, Lucia (1983) expressed the initial water saturation (S_{wi}) as a function of reservoir height (H) and porosity (ϕ) as follows:

$$S_{wi} = aH^{-b}\phi^{-c} \quad (11)$$

Since permeability of carbonate rocks can be expressed as a function of porosity as in:

$$k = a\phi^b \quad (12)$$

and that capillary pressure relates to reservoir height; $P_c = f(H)$. Then, Lucia's equation (11) can be articulated in the following form, where S_{wi} is written as a function of P_c , ϕ , and k :

$$S_{wi} = f(P_c, \phi, k) \quad (13)$$

Statistical Theory

Equation (13) was used as a basis for the empirical

equation developed in this study. Multiple linear regression analysis techniques were utilized to express water saturation, S_w , as a function of capillary pressure, P_c , porosity, ϕ , and permeability, k . T-statistic, p-values, the coefficient of multiple determination, R^2 , and analysis of variance (ANOVA) were all used to assessment of the empirical model.

Measured laboratory data was utilized in the statistical analysis. The laboratory data set was used for model development and an independent one was employed in testing and validation. The developed empirical correlation was compared to Lucia's model [20] which was established for carbonate rocks and applies to this study.

Results and Discussion

Core properties of the tested core samples are summarized in Table 1. Porosity of core samples ranged from 11.22 to 23.26%. Permeability varied from 8.89 to 72.27 md. Irreducible water saturation array was from 20.33 to 33.54%.

Sample No.	Porosity, fraction	He pore volume, cc	Permeability, md	S_{wi} fraction	Capillary pressure, psia
1	0.2133	13.95	20.15	0.2524	200
2	0.2326	15.67	14.46	0.2086	190
3	0.1563	10.19	23.07	0.2033	180
4	0.1586	10.23	10.36	0.3354	200
5	0.1132	7.26	21.15	0.2156	200
6	0.1122	7.36	8.89	0.246	200
7	0.1854	12.33	22.84	0.286	200
8	0.1848	12.23	72.27	0.2475	200
9	0.2002	12.97	12.2	0.294	195
10	0.1497	10.14	14.54	0.2381	180

Table 1: Core properties of the tested samples.

Capillary pressure profiles for the corresponding rock samples are depicted in Table 1. The capillary pressure plots

were displayed to classify rock samples.

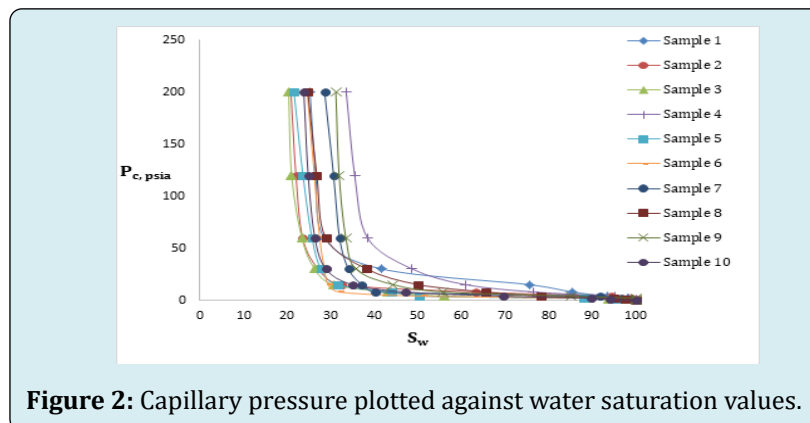


Figure 2: Capillary pressure plotted against water saturation values.

Figure 2 was unconvincing, and a better approach would be to use the J-function method to better distinguish between rock types. The RQI for each sample was calculated. The

J-functions were generated and plotted against normalized water saturation values (Figure 3).

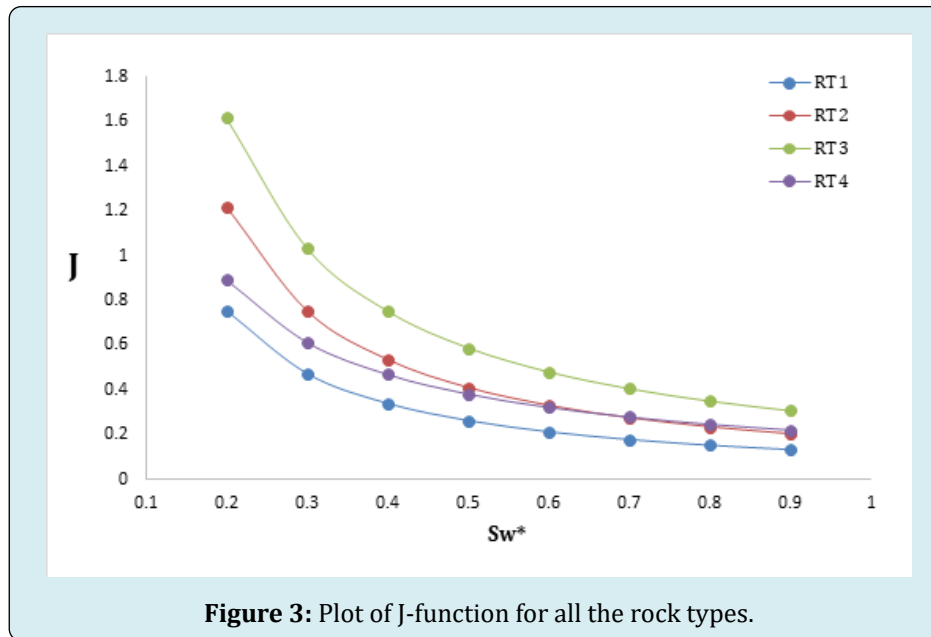


Figure 3: Plot of J-function for all the rock types.

Rock types RT1, RT2, RT3, and RT4 have been identified based on porosity range and average percentage of dolomite. The presence of dolomite impacts porosity. Dolomitic granular carbonates become be less porous with increasing dolomite percentage as increasing mud and compaction effects diminish macro-pores in denser grainstones. Table 2 classifies the used rock types.

Porosity Range	Rock Types	Average Dolomite %
~ 0.11	1	100
~ 0.15	2	22
~ 0.18	3	10
~ 0.2	4	7

Table 2: Rock types based on porosity range and dolomite percentage present.

The J-functions were plotted for the four different rock types. Since the difference between RT2 and RT4 is very

insignificant, it was decided to consider only three types: RT1, RT2, and RT3. Moreover, the initial water saturation, S_{wi} , was correlated against capillary pressure, porosity, and permeability to generate a regression model. The following formulation was utilized in the development of the empirical model for the Permian Arabic Peninsula carbonates:

$$S_{wi} = a(P_c)^b (\phi)^c (k)^d \quad (14)$$

From multiple linear regression analysis, the generated empirical correlation is as follows:

$$\log(S_{wi}) = -9.6 + 3.81 \log(P_c) - 0.631 \log(\phi) - 0.137 \log(k) \quad (15)$$

To determine whether the independent variables, P_c , ϕ , and k were enough to explain the variation in the estimation of the dependent variable, S_{wi} , a regression coefficient table is presented (Table 3). Table 3 summarizes regression coefficients, t-statistic, and p-values for each variable in the developed equation.

	Coefficients	Standard Error	t-stat	p-value	Lower 95 %	Upper 95%
Intercept	-9.5959029	1.412487177	-6.7936	0.00245	-13.51759602	-5.6742098
P_c	3.81253997	0.595066043	6.40692	0.00305	2.160371765	5.4647082
ϕ	-0.6313315	0.171705197	-3.6768	0.02126	-1.108061556	-0.1546015
k	-0.1370607	0.040799731	-3.3594	0.02832	-0.250338933	-0.0237825

Table 3: Summary statistics for the new model.

Moreover, hypothesis testing was used to decide whether there is sufficient statistical evidence in favor of the equation regression parameters. The null hypothesis (H_0) tests whether each variable coefficient is zero. It is a typical statistical theory that suggests that no statistical relationship and significance exists in a set of given single observed.

$$H_0 : \beta_i = 0$$

On the other hand, the alternative hypothesis (H_a) examines the exclusive statement that these coefficients are not zero. It is what will be tested in the hypothesis. It is the answer to the research question.

$$H_a : \beta_i \neq 0$$

If the coefficient of a particular variable is zero, then the variable drops out of the model as it does not contribute to the explanation of the dependent variable, S_{wi} . A p-value that is less than or equal to 0.05 is frequently used to test whether there is evidence against the null hypothesis. If the p-value is less than 0.05, the null hypothesis is rejected. The p-value for each variable is less than 0.05 (Table 3 above). Hence the null hypothesis is rejected, and all the empirical equation independent variables can be used to explain the variation in the dependent variable.

The coefficient of determination (R^2) is the proportion of variability in the observed response. An R^2 value of more than 0.8 indicates a high degree of correlation. In this study, the regression R^2 for the developed correlation is about 0.92. This suggests a strong correlation between the dependent variable (S_{wi}) and the independent variables (P_c , ϕ , k). An adjusted R^2 value of 0.86 indicates that the inclusion of the variable permeability in the new correlation has yielded superior results. It is evident from Table 4 that we only used 8 data points instead of 10. Two of the data points were discarded since there was ambiguity about their measurement. The number of samples used in this study is limited. The eight data points explained the relationship between the dependent and independent variables for the geological formation under study and yielded a considerable degree of fit.

Regression statistics	
Multiple R	0.9594759
R^2	0.9205941
Adjusted R^2	0.8610396

ϕ	0.2024	0.28	0.1663	0.1386	0.135	0.188	0.11	0.219
k , md	22.13	16.45	223.7	8.36	24.54	170.7	645	12.8

Table 6: Independent data set.

Standard Error	0.0277656
Observations	8

Table 4: Regression statistics for the new model.

To depict the results of regression statistics, data from the developed model (model generated S_{wi}) has been plotted against measured S_{wi} (Figure 4). The R^2 value of 0.92 confirms the excellent agreement between estimated and measured data.

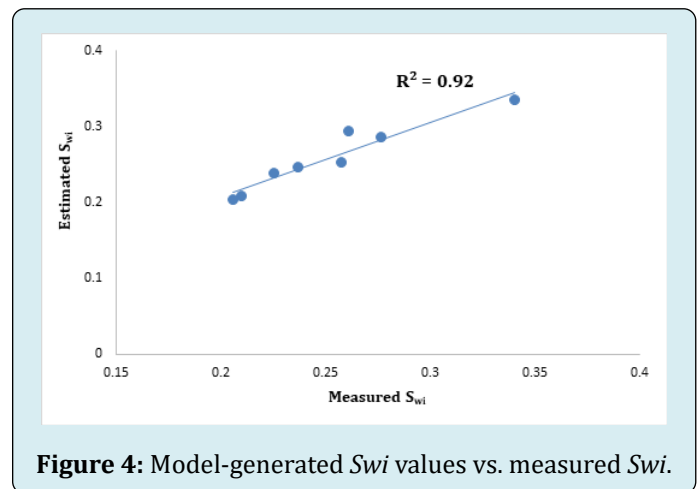


Figure 4: Model-generated S_{wi} values vs. measured S_{wi} .

The analysis of variance (ANOVA) for the new correlation is shown in Table 5. ANOVA results indicate that the variability between sample means is much higher than the variation among samples ($F = 15.5$). The p-value of the F-test is around 0.01 and is much lower than 0.05. This confirms that the regression coefficients of the independent variables are significant and that the null hypothesis should be rejected.

	Df	SS	MS	F	p-value
Regression	3	0.035751	0.0119	15.46	0.0115047
Residual	4	0.003083	0.0008		
Total	7	0.038834			

Table 5: ANOVA results.

Cross-validation or out-of-sample testing using an independent data set (Table 6) was performed to test the validation of the developed model. The testing data set porosity ranged from 11 to 28%. Permeability varied from 8.36 to 640 md. Both ranges are vast, and validation will imply that the correlation is consistent.

Moreover, the predicted S_{wi} has been plotted against S_{wi} from a testing data set. Figure 5 shows an excellent

agreement between the predicted and testing data. It also verified the developed empirical model validity.

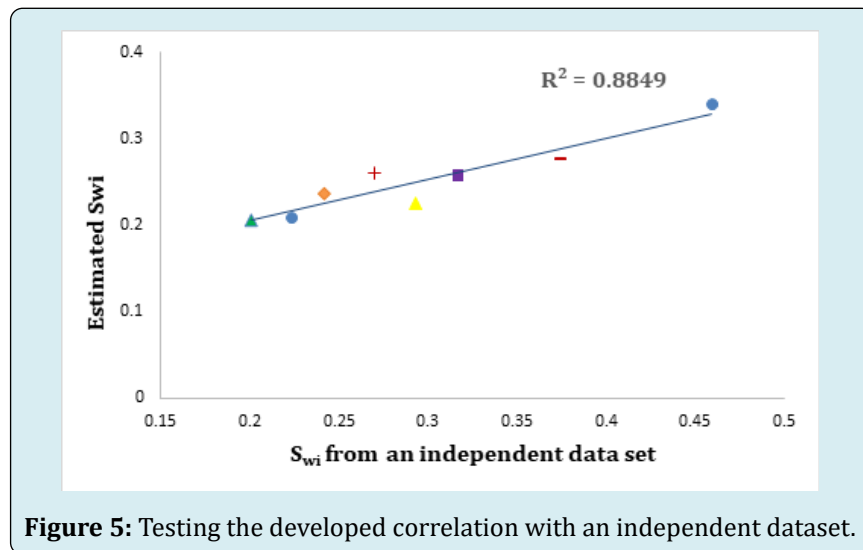


Figure 5: Testing the developed correlation with an independent dataset.

The new correlation produced an R^2 value of 0.88, indicating a good fit, considering the wide variability of porosity and permeability, as depicted in Figure 5 and Table 6. This implies that the correlation is valid and can be used in different carbonate reservoirs within the model testing range

of 11 to 28% for porosity and 8.36 to 640 md for permeability. In addition, Figure 6 depicts a comparison between the newly developed correlation and Lucia's empirical model (1995), an industry standard for carbonate rocks.

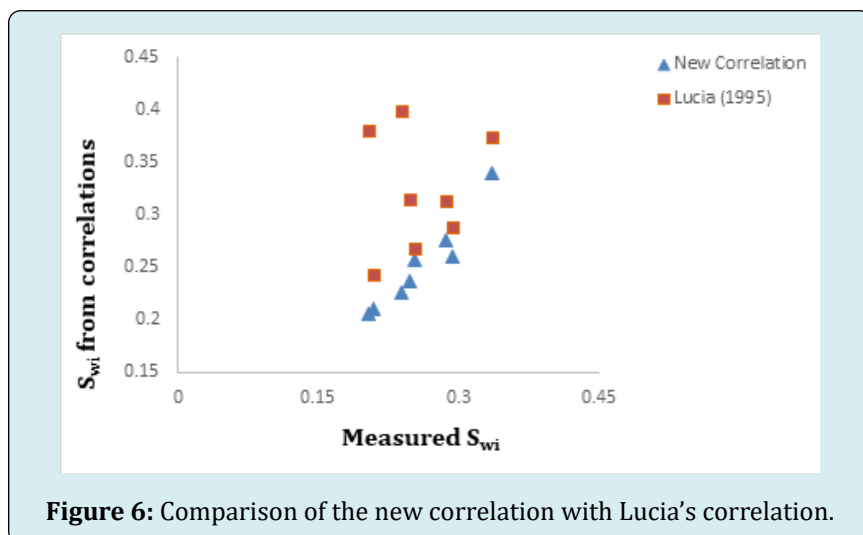


Figure 6: Comparison of the new correlation with Lucia's correlation.

The results presented in Table 7 show that the developed correlation yielded better results than models developed by Lucia, et al. [14,21,37]. The newly developed empirical

equation gave a lower error sum of squares (SSE) of 0.003, a lower mean squared error (MSE) value of 0.0008, and a lower p -value of 0.01.

Statistics	New correlation	Lucia (1995)	Wang et al. (2006)	Guo et al. (2005)
SS_E	0.003084	0.011784	0.036193	0.013831
MS_E	0.000771	0.002357	0.006032	0.002305
p -value	0.011505	0.050718	0.532705	0.77326

Table 7: Correlation comparison table.

Conclusions

A new initial water saturation empirical correlation has been developed based on laboratory measurements of Arabian Peninsula carbonate rock samples. The new equation yielded an R^2 value of about 0.92. The student's t-test and F-test p-values were much lower than 0.05. The new model has been tested against an independent data set. The coefficient of multiple determination of predicted S_{wi} against the independent data set yielded an R^2 of 0.88. The degree of fit is deemed significant given the wide range of test data. The new model was compared to Lucia's, an industry standard for carbonate rocks and showed better results.

Laboratory experiments remain the most trustful means of reservoir property measurement if they can be afforded Tariq, et al. [11]. In the absence of such measurements however, k , ϕ , and P_c can be collected from well logs, well testing data, and perhaps other laboratory measurements from analogous formations in the region. Besides, like other parametric equations, the idea is to utilize the correlation to replace some of the costly laboratory data collection methods.

Conflict of Interest

On behalf of all the co-authors, the corresponding author states that there is no conflict of interest.

Statements and Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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