

**PREDICTION OF FORMATION
PRESSURE FROM WELL LOGS USING
ARTIFICIAL INTELLIGENCE
TECHNIQUES**

BY

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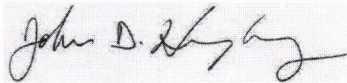
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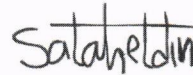


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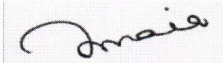
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Dedication

I dedicate this work to my family, my mother, my wife and especially my son Murad, and my soon to be born daughter whose presence in my life always motivates me to work even harder and never give up.

And to my advisor and professors in KFUPM.

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LIST OF ABBREVIATIONS

ANN	:	artificial neural network
AAPP	:	average absolute percentage error

ABSTRACT

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The ability to predict the formation pressure gradient in real time is crucial, particularly for drilling operations. It has the potential to improve the quality of decisions made as well as the economics of drilling operations. Even though the pressure while drilling (PWD) equipment can provide pressure data during drilling, its cost and availability limit its application in many wells. The available pressure gradient prediction methods in the literature are based on well logging or a mix of drilling parameters and well logging. The goal of this study is to create models for real-time pore pressure gradient prediction using available logs and core data from Energean Oil S.A. in Greece testing the following artificial neural network (ANN), radial basis function model, and general regression neural network. Of the three methods, the ANN was the most accurate one. Thus, the equation developed in this study was based on ANN.

ملخص الرسالة

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تاريخ الدرجة العلمية: يناير 2023

تعد القدرة على التنبؤ بتدرج ضغط التكوين الجيولوجي في الوقت الفعلي أمرًا بالغ الأهمية ، خاصة لعمليات الحفر. لديها القدرة على تحسين جودة القرارات المتخذة وكذلك اقتصاديات عمليات الحفر. على الرغم من أن معدات الضغط أثناء الحفر (PWD) يمكن أن توفر بيانات الضغط أثناء الحفر ، فإن تكلفتها وتوافرها يحدان من تطبيقه في العديد من الآبار. تعتمد طرق التنبؤ بالتدرج في الضغط المتاحة في الأبحاث المنشورة على تسجيل البئر أو مزيج من معلومات الحفر وتسجيل الآبار. الهدف من هذه الدراسة هو إنشاء نماذج للتنبؤ بتدرج ضغط المسام في الوقت الفعلي باستخدام السجلات والبيانات الأساسية المتوفرة من Energean Oil S.A في اليونان لاختبار الشبكة العصبية الاصطناعية التالية (ANN) وطريقتين أخريين من الطرق الثلاث ، ANN أظهرت نتائج أدق. وبالتالي ، استندت المعادلة التي تم تطويرها في هذه الدراسة على ANN.

CHAPTER 1

INTRODUCTION

The pressure exerted by the fluids present in the porous media is called formation pressure or pore pressure. The water column weight at a known depth to the surface produces the normal pore pressure. The values for normal pressure gradient ranges from 0.433 psi/ft to 0.465 psi/ft for fresh water and salt water respectively. We can describe the values deviating from the normal gradient as abnormal pressure which can be subnormal or overpressure. Overpressure, also known as geopressured, occurs when pore pressure exceeds normal pressure. This pressure results from an additional source of pressure being added to the regular pressure, and it can result in kicks and blowouts. Excess of pressure can be caused by geological, mechanical, geochemical, geothermal, or a combination of these factors. On the other hand, subnormal pressure is less than normal pressure and might result in a differential pipe sticking and circulation loss. Real-time pore pressure prediction may improve well trajectory, casing, and mud program designs, and provide better wellbore stability analyses, saving drilling time and expense.

Many proposed methods that have used formation properties, well logging data, and logging and drilling data combined to predict formation pressure using machine learning methods. These methods produced very good models that showed the missing data points.

The purpose of this work is to use Machine Learning techniques to predict pore pressure using well logs data e.g., resistivity, GR, bulk formation density, sonic porosity, neutron porosity. A

portion of the data will be used for training the ML models, another portion will be used for testing, while the rest will be used validation of the trained models.

1.1 Field Background

The Prinos Basin is the only productive hydrocarbon area in Greece and the Epsilon oil field is considered the latest field brought to production. The Epsilon oil field is in the north Aegean Sea between the Greek mainland and the island of Thassos, approximately 11 km S-SE of the city of Kavala (Fig. 1).

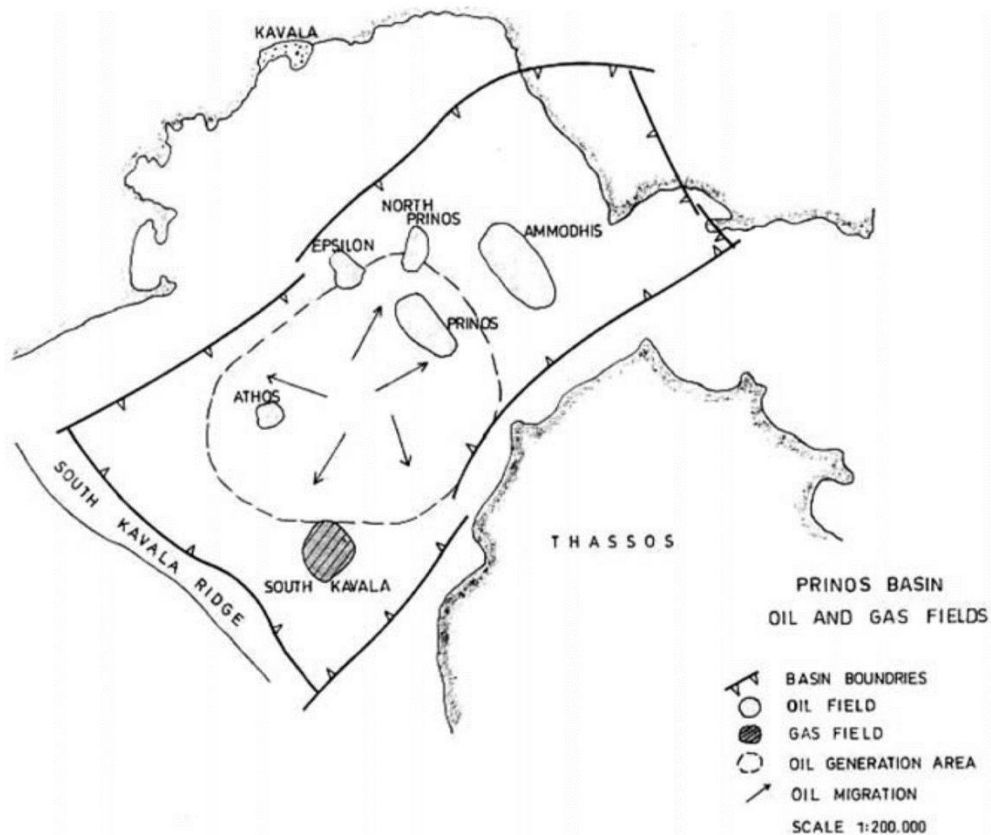


Figure 1: The Epsilon oil field is in the middle and north part of the basin of Prinos (N. Aegean Sea). Along with Prinos field, Prinos North field and South Kavala gas filed are the only productive hydrocarbon fields in Greece. The oil generation and the migration paths are shown. Figure from Proedrou and Papaconstantinou (2004).

There were five drilling attempts 1976, 1994, 1996, 2004 and 2009 that kept the field in production until today. The in first productive well was drilled 20 km east of Thassos isand in 1971 but discovered very low gravity oil. In 1972-1973 the next two wells were drilled west of the island and led to the discovery of South Kavala gas field in 52 m of water depth. The fourth drilling attempt, was at the end of 1973, at the center of Prinos basin and led to the discovery of Prinos oil field in a water depth of approximately 30 m.

The stratigraphy model of the taphrogenetic basin has been presented by Pollak (1979) and Proedrou (1979) (Fig. 2). According to this, the generalized stratigraphic column is divided into three series:

- The Pre-Evaporitic Series.
- The Evaporitic Series.
- The Post-Evaporitic Series.

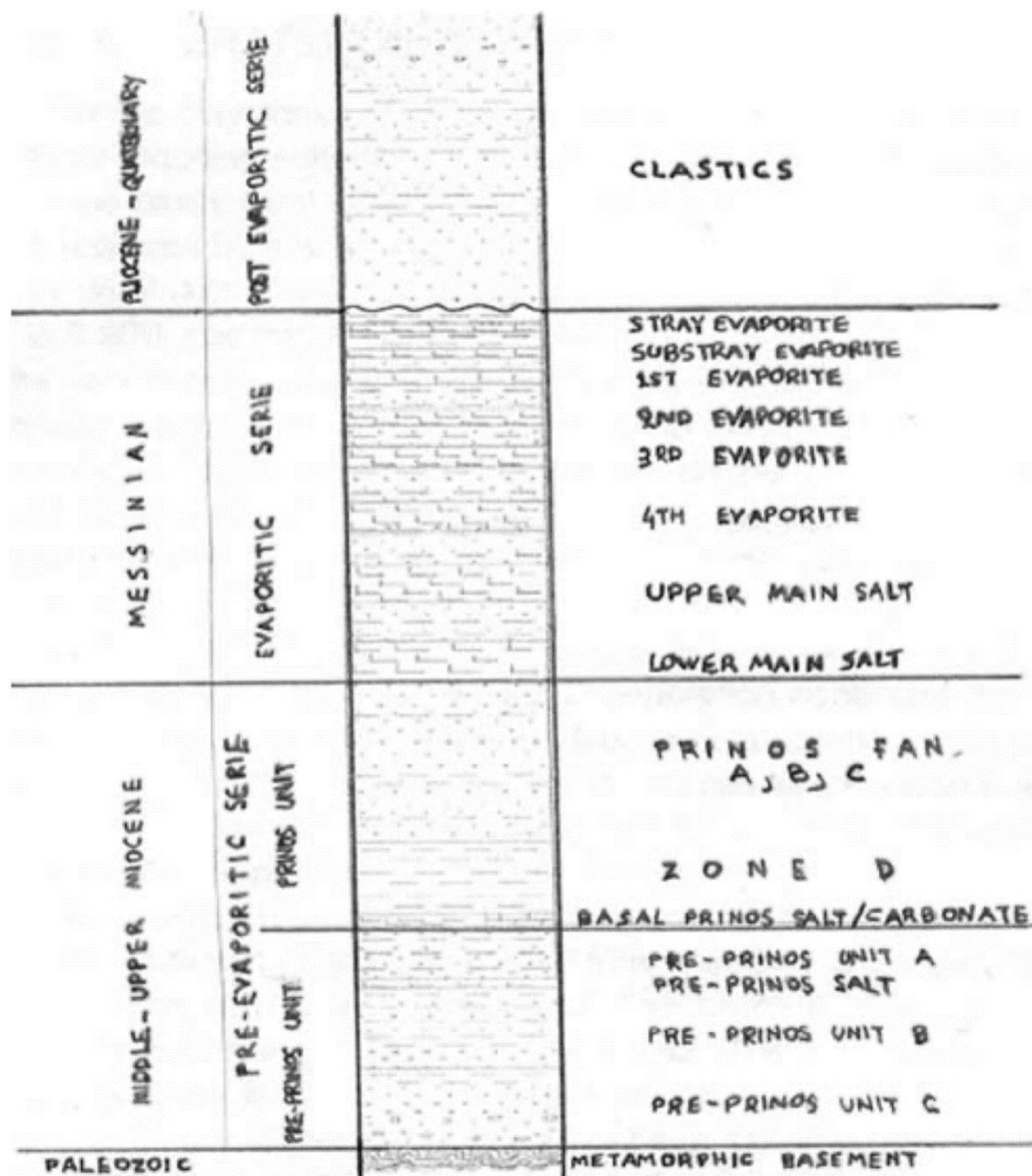


Figure 2: Generalized chronostratigraphic column of Prinos basin. Figure from Proedrou and Sidiropoulos.(2004)

The general structure of the taphrogenetic basin, it is a dome-like anticline formed by NW-striking and SW-dipping syngenetic faults also related to the trapping mechanism (Proedrou and Papaconstantinou, 2004).

Reservoirs are mainly sandstones and secondly siltstones, that resulted of the uppermost Miocene depositions from deltaic, marine and turbiditic environments. The evaporites cover the whole basin, keeping hydrocarbons below them, except from an upward movement of hydrocarbons in South Kavala and Ammodhis fields, probable due to fault activation. Generally, porosity and permeability are decreasing with increasing depth, due to weight overlay, clay content and dolomitization (Proedrou and Papaconstantinou, 2004).

CHAPTER 2

LITERATURE REVIEW

Pore pressure prediction in real-time can be either qualitative or quantitative. The proposed methods in the literature used well logging data, formation properties, and logging and drilling parameters data combined in a few studies. Based on logging data from Miocene and Oligocene shales, Hottman and Johnson (1965) predicted the pore pressure. The authors created cartesian cross-plots that correlated the pressure gradient with the difference in sonic travel time or resistivity ratio between the observed and normal trends. Pennebaker (1968) used the sonic travel time ratio rather than the sonic travel time difference used by Hottman and Johnson. For the same correlation as Hottman and Johnson, Matthews and Kelly (1967) used a semi-log scale rather than a cartesian one. Eaton (1975) stated that what controls both log-derived data are pore and overburden pressures. To estimate the pore pressure gradient in shales, Eaton developed an empirical sonic-based model. Gardner et al. (1974), after analyzing the data provided by Hottman and Johnson, made a new attempt to predict pore pressure by including overburden pressure data. From the sonic data (slowness), Bowers (1995) was able to predict the pore pressure by using $(\alpha - \text{pore pressure})$ instead of the effectiveness stress (αV) .

Predicting pore pressure using electrical well logs was introduced for the first time when Foster and Whalen (1966) used the equivalent depth method. In order to estimate the pore pressure and know the required mud density, Ham (1966) also used the equivalent depth method with resistivity, density, and sonic data. Eaton (1975) proposed empirical models

based on resistivity and conductivity to predict formation pressure gradient from well logs in shales. To account for the ROP for changes in hole diameter, weight on bit (WOB), and RS, Bingham (1965) devised the D exponent. Jorden and Shirley (1967) made a modification on Bingham's approach by adding the term d_{exp} . However, to account for the mud weight effect, Jorden and Shirley's d_{exp} was modified by Rehm and McClendon (1971). Eaton noticed a similarity between the corrected d exponent plot and the resistivity log plot.

Abdelaal et al. (2019) introduced a model for estimating pore pressure at any depth using the observed d_c , normal d_c trendline value, and both the overburden and normal pressure gradients and was able to predict the pore pressure gradient for unseen data points using machine learning models. Using the available drilling parameters and based on their continuous profiles, the models predicted a continuous profile of the pressure gradients as shown in figure 1. The models predicted the pore pressure gradient with high a R of 0.99 for RF and SVM models while it was 0.98 for FN model between the actual and predicted results for validation.

CHAPTER 3

METHODOLOGY

3.1 Data Preparation

For pore pressure prediction, 48 data points of formation temperature, porosity, and water saturation in addition to their corresponding pore pressure were collected from Well-3.

In the first stage the data was preprocessed to remove all non-real values, for example all inputs with water saturation values less than zero or greater than 1.0 were considered as non-real inputs and removed from the input parameters. Then the outliers were also removed, for this purpose the input parameters were studied mathematically, and all values outside a range of ± 3.0 standard deviation were treated as outliers and removed from the input dataset.

3.2 ANN Model Learning

After the stage of data preprocessing, 46 datasets were left as valid data for model learning. Then the artificial neural network model was learned to predict the pore pressure, during this learning step the percentage of training data points in addition to the design parameters of the ANN model including the learning function, the number of learning layers, the number of learning neurons per each layer, and the transferring function were optimized. The percentage of the training data was optimized between (40% to 95%). The performance of several training functions including Levenberg-Marquardt backpropagation function, resilient backpropagation function, and Bayesian regularization backpropagation function. The ability of various transferring functions for prediction of pore pressure was also performed this include the tangential sigmoidal function, logarithmic sigmoidal function, and the linear function. The use of single, two or three layers for learning the model with 4 to 30 neurons per each layer was also studied. The results of the learning stage concluded that the use of 91% of the data for training using a single learning layer associated with five neurons, the Bayesian regularization backpropagation function for training and Logarithmic sigmoidal transferring function was the optimum for pore pressure prediction. Figure 1 shows schematic of the optimized ANN model which is proposed for pore pressure estimation, other properties of this optimized model are summarized in Table 1. The statistical features and ranges of the training datasets are listed in Table 2.

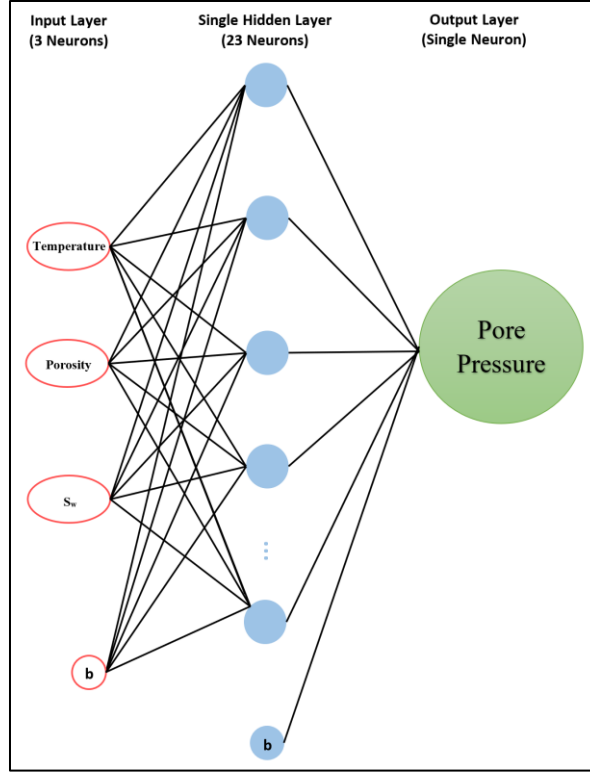


Figure 3: Schematic of the optimized ANN model for pore pressure prediction.

Table 1: The optimized parameters for pore pressure prediction

Parameter	Optimum Value
Training layers	Single
Number of neurons	23
Training function	Bayesian regularization backpropagation
Transferring function	Logarithmic sigmoidal function

Table 2: The statistical features of the 42 datasets used to train the ANN for pore pressure estimation.

	Temp. (°C)	Porosity (frac.)	S _w (frac.)	Pore Pressure (psi)
Minimum	137.3	0.037	0.001	4254
Maximum	149.2	0.182	0.999	6496
Average	143.0	0.104	0.510	5473
Mean	142.9	0.098	0.352	5440
Median	142.8	0.106	0.473	5165
Standard deviation	3.139	0.036	0.289	615.5

Extracting equation from the optimized ANN model

The ANN model shown in figure 3 and with the properties in table 1 was then considered for developing new equation for pore pressure estimation. This model could be generally expressed as shown in Eq. (1).

$$\begin{aligned}
 P_{p,n} &= \sum_{i=1}^I w_{oi} \logsig \left(\sum_{j=1}^J w_{ti,j} Y_j + b_{ti} \right) + b_o \\
 &= \sum_{i=1}^I w_{oi} \frac{1}{1 + e^{-(\sum_{j=1}^J w_{ti,j} Y_j + b_{ti})}} + b_o
 \end{aligned}
 \tag{Eq. (1)}$$

Where $P_{p,n}$ is the normalized pore pressure, I and J denote the total number of neurons and input parameters which are five and four, respectively, in this case. w and b represent the weights and biases, respectively. t denotes the training layer while o represents the output layer.

It is important to mention that the parameters introduced into the ANN model are usually automatically normalized by the two-points slop explained by Eq. (2) and Eq. (3) to have a value in the range between 1 and -1.

$$\frac{Y_n - Y_{n,min}}{Y_{n,max} - Y_{n,min}} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad \text{Eq. (2)}$$

$$Y_n = \left(\frac{Y - Y_{min}}{Y_{max} - Y_{min}} \right) (Y_{n,max} - Y_{n,min}) + Y_{n,min} \quad \text{Eq. (3)}$$

Where Y denotes the input parameter which could be in this case the formation temperature, porosity, water saturation or the pore pressure, the subscript n indicate the normalized parameter, min and max represent the minimum and maximum, respectively. Since the input parameters are normalized between -1 and 1, $Y_{n,min}$ will be -1 and $Y_{n,max}$ will be 1, therefore Eq. (3) could be written as in Eq. (4).

$$Y_n = 2 \left(\frac{Y - Y_{min}}{Y_{max} - Y_{min}} \right) + 1 \quad \text{Eq. (4)}$$

General expressions for normalizing the four inputs considered in this study could be derived by substituting for the minimum and maximum values of each parameter as listed in table 2 to get the expressions in Eq. (5) to Eq. (7).

$$Temp_n = 0.168 (Temp - 137.3) + 1 \quad \text{Eq. (5)}$$

$$\phi_n = 13.76 (\phi - 0.037) + 1 \quad \text{Eq. (6)}$$

$$S_{w,n} = 2.005 (S_w - 0.001) + 1 \quad \text{Eq. (7)}$$

Where $Temp_n$, Φ_n , and $S_{w,n}$ are the normalized formation temperature, porosity, and water saturation, respectively. Now Eq. (1) could be expanded and written as a function of these normalized parameters as in Eq. (8).

$$P_{p,n} = \sum_{i=1}^I w_{oi} \frac{1}{1 + e^{-(w_{ti,1} Temp_n + w_{ti,2} \Phi_n + w_{ti,3} S_{w,n} + b_{ti})}} + b_o \quad \text{Eq. (8)}$$

The normalized parameters in Eq. (8) could be calculated using Eq. (5) to Eq. (7) while the weights and biases needed in this equation were extracted from the optimized ANN model and listed in Table 3.

Table 3: The extracted weights and biases for pore pressure estimation.

		Input Layer			Output Layer		
		Weights (w_1)			Biases (b_1)	Weights	Bias (b_2)
		j = 1	j = 2	j = 3		(w_2)	
Number of neurons	i = 1	-1.825	2.375	1.390	4.202	-1.042	-0.517
	i = 2	-1.431	3.561	0.507	3.376	-1.318	
	i = 3	1.006	-3.680	0.470	-2.797	-0.071	
	i = 4	-1.945	2.549	2.255	2.814	1.344	
	i = 5	2.297	-1.653	2.230	-2.424	0.362	
	i = 6	-2.276	2.811	0.491	1.865	0.698	
	i = 7	2.451	0.371	-3.713	-1.987	3.041	
	i = 8	1.078	-3.616	1.589	-0.991	1.077	
	i = 9	-0.665	-3.647	-2.651	0.932	-1.268	
	i = 10	3.202	-2.151	-0.666	-0.737	-1.491	
	i = 11	0.972	3.684	-3.220	-0.105	-1.330	
	i = 12	-0.597	-0.094	4.154	0.021	0.340	
	i = 13	-3.951	-0.706	-1.273	-0.564	-1.303	
	i = 14	-2.755	0.112	-2.463	-0.358	0.044	

i = 15	-1.428	0.139	4.810	-1.523	-2.601
i = 16	-0.660	1.727	-3.608	0.118	-0.939
i = 17	-1.077	-1.853	-2.772	-2.021	-0.915
i = 18	-3.461	1.505	-0.247	-1.509	0.546
i = 19	-1.757	2.869	-1.241	-2.478	-0.020
i = 20	1.473	-3.009	-1.478	2.658	0.130
i = 21	0.104	-4.950	0.983	3.967	3.653
i = 22	1.288	3.016	1.916	2.977	0.020
i = 23	-3.257	2.202	-1.787	-3.718	2.052

The pore pressure as calculated from Eq. (8) is in the normalized form which require denormalization to obtain the actual values of pore pressure, the denormalized pore pressure could be calculated using Eq. (9) which is derived by rearranging of Eq. (4) and substituting for pore pressure instead of Y.

$$P_p = \frac{(P_{p,n} + 1)}{2} (P_{p,max} - P_{p,min}) + P_{p,min} \quad \text{Eq. (9)}$$

3.3 Testing the suggested equation for pore pressure

The developed correlation of Eq. (9) was then tested using the remaining datasets collected from Well-3, 4 data points. The accuracy of Eq. (9) was evaluated by considering the AAPE and correlation coefficient between the actual and predicted pore pressure.

CHAPTER 4

Results and Discussion

4.1 Learning the artificial neural networks model

Figure 4 shows a comparison between the actual and estimated pore pressure for training data collected from well 3 (42 datapoints). The high correlation coefficient (R) of 0.875 and the average absolute percentage error (AAPE) of 4.22% indicate that the results shown in figure 4 are of high accuracy for the trained ANN model in predicting the pore pressure. When compared, the actual and estimated pore pressure plots indicate the high machining which confirmed the high accuracy of the ANN model.

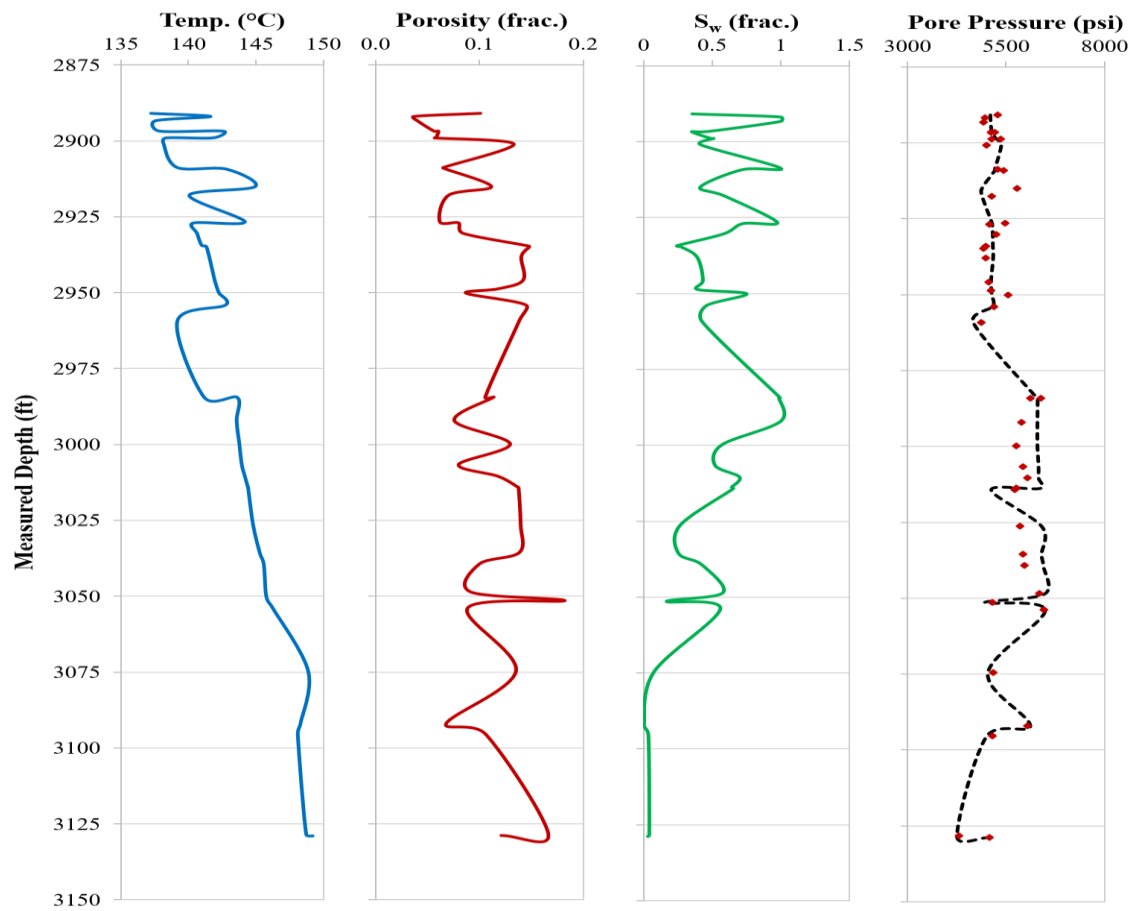


Figure 4: ANN training, showing the used paramters.

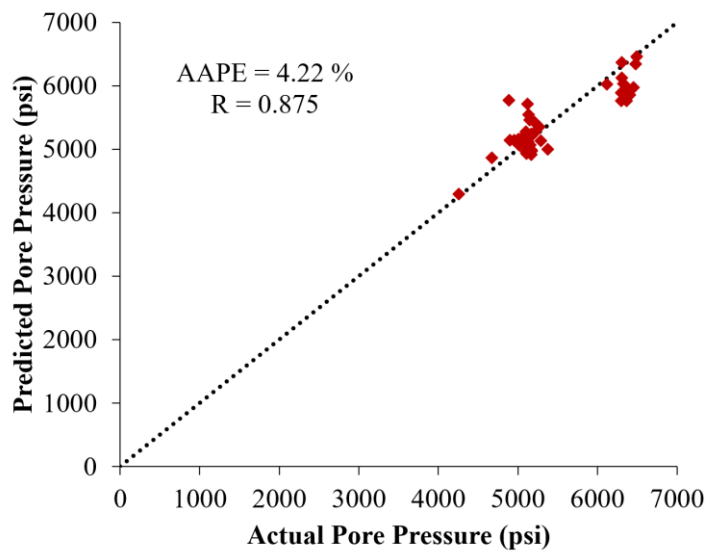


Figure 5: Actual Pore pressure

4.2 Testing the suggested equation for pore pressure

The developed equation (9) was tested using the remaining datasets collected from Well-3, 4 data points. As shown in figure 6, the results indicate the high accuracy of the trained ANN model in predicting the pore pressure with a high correlation coefficient (R) of 0.957 and an AAPE of 5.44%.

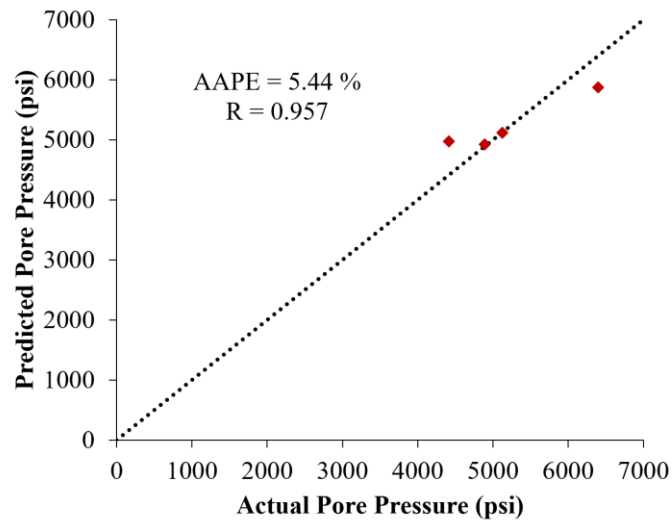


Figure 6: Results of remaining datapoints

Chapter 5 Conclusion

An empirical formula was introduced in this study to predict pore pressure based on ANN model. It evaluated pore pressure from other measured parameters. The results of the study show that:

- (i) For the training data, the learned ANN model predicted pore pressure with an AAPE of 4.22%.
- (ii) The extracted equation was tested on data gathered from the same training well where it estimated the pore pressure with AAPE of 5.44%.

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