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PREDICTION OF RESERVOIR PROPERTIES FOR BLIND WELL USING NEURAL NETWORK AND SEISMIC KNOWLEDGE

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ABSTRACT

Well Drilling costs a lot without knowing porosity distribution. Geoscientists use the seismic waves to overcome this problem and reduce the exploration risk. The current paper proposes a system to predict porosity of well from other wells already drilled incorporating with seismic data. This proposed workflow aims to estimate porosity values from three-dimensional seismic data and wells records from F3-block North Sea data. We used porosity interpretations from two wells (F2-1 and F3-2) and three-dimensional seismic attributes for neural network training. for assessing the result of porosity prediction, we used data from another well (F3-4) as a blind well. Correlation in the three stages of training, validation, and testing are discussed. Test results indicate the superiority of the proposed Neural Network to predict porosity compared to other techniques in current use. By implementing Neural Network to predict porosity in blind well it is found that correlation R=0.98.

Keywords: *Seismic attributes, Well logging, Neural Network, Porosity, Prediction.*

1. INTRODUCTION

Oil found from deep depths beneath the earth's surface. Drilling is the only way to extract oil, but drilling will cost a lot without knowing the place of hydrocarbons.
Geoscientists use the seismic waves to overcome this problem and reduce the risk of exploration.[1]
Like X-ray to diagnose the disease Seismic gives geoscientists knowledge about what is inside the earth by creating artificial seismic waves at a certain point in the region then recording the reflected and refracted waves from another point.[2]
Increasing profit in the oil industry either by increasing revenue or reducing expenses and risks in the exploration phase, the risk ratio can be reduced through the application of modern intelligent methods.
Some of oil exploration problems can be classified as shown in Table 1.

This paper aims to predict porosity values using both seismic and well log data. by proposing a Neural Network (NN) model based on data obtained from two wells which their porosity was known, and then to estimate the porosity of another well as blind well.

Table 1: Some of Oil Exploration Problems Classification.

Category	Reservoir Property	Structural Geology
Regression	Predicting Reservoir Property	Predicting Reservoir's Thickness
Classification	Predicting Hydrocarbon Deposits	Fault Detection
Clustering	Lithologic Analysis	Mapping

The rest of the paper is organized as follows: The 2nd section is background materials. Previous work is given in section 3. In section 4 we propose a new system to predict porosity of well from other wells. Test results are given in section 5. Finally, Conclusion and Future work are suggested.

2. ESSENTIAL BACKGROUND MATRIALS

2.1 Seismic Exploration

One of the sciences that are interested in

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studying and exploring the subsurface is seismology. These objectives can be done by making maps of Earth’s interior to locate underground oil formations. Geoscientists use effectively and widely seismic reflection in hydrocarbons exploration. Measurements collected from the seismic survey are the source of information and decision-making for interpreters, whether in the form of 2D; 3D or 4D depending on the stage of exploration and purpose[2].

These measurements are called by geophysics “seismic attributes”. Seismic attributes (kinematic, dynamic, statistical or geometric) are extracted from seismic data to acquire accurate knowledge leading to a better interpretation about changing in structural (horizon depth, faults, reservoir thickness, etc.), petrophysical properties (permeability, porosity, etc.) or hydrocarbon properties (thermodynamics, product, etc.) of the seismic survey domain [3]-[4].

There are many geophysical works in literature discussing the classification of seismic attributes and their association with geologic features or reservoir properties, such as ([5],[6]).

2.2 Well Logging Exploration

A well logging in the oil industry produces a detailed record of reservoir characteristic. Measure different physical properties of surrounding rocks are made by measure equipment (logging tools) located in a borehole [7]-[8]
The main objectives of well logging are:

- Identification of geological formations
- Identification of fluid formation in the pores
- Evaluation of the production capabilities of a reservoir formation.

The primary information obtained from analyzing and interpretation of well Log data can be summarized as in Table 2 [2].

Table 2: Type and Application of Some of Modern Logs.

Log Type	Log Name	Application
Acoustic Logs	Sonic logs (DT)	Porosity calculation, rock physics properties, wave velocity calculation.
Radioactivity Logs	Density (RHOB)	Porosity calculation, finding hydrocarbon bearing zone, Lithology interpretation, rock physics properties.
	Gamma-Ray (GR)	Porosity calculation, lithology interpretation, permeability calculation, wave velocity calculation, etc.
Electrical Logs	Resistivity (LLS, LLD, and ILD)	Finding hydrocarbon bearing zone, Lithology interpretation, calculate water saturation, etc.

2.3 Artificial Neural Network (ANN)

Inspired from neural system of human, McCulloch and Pitts proposed nonlinear computational algorithm called Artificial Neural Network which have evolved in various topologies by many scientists and applied by more in different fields.[9] There are three main processes (training, validation, and testing) in ANN algorithm. Data is divided into three parts. every part measures the process performance. Basic algorithm of ANN is represented by the equation:

$$y(x) = \sum_{node(i)} w_i \, f(x_i) \qquad (1)$$

Where in this work, y represents the target vector (reservoir property),x is the vector of seismic attributes inputs, and w_i is the weighting vector.[10]-[11]

3. PREVIOUS WORK

The problem under consideration many researchers presented different techniques to sort out it.
Ali, Aamir, et al. [12] Used linear regression technique to find correlation coefficient for estimating porosity from acoustic impedance based on linear relationship between them in nature. Hatampour, Schaffie et al.[13] integrated well log data and 3D seismic data collected from gas field in the Persian Gulf to estimate Nuclear magnetic resonance (NMR) log parameters by applying three different intelligent techniques.

Ma, Gomez et al.[14] discussed a model of porosity based on integration of three seismic attributes and eight well logs as principal component analysis (PCA) and supervised ANN regression problem.
Fattahi and Karimpouli et al. [15] using data from carbonate gas reservoir in Iran to Made a comparison between different techniques in porosity and water saturation prediction then they showed that adaptive-network-based fuzzy inference system subtractive clustering method (ANFIS-SCM) method, in this case, generates a lower Mean Square Error (MSE) in comparison with support vector regression with particle swarm optimization (SVR-PSO).
Applied on Kansas gas field Singh, Kanli et al. [16] used back propagation neural network (BP-ANN) technique which uses well data as inputs to estimate the porosity.
Wu, Hao et al.[17] used inverted results of F3-block North Sea post-stack seismic data and well log data to predict the porosity, and constructed relationships between acoustic impedance (AI) and porosity.
Mojeddifar, Kamali et al.[18] studied the data from the North Sea Basin and implemented a Pseudo-Forward Equation (PFE) based on similarity attribute to predict porosity.
Hosseini, Ziaii et al. [19] Used (2D) seismic With well logs data from Burgan oil field to predict hydrocarbon reservoir porosity by using three different types of artificial neural Network. The comparison of the three types shows that probabilistic neural network (PNN) is the best predictor of porosity using seismic attributes.
In Viking Graben area For the porosity network Helle, Bhatt et al. [20] using BP-ANN ,they found that porosity values from grain density and in situ bulk density data gave more consistent results than using standard helium core porosity data.

4. MATERIAL AND METHODOLOGY

In the previous section, we discussed some previous assumptions that relied on smart systems to solve the problem of the prediction of porosity distribution. In this section, we investigate a new technique aims to estimate porosity from the 3d seismic and well log data.

What is new in our proposed system is our adoption of new inputs and changing the structure of the neural network and the flexibility of the system where more precise algorithms can be used in the model building stage. The dependence of our system on the diversity of seismic variables is what distinguishes it from the previous systems, which made our system superior. Data taken from F3-block North Sea, which become publicly available and is provided by Aminzadeh and Groot [21]. We use two wells (F2–1 and F3–2) as inputs with seismic data to train and test NNs and use data from anther well (F3–4) to estimate porosity.
The proposed work flow to model porosity from seismic data is shown in Figure 1.

4.1 Preprocessing Stage

Seismic data measured in time domain, with well data measured in depth are used as inputs for this stage.

processing in this stage should take consideration of the following points:

- Each of two datasets has to process after collecting from survey area with geophysics workflow.
- Then extraction of physical properties from well data and seismic attributes from seismic data is with less noise.
- Because of difference between domains of the two samples so we need to convert well dataset from depth to time domain to get integrated dataset in the time domain.

In our work, we use open detect (geophysics open source software) to get Integrated data set (seismic data with well data) to complete this stage.

4.2 Model Building

Integrated data set is divided into training validation and testing (70%, 15%and 15%). Before the training process, random values of weights are determined. In training process, these weights are changed according to the amount of error between the NN output value and actual value. until reaching the minimum value of performance function. we used mean square error (MSE) as performance function for this NN. Satisfied minimum MSE of the training process moves us to the test process which verifies the accuracy of the NN using MSE. If the accuracy of NN satisfied we save NN with its weights to apply it in the next step.

4.3 Post-processing

The objective of this stage is to use the best model, saved in previous step, for predicting the

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porosity of a new well other than what we used in the Model building stage.

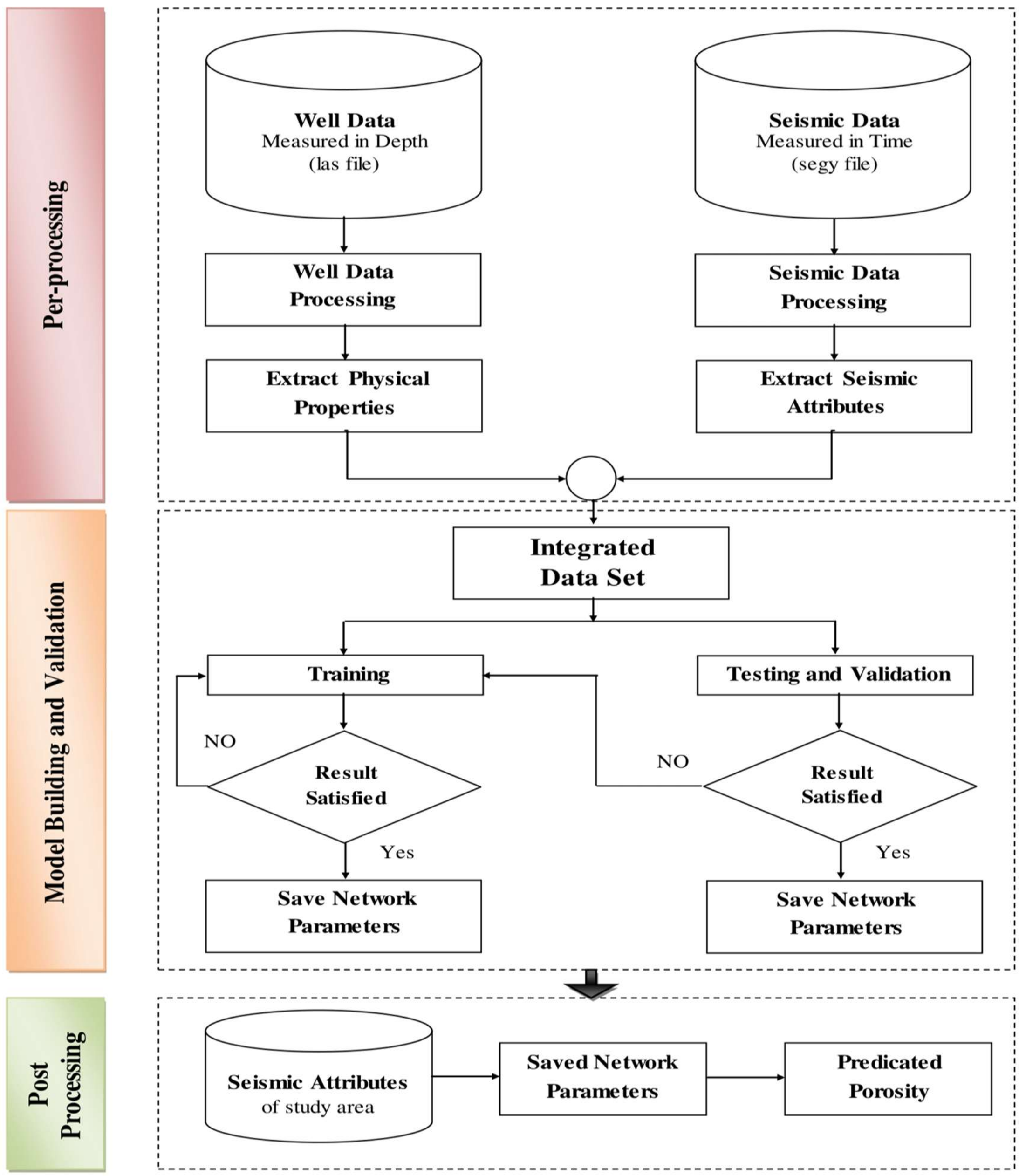

Figure 1: The Proposed Work Flow to Model Porosity From Seismic Data.

4.4 Data Description

In the beginning, it is worth mentioning that the 3d seismic and well log data are taken from F3-block North Sea data. After integrating the available vertical three well logs (F2–1, F3–2 and F3–4) data measured in depth with the Seismic data measured in time domain our target area located around 500ms to 1100ms. Figure 2 shows a map of seismic intersection throughout the study area and porosity logs in the three wells. For porosity prediction in this study, input data are different types of seismic attributes extracted from seismic data. For the seismic data, fifteen variables were used as input to this system along with the coordinates of the well points as shown in Table 3. All three wells have

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gamma ray and sonic logs, but only wells (F2–1, F3–2) have density logs.

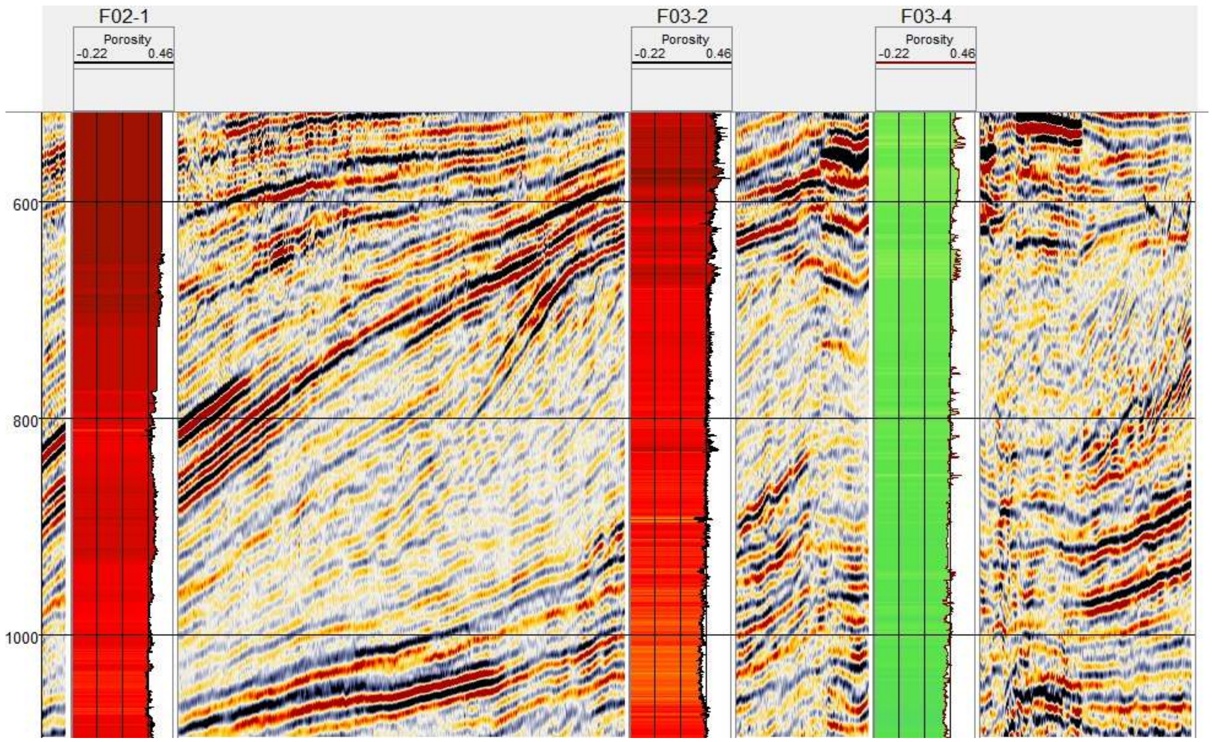

Figure 2: Intersection Map Seismic Section and Porosity Logs in The Three Wells

Table 3: Input Features

NO.	Features	Symbol	NO.	Features	Symbol
1	Well Coordinates	X	10	Instantaneous Amplitude	IA
2		Y	11	Instantaneous Amplitude 2nd Derivative	IA_2ndD
3	Time	Z	12	Cosine of the Instantaneous Phase	Cos_IP
4	Measure Depth	MD	13	Envelope Weighted Phase	EWP
5	P-Impedance	PI	14	Envelope Weighted Frequency	EWF
6	Similarity	S	15	Band Width	BW
7	Energy	E	16	Average Frequency	AF
8	Instantaneous Frequency	IF	17	Spectral Decomposition	SD
9	Instantaneous Phase	IP	18	Maximum Spectral Amplitude	MAX_SA

4.5 Linear Correlation

The conventional feature selection methodology is based on the linear correlation among the features. The purpose of this correlation test is to have a view of how the 18 features are linearly correlated to the target Porosity. In nature, it would be known that the relationship between each of these features and Porosity is extremely non-linear. Figure 3 shows the result of the correlation test of the combined features against Porosity.

Part of the data set used in this paper, which consists of 3855 rows, shown in Table 4.a,b.

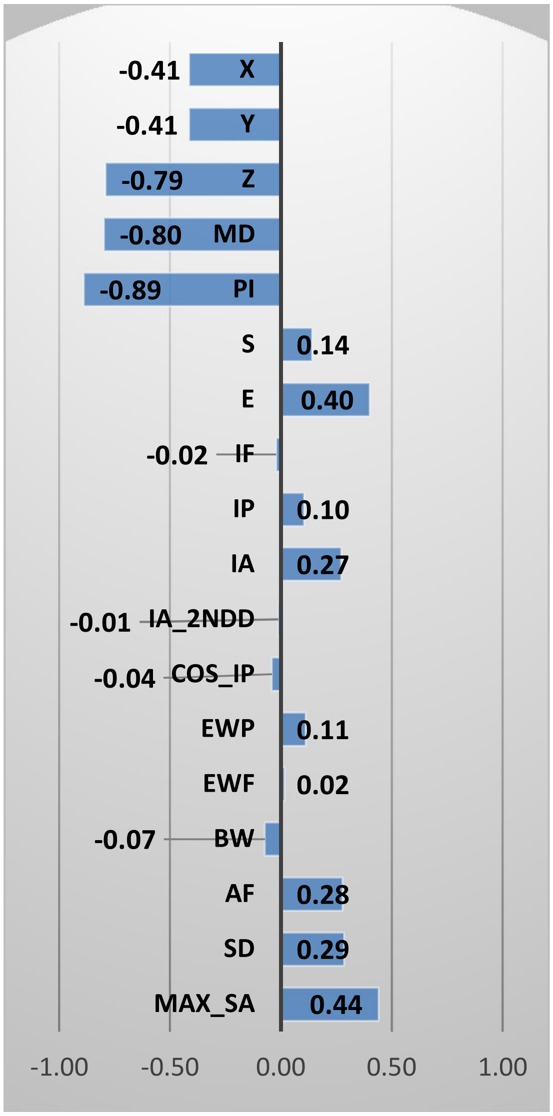

Figure 3: Correlation of Each Feature With Porosity.

4.6 Descriptive Statistical Analysis of The Integrated Data

The basic set of descriptive statistics of the integrated seismic and log data comprising mean (μ), median (Med), minimum (Min), maximum (Max), standard deviation(σ), and variance (σ^2) is shown in Table 5.

5. RESULTS

5.1 Experimental results

In this study, a five-layered neural network model, three hidden layers between the input layer and the output layer, has been used.
The performance of the training NN is shown in Figure 4, which indicates that global minimum of the mean square error is found at epoch 31 with best validation performance 0.000010705.

The correlation (R) in the three stages training, validation and testing are shown in Table 6. Figure 5 show the cross plot between predicated data and target data in each of these three stages.

Table 6: Correlation in The Three Stages (Training, Validation and Testing)

	R
Training	0.99683
Validation	0.9962
Testing	0.99705

According to these results, we implemented these NN to predict porosity in a blind well which gives correlation R=0.9847. Figure 6 presents comparison between measured and predicted porosity. MATLAB is used to confirm these results.

5.2 Comparison results

The accuracy of the proposed NN is very high compared to previous work as shown in Table 7.

Table 7: Comparison of Proposed System With Previous Work.

	R	Reference
Proposed (NN)	0.9847	
PEE	0.720	[18]
PNN	0.609	[19]
MLFN	0.554	[19]
RBFN	0.444	[19]

6. CONCLUSION AND FUTURE WORK

In this paper, a novel system based on a neural network has been applied to predicate porosity as reservoir characteristic in blind well.
proposed workflow aims to estimate porosity values from the 3d seismic and well log data taken from F3-block North Sea data. The study is based on two wells (F2–1 and F3–2) as inputs with seismic data to train and test NNs and use data from another well (F3–4) as blind well to estimate porosity.

From the analysis of the results of this work, we observed and conclude as follows :
Advantages

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- The superiority of the proposed model in its three stages training, validation and testing.
- The dependence on different types of seismic variables gives better results than determining a type or two as in previous studies.

Disadvantages

- Usually, relying on real data in these systems requires a lot of time and effort to train and test the efficiency of these systems. And that because of the scarcity of data.
- This system is applied in areas where wells have already been drilled. This disadvantage is common in many previous works

There are many possible directions in the future, we suggest as follows:

- To avoid the smallness of datasets in some area, the integration of data from different regions should be put under study.
- The possibility of using this system as a kernel for hybrid systems used to construct the porosity map of the area or to locate a new well.

7. ACKNOWLEDGEMENT

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Table 1.a. Partial Dataset.

Sample	X	Y	Z	MD	PI	S	E	IF	IP
1	606552.285	6080128.815	0.861	857.27	4882680	0.938	5468677.5	63.874	1.368
2	606552.285	6080128.815	0.862	858.27	4833530	0.938	5394494.0	65.779	0.276
3	606552.285	6080128.815	0.862	859.27	4757310	0.937	5324762.0	66.832	-0.841
4	606552.285	6080128.815	0.863	860.27	4847500	0.937	5271615.5	66.919	-1.828

Table 4.b. Partial Dataset.

Sample	IA	IA_2ndD	Cos_IP	EWP	EWF	BW	AF	SD	MAX_SA	Porosity
1	2045.257	47128108	-0.746	0.525	55.951	12.238	48.307	13662.334	1275825200	0.332
2	1910.794	48763200	-0.757	0.362	57.384	9.360	48.108	13286.298	1216593400	0.331
3	1826.866	48101028	-0.703	0.188	58.403	6.522	47.941	12759.106	1162893400	0.337
4	1798.725	44963976	-0.585	0.016	58.898	4.112	47.822	12102.517	1118147600	0.335

Table 2 Descriptive Statistical Analysis of The Integrated Data.

	µ	Med	Min	Max	σ	σ^2
X	612886.1643	619095.311	606552.3	619120.9993	6272.224027	39340794.25
Y	6084846.092	6089482.689	6080104	6089507.678	4685.71743	21955947.83
Z	0.812449906	0.81849325	0.5	1.09939885	0.172334209	0.029699079
MD	814.9243506	815.0499878	493.05	1140.050049	185.525254	34419.61988
PI	4650809.899	4724150	2853580	5870370	550686.9151	3.0325E+11
S	0.899498311	0.90341544	0.792959	0.95573896	0.032608933	0.001063343
E	4768576.628	3629388	335757.9	16897086	3817818.923	1.4575E+13
IF	48.19308593	44.6967659	-3.11285	134.9695129	25.47731772	649.0937181
IP	-0.0626432	-0.02090457	-3.44703	3.72124434	1.71911703	2.955363362
IA	2514.748049	2013.351563	50.87183	11063.44336	1798.402106	3234250.133
IA_2ndD	384808.9995	165401	-1.4E+08	140330540	36998610.13	1.37E+15
Cos_IP	-0.0352006	-0.05950966	-1.03202	1.04450524	0.683073991	0.466590077
EWP	-0.0421417	0.00485405	-3.13723	2.82056665	1.185309279	1.404958087
EWF	45.15737692	45.09309387	3.780361	119.4358902	16.14661018	260.7130204
BW	12.79139868	9.99038029	-0.51094	77.88677216	10.38622726	107.8737166
AF	44.3233212	45.67515182	25.32577	63.09466553	7.235100213	52.34667509
SD	16421.09378	13998.72656	459.6632	66217.39063	10829.0001	117267243.2
MAX_SA	922673447.7	604372670	21662474	4418341900	816019504.2	6.66E+17
Porosity	0.323690289	0.31736666	0.231135	0.45453292	0.037632798	0.001416227

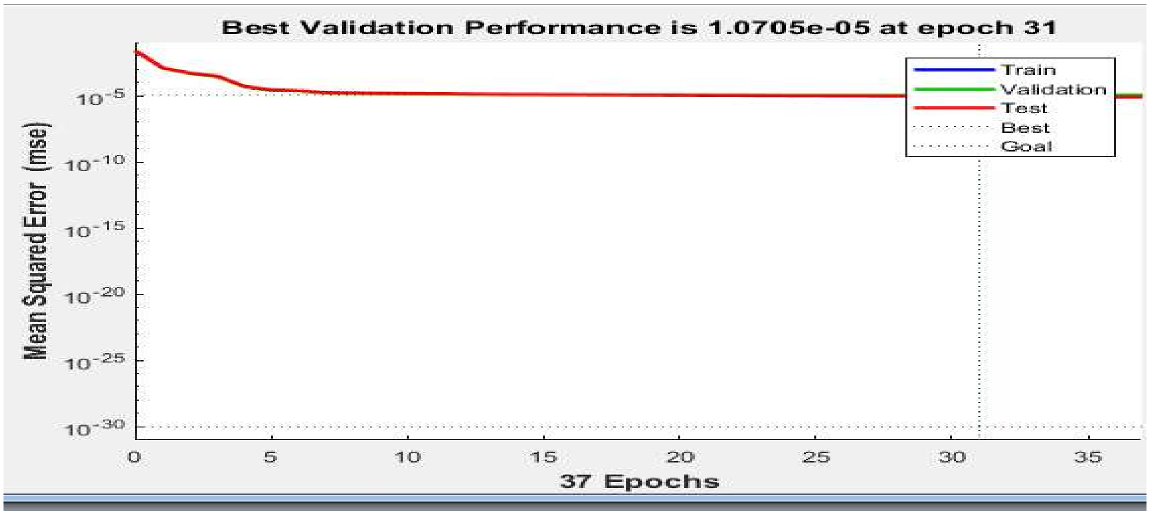

Figure 4: Performance of The Neural Network.

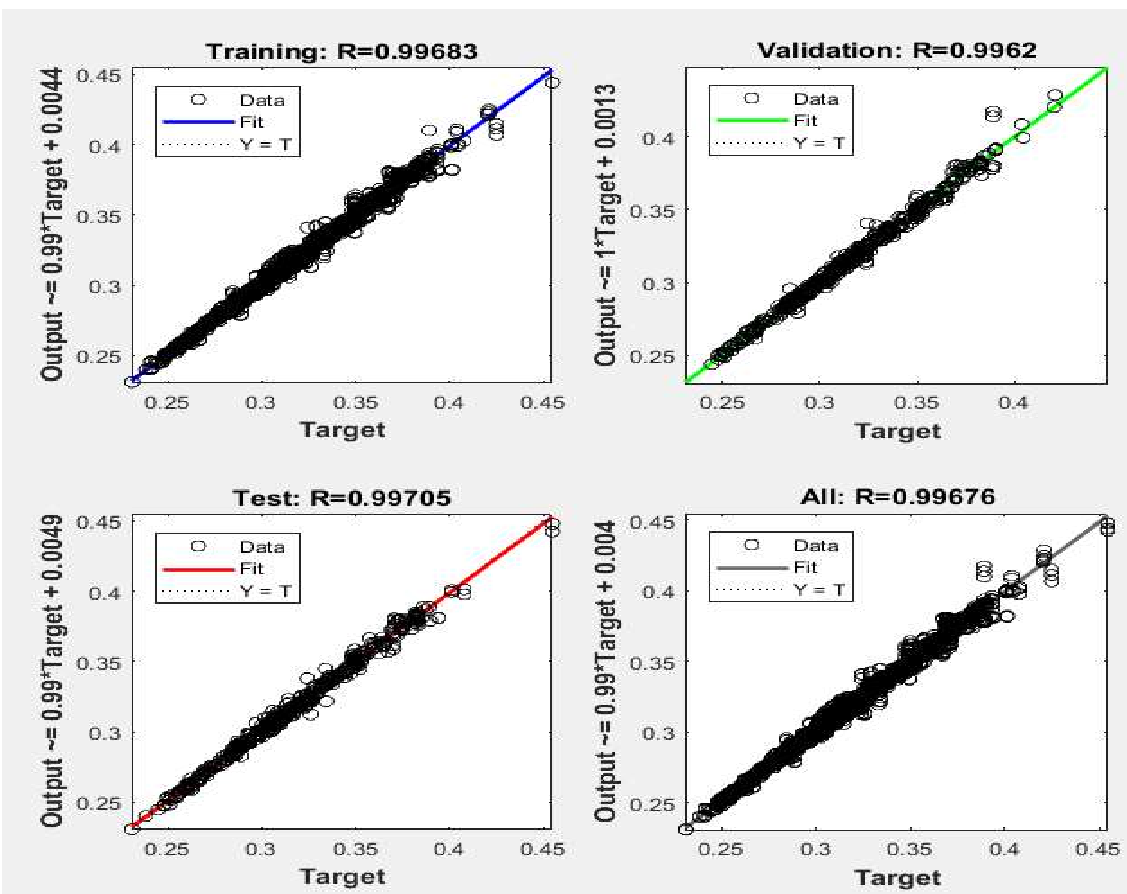

Figure 5: The Cross Plot Between Predicated Data and Target Data in The Three Stages Training, Validation and Testing.

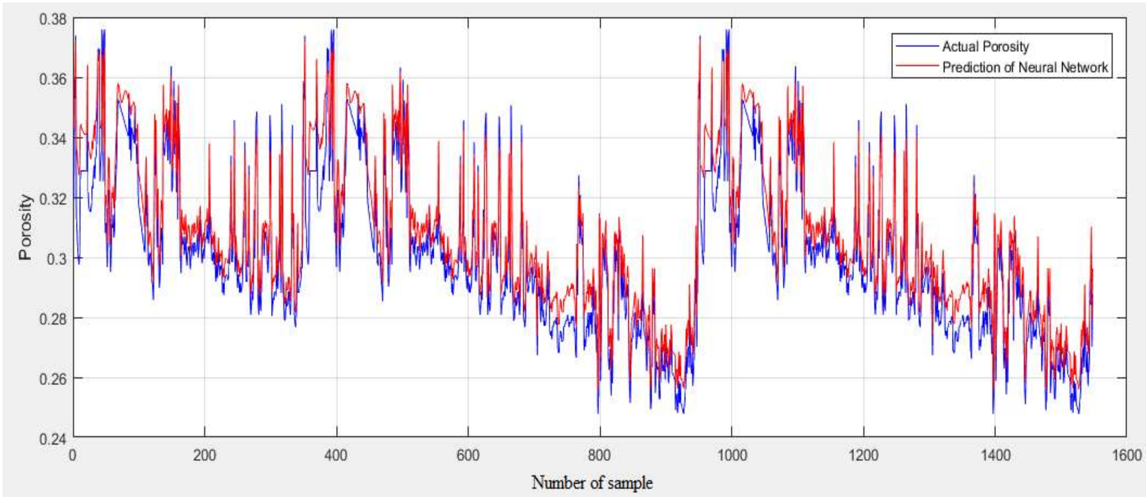

Figure 6: Comparison Between Measured and Predicted Porosity.