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*Full Length Research Paper*

# Prediction of permeability from reservoir main properties using neural network

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**Prediction on permeability is an essential task in reservoir engineering as it has great influences on oil and gas production, while porous media grain size, sorting, cementing, porosity, specific surface area, direction and location of grain and irreduction water saturation have effects on permeability. In this project we studied the effect of porosity, specific surface area and irreduction water saturation as main parameters on permeability distribution in the reservoir; the main goal of this research was permeability prediction in carbonat reservoir using neural network approach. Our studies showed a good agreement between our neural network model prediction and lab data or core analysis. This approach can be a useful tool for prediction permeability when core tests are not available.**

**Key words:** Permeability prediction, neural network, specific surface area, irreducible water saturation, porosity.

## INTRODUCTION

It is well known in reservoir engineering that there is a powerful relation between permeability and effective porosity (Dullien, 1991). Porous media are permeable only when the pores are interconnected, and the interconnection shape and frequencies make difficult to estimate the permeability as function of porosity. Also, it should be noted that permeability is a rock dynamic property and porosity is a rock static property, hence it seems that this relation is complex. Many researchers focused on this subject. Kozeny and Carman (1927) proposed different correlations between permeable and porosity. Panda and Lake (1994) on the basis of grain size and unconsolidated porous media modified the Kozeny Carman equations and considered the grain size effects. As mentioned, in most of these researches, the effects of only one or two parameters on permeability were experimentally considered. It seems that the complexity of permeability prediction needs new approach to consider the influences of more parameters. (Koponen and et al, 1997; Babadagli and Al-salmi, 2004). New intelligent methods, such as a powerful tool, were used for this purpose. In this paper, we present a suitable artificial neural network model that enables us to predict permeability from porosity and other main reservoir parameters with the lowest error. Usually in the oil industry, to determine the permeability of the direct methods (cores and well tests) and indirect (graphical petrophysical evaluation) are used. Since the oil fields of 'petrography' and sedimentation are heterogeneous and with their subtleties, for more accurate determination of reservoir permeability must be prepared cores from wells that by attention to the vast majority of field and multiplicity of wells, such a method that cost and time would be great. Also determine of this parameter with helping of well test due to high spending and halt production during the experiment is not very cost effective (Nelson, 1994). Error back-propagation artificial neural networks is one of the new methods, inexpensive

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and accurate that by using of graphical petrophysical parameters can determine permeability in the least time possible. These networks, biological neural network model can be put so much; these have high power in the learning process and desired and output and inputs have to adapt.

By using these methods, we can have an accurate estimation of petrophysical permeability in wells that their permeability for whatever reason (not cores, the fracture of samples, etc.) are not possible. Achieving this goal is difficult, because a log that can directly measure permeability in a well has not been developed. Artificial neural network (ANN) is an information processing system that performs its duties and acts like a neural network in the body of humans. Neural networks, as generalized mathematical models of the human mind and perception, are based on assumptions that are divided into the following:

1) Processing is doing in ‘simple’ units called neurons.
2) Signals pass through connections between neurons.
3) Each communication connection has self specific gravity that a neural network will multiply this weight at signal transmission.
4) Each neuron is a function (usually nonlinear) on the inputs used to close until obtaining the desired output.

These networks are included several simple elements (such as neurons, dendrite). Each neuron has input (Ii) that is multiplied by its own weight (Wi) and each artificial neuron can be a lot of input while only one is output. These inputs are added together and then transferred to the active network and the output is achieved. The error will be returned back to the network and again the weights to reduce error; they adapted to their new circumstances. To reduce errors and to reach the desired output, training process is repeated several times because until we reach the ultimate goal. To determine the number of neurons and the middle layer, there is no law but increase or decrease in each of them has an important contribution in learning process of network. Therefore, determining of them must changed number of them in each iteration of the learning process of network until it gets the best results. These networks have two advantages:

1) Received more than one type of input (a variety of graphic related to permeability).
2) A mathematical model for determining the permeability of the reservoir and graphical input to the network.

We use our developed model to predict permeability in carbonate reservoirs. More than 160 different sets of core analysis data will be discussed in more details.

## DATA DESCRIPTION

As discussed before, irreducible water saturation porosity and specific surface area have main effects on permeability in carbonate reservoirs. Data that we used in this article is from zone 3 of the parsi oil field that this zone was composed of limestone and shale and than the other zones has fewer shale components and has good porosity. 2 units of shale is detected in this zone, the thickness of them is between 1 to 2 m. Average stratigraphic thickness of this zone is 66 m, the average porosity of net thickness is 11/8%, water saturation is 23% and net to gross ratio is 0. 6. In this study, while we used from parameters of the porosity, specific surface area and irreducible water saturation as an input of network that is based on previous study to obtain the permeability from characteristics of the rock pores and grains such as grain size, sorting coefficient, tortuosity…. more accurately calculated but for this reason we chose these data as the input network that each of the input parameters have direct contact with the granular rocks; for example irreducible water saturation has direct contact with pore size, pore space or specific surface area has contact with pore-channel tortuosity. To develop the model, 166 set of data were used. 114 sets were used to train the network and the other data used to test it. It is possible to predict the permeability and study the relation between each of the mentioned parameters and permeability by our developed model. For example the model shows that amount of permeability increased by increasing porosity (Figure 1), decreasing irreducible water saturation or specific surface area increased permeability (Figures 2 and 3).

## RESULTS AND DISCUSSION

The purpose of utilizing artificial neural network is to solving this problem and to find relation between input and output data, until we find this relation and save it finds weights network synapse universalization authority. In this search for prediction permeability using from this network, network design for prediction permeability, a network MLP with a hidden layer and function hyperbolic tangent and a function linear transfer in output layer. The first layer have major role in extracting of main particulars and other secondary layer try to extract secondary in particular. Neurons are used for determination of its output from transition function. Famous of this transition function can reference to tan sigmoid and pure line and hyperbolic function that each other of them to apply with due attention to problem. The artificial neural network with due attention to structure that explained them to enable learning each linear and nonlinear correlation between input and output data in encountering with data that has not been seen beforehand, having presented answer acceptable. Recommend structure of network for solving this problem has 6 input, an output and a hidden layer (Figure 4). The optimum number of neurons in middle layer after of test chose network prediction that 7, 11, 13 and 18 neuron. By comparison regression constant, $R^2$ amount of neurons 13 and 18 shown in hidden layer convergent is minimized. In addition to

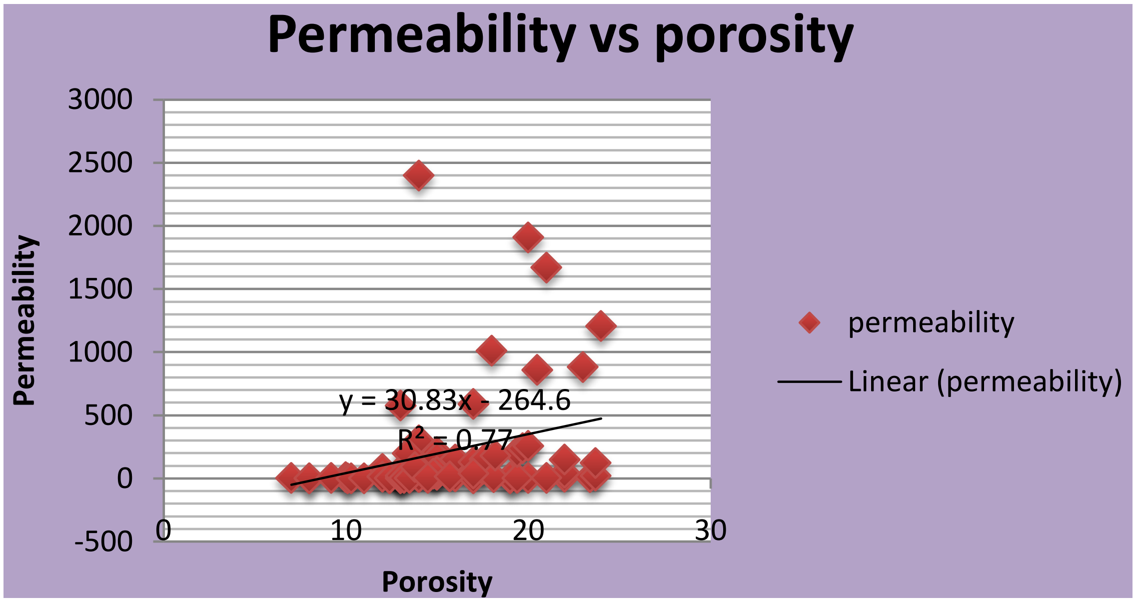


**Figure 1.** Comparison of actual permeability and porosity data (field).

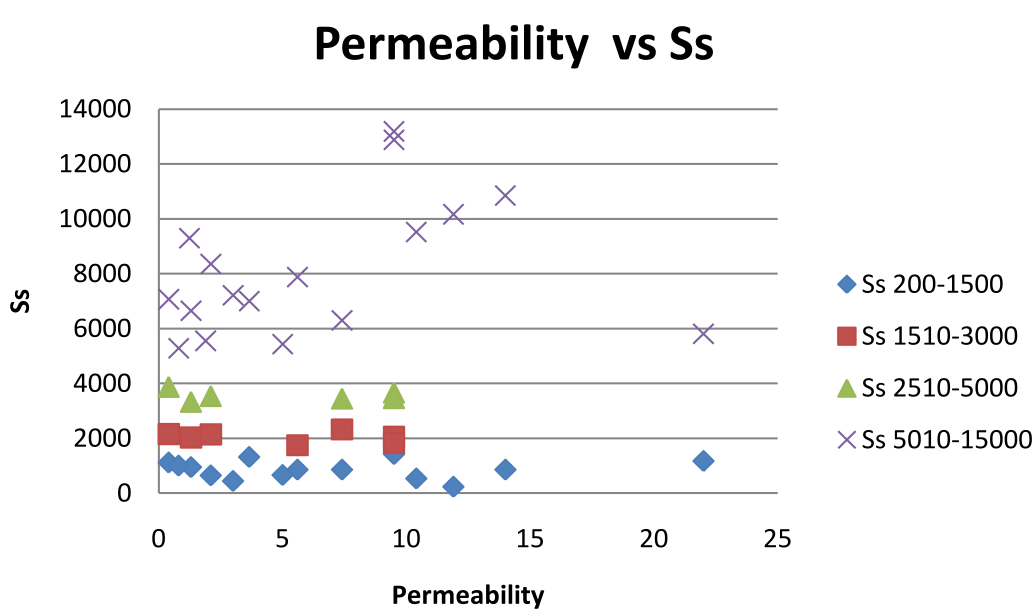


**Figure 2.** Comparison of actual permeability and specific surface area (field).

negative effect prediction to observe in this two items or case effective prediction by using of 11 number neuron in hidden layer showed the highest $R^2$ (Figure 5). Comparison between graph production of data permeability on wellhead and prediction that by network in durance period training that include 114 data with range permeability between 0.8 until 2224 md shows that result of training has fit very extremely with real data that showing recommend model has authority to give a relation between input and output parameters (Figure 6).

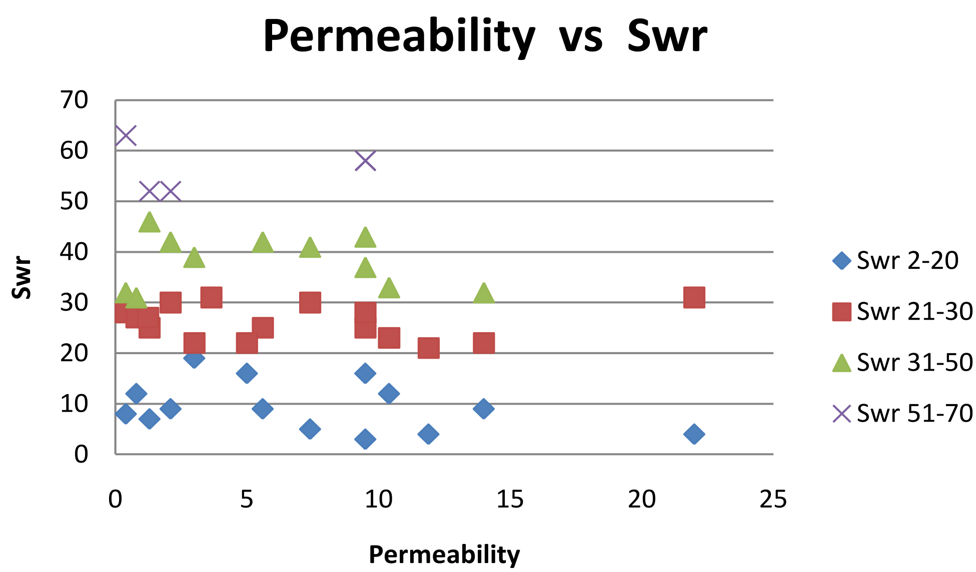


**Figure 3.** Comparison of actual permeability and irreducible water saturation (field).

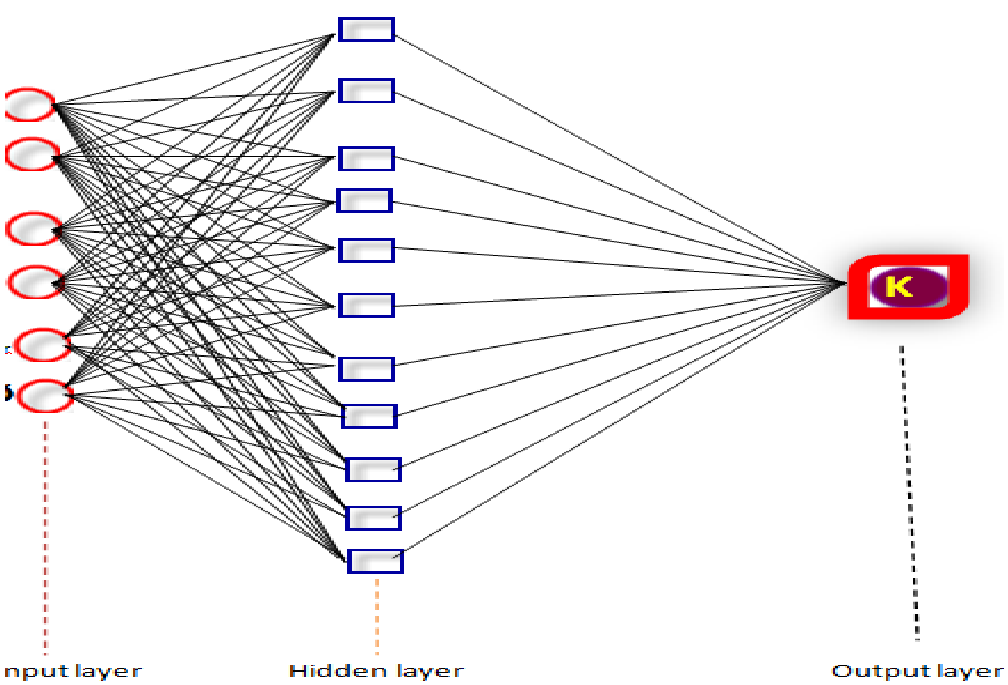


**Figure 4.** Structure of network for solving this problem.

In this study to predict of permeability, two data sets have been used for network training and testing. Proper network design in order to discover the relationship between input and output and provide an answer with the least error of the objectives of this investigation. Since the neural network performance depends on various parameters such as the transmission type, number of layers, learning algorithm, the number of neurons and the

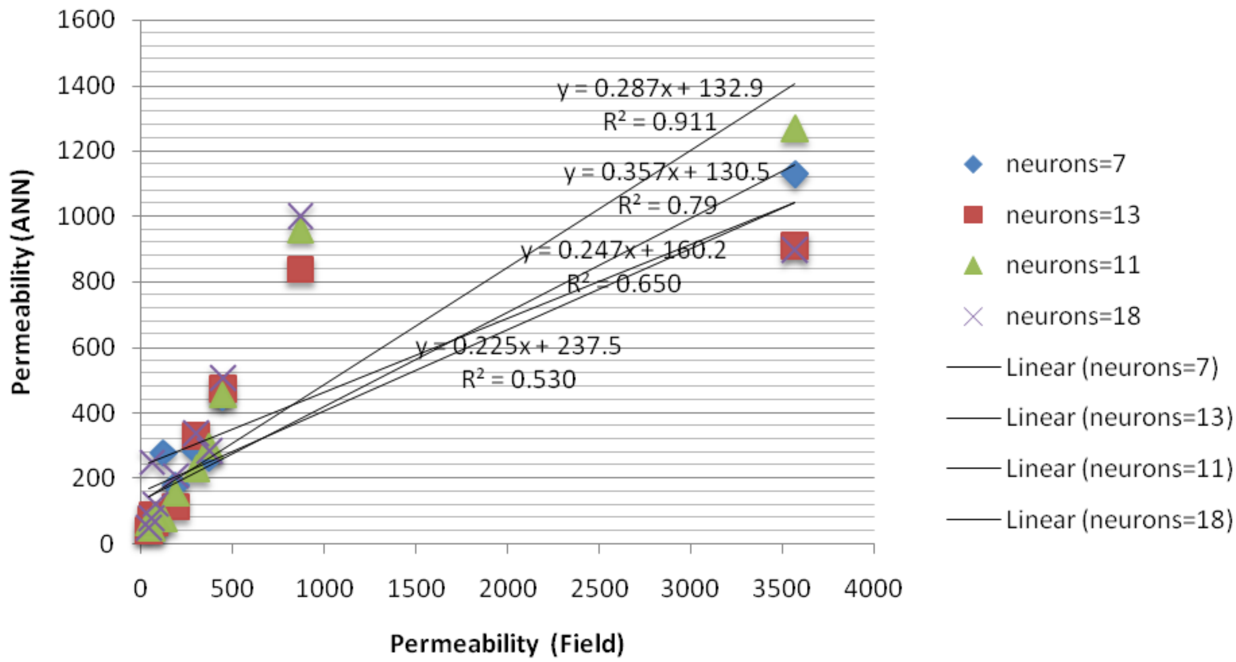


**Figure 5.** Comparison regression constant $R^2$ amount of neurons 7, 11, 13 and 18.

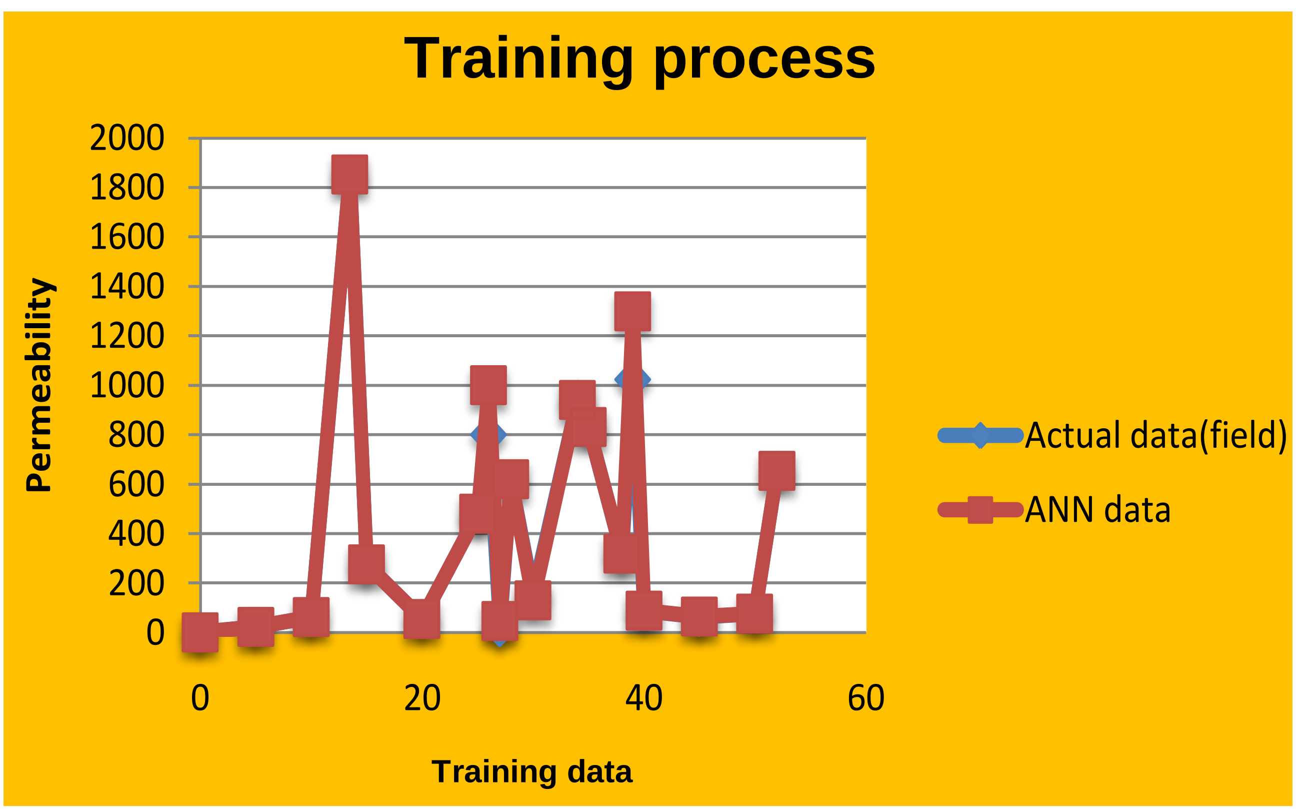


**Figure 6.** Comparison between graph produce of data permeability in lab and prediction by ANN in training process.

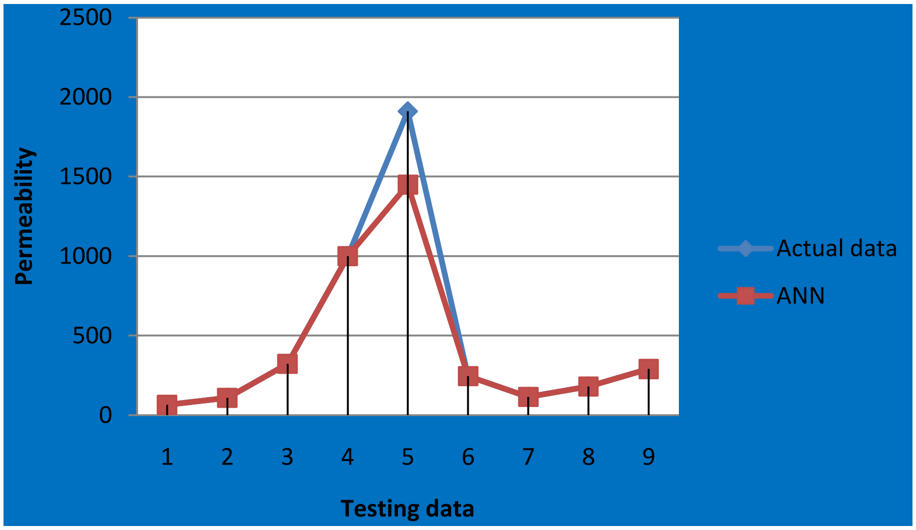


**Figure 7.** Comparison between graph produce of data permeability in lab and prediction by ANN in testing process.

**Table 1.** Field data has been selected to comply with the network permeability.

| Number of data | Swr (%) | Ø (%) | Ss ($cm^2/cm^3$) | K (md) |
|---|---|---|---|---|
| 1 | 12 | 12 | 1113 | 261 |
| 2 | 22 | 17 | 1316 | 420 |
| 3 | 31 | 11 | 5810 | 95 |

normalization methods in this article has attempted to determine the optimal parameters. All 166 data is divided to two sets of training data (54 data) and testing (114 data). Comparison between plots of ANN permeability data and laboratory data in the test process, a complete agreement is observed except in the fifth set of data that in this set of data, ANN is calculated as 1450 md instead of the actual permeability of it that in 1910 md for 20% porosity, 4% irreducible water saturation and 441 $cm^2/cm^3$ of specific surface area (Figure 7).

In order to perfectly ensure from results obtained of the testing process of network, (Table 1) we have examined 3 sets of field data with the permeability of the networks for compliance that these data include the following: as shown in Figure 8, it can be seen that in each of the three sets of field, data was selected randomly in different porosity; there exists perfect match between the permeability of the network and field data. Gaussian and linear normalization methods including methods that are used in this study. Gaussian normalization offers a minor error lower than the linear method for permeability. Because in this study used from permeability data, we require two different networks to discover the hidden knowledge of the data to provide a good answer. By using of the Gaussian method, it can be expressed a good correlation between learning and testing data as shown in Figure 9. To indicate the degree of match between the permeability of the Gaussian method and field data, we have compared 65 sets of data as shown in Figure 10. However, when the network is designed for permeability, Gaussian normalization method used gives an error equivalent to 1.7%. While this network if using style normal linear, error equally is 3% for learning data shown in Table 2. While that error of network for testing data is equal to 7%, steps to obtain the errors are shown in Table 4. Here, we want to compare the results of the general regression neural network (GRNN) with ANN. The main difference between these two methods is that the objective function of GRNN is not related to its internal structure and this model will be considered some aspects of non-linear of the problem to predict and it cannot ignore unrelated inputs without major

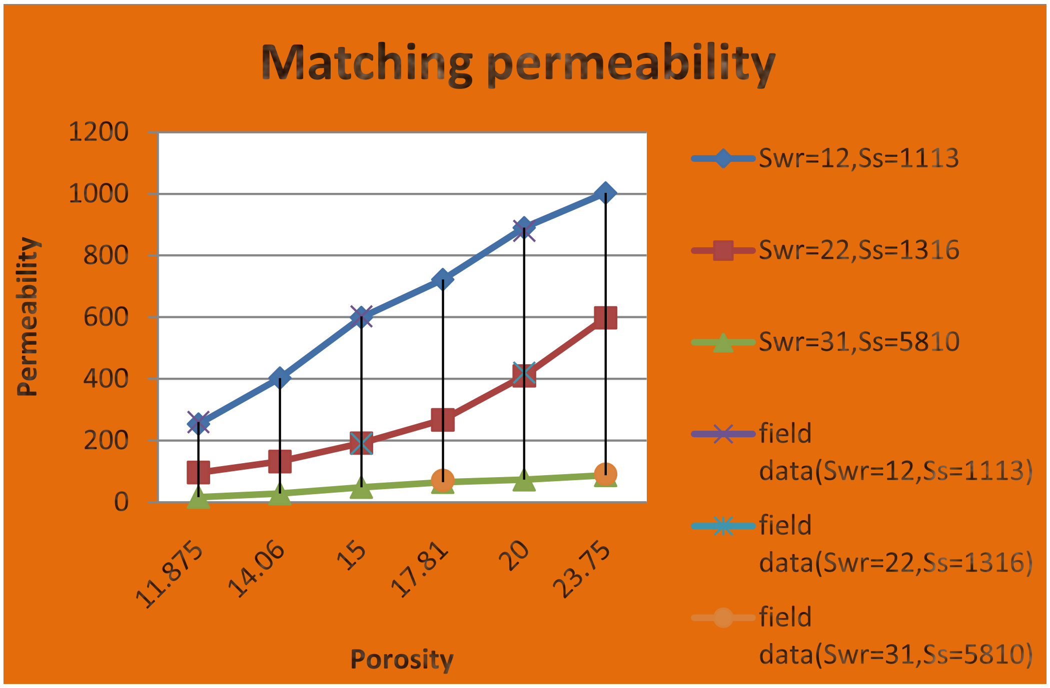


**Figure 8.** Matching field data with network data in testing process.

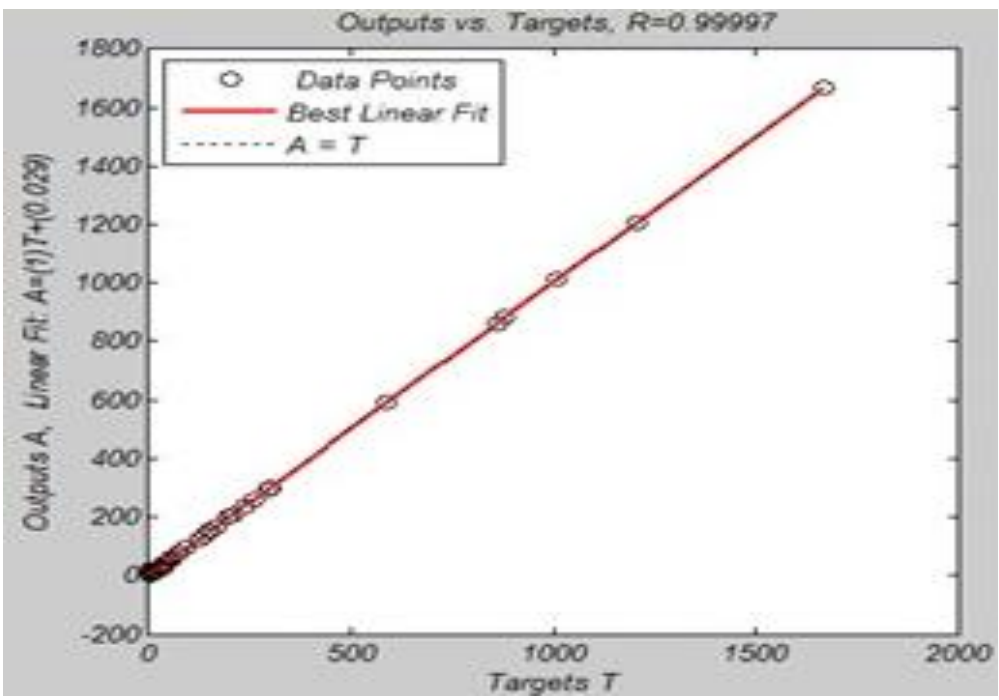


**Figure 9.** Agreement of data examined in lab with network output in Gaussian style.

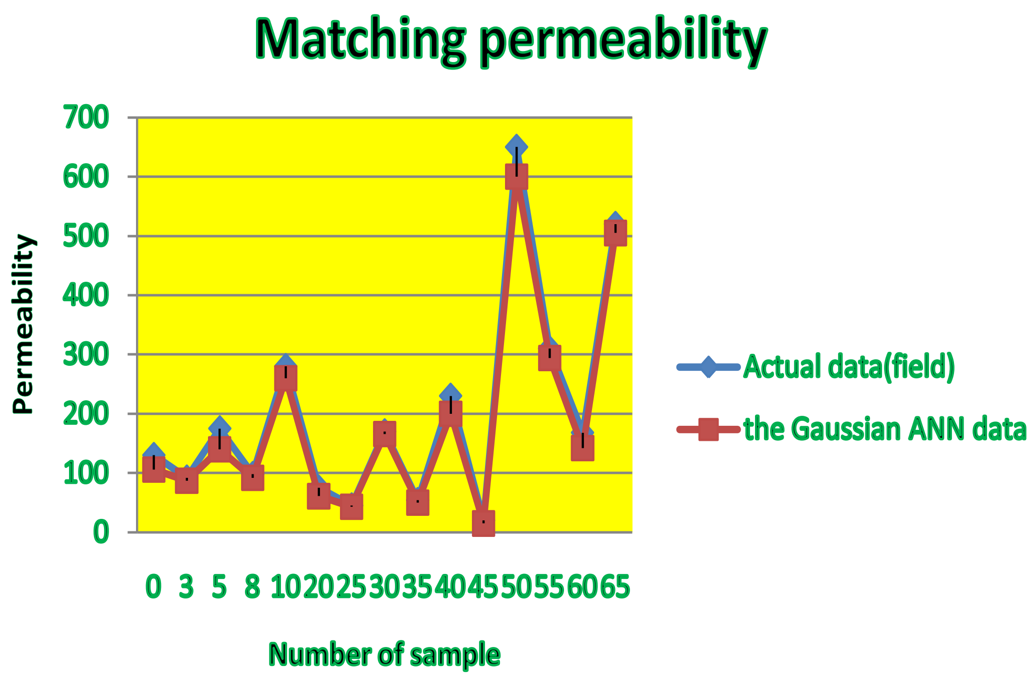


**Figure 10.** Comparing between permeability produced of Gaussian method examined in lab.

**Table 2.** Comparing between results of 2 style normalizing.

| Learning function | Automated regularization | | |
|---|---|---|---|
| Style of normaling | Linear | | Gaussian |
| A set of testing data | Porosity<br>20 | $S_{wr}$<br>4 | Specific surface<br>441 |
| Absolute error | 3 (%) | | 1.70 (%) |
| Optimum permeability | 1910 | | 1986 |

modifications in the original algorithm. In order of comparison between these (GRNN and ANN), need to be factors that are shared in any way. The first factor include: mean squared error index (MSE), the index acquired sum of square, the error difference divided by the period and the second index is mean absolute percentage error (MAPE), an index that is useful when calculating the prediction error of 'percental' is used of this index. The third index is 'coefficient of determination' ($R^2$), the most important criterion is that it can explain the relationship between two variables. If we want to explain general regression neural network model used in this study briefly, it can be stated that we consider six variables as inputs and permeability as outputs and the amount of spread = 0.81 because if the spread was larger than 1 that fit over the network and lead to greater regional mapping of input to specific output is given.

In contrast to the slight of it is increased forecast error. The design of a general regression neural network, three layers used six neurons in input layer and fourteen neurons in the middle layer and one neuron in output layer. To obtain the GRNN network model, we perform two methods. One of them to obtain a model that is untrained and has a real error that this model includes:

**Table 3.** Comparing between results of GRNN and ANN.

| Network | MSE | MAPE | $R^2$ |
|---|---|---|---|
| GRNN | 29.4 | 1.605 | 0.986 |
| ANN | 36.95 | 3.21 | 0.99 |

**Table 4.** Steps to obtain error by ANN.

| | |
|---|---|
| TRAINLM-calcjx, Epoch 0/350, MSE 0.248179/1e-007, Gradient 2.58192/1e-010. | TRAINLM-calcjx, Epoch 200/350, MSE 4.02255e-007/1e-007, Gradient 0.000364982/1e-010. |
| TRAINLM-calcjx, Epoch 25/350, MSE 4.94889e-006/1e-007, Gradient 0.000167163/1e-010. | TRAINLM-calcjx, Epoch 220/350, MSE 9.52351e-008/1e-007, Gradient 0.000108648/1e-010. |
| TRAINLM-calcjx, Epoch 50/350, MSE 3.29588e-006/1e-007, Gradient 2.0215e-005/1e-010. | TRAINLM, Performance goal met. h = 0.0035, 0.0043, 0.0043, 0.2519, 0.2597, 0.3659 and 0.3987. |
| TRAINLM-calcjx, Epoch 75/350, MSE 2.60616e-006/1e-007, Gradient 6.96934e-005/1e-010. | h = 0.4748, 0.4753, 0.4794, 0.4796, 0.4819, 0.4831 and 0.5233. |
| TRAINLM-calcjx, Epoch 100/350, MSE 1.96494e-006/1e-007, Gradient 0.000552866/1e-010. | h = 0.5600, 0.6651, 0.6651, 0.8320, 0.8703, 0.8734 and 0.9550. |
| TRAINLM-calcjx, Epoch 125/350, MSE 1.63346e-006/1e-007, Gradient 9.35495e-005/1e-010. | h = 0.9862, 0.9862, 0.9913, 0.9974, 0.9983, 1.0007, 1.0016. |
| TRAINLM-calcjx, Epoch 150/350, MSE 1.4545e-006/1e-007, Gradient 6.77509e-005/1e-010. | h = 1.0038, 1.1971, 1.2289, 1.2354 and 1.2396. |
| TRAINLM-calcjx, Epoch 175/350, MSE 1.02631e-006/1e-007, Gradient 0.000108092/1e-010. | Total = 3.7565 and 7.0971 |

$$y = -4.43 + 7.219x_1 + 2.008x_2 + 5.802x_3 - 0.000249x_4 - 0.586x_5 + 0.911x_6$$

$X_1 = Ø$, $x_2 = Ss$, $x_3 = S_{wr}$, $x_4 = S_s*Ø$, $x_5 = S_s*S_{wr}$, $x_6 = S_{wr}*Ø$

The second model is the model that learning algorithm applies; the first model that caused the error is minimal; this model includes:

$$y = -13.198 + 9.616x_1 + 3.7005x_2 + 6.706x_3 - 0.0000872x_4 - 0.3309x_5 + 0.7065x_6$$

The results of GRNN and ANN are compared in Table 3 that can be seen that GRNN method in predicting than the ANN method has been much stronger because it will run parallel and are more fault tolerant.

## Conclusion

Since the permeability is one of the very important parameters of reservoir, its calculation in the design and production process is very important. Accurately determine and correct the permeability in wells that measurements are not possible for any reason (no core, fractures in the samples….), this makes it difficult to reach target because log cannot be achieved permeability directly and also be time consuming and costs a lot of other reasons for the lack of accurate estimates of permeability. In this study, we used ANN and GRNN to obtained permeability with regard to minimum parameters such as porosity, specific surface area, irreducible water saturation that these ways estimate fairly reasonable of permeability that in between, GRNN gives better results than ANN. It is worth mentioning that from neural network, it is used in reservoirs that terms of the properties of the rock face with minimal changes that they can be used regardless of conditions of all the wells. In reservoirs that are heterogeneous and their basins is sedimentary, such a reservoir that we have studied, neural networks have the best predictions but in non-sedimentary reservoirs and salt, this network is not able to predict. According to the results of GRNN and ANN, GRNN network has lower error rate and more accurate forecasts of permeability. With testing, the results of it on other wells would provide an acceptable result that the correlation coefficient is equal to 0.79. As suggested, there are other ways to achieve permeability for example, data that is obtained from well log data include porosity logs (neutron, density and sound), and resistivity logs, logs and caliper logs GR.

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