

## Application of Neural Network in the Identification of the Cumulative Production from AB unit in Main pays Reservoir of South Rumaila Oil Field.

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### Abstract

*A common field development task is the object of the present research by specifying the best location of new horizontal re-entry wells within AB unit of South Rumaila Oil Field. One of the key parameters in the success of a new well is the well location in the reservoir, especially when there are several wells are planned to be drilled from the existing wells. This paper demonstrates an application of neural network with reservoir simulation technique as decision tool. A fully trained predictive artificial feed forward neural network (FFNNW) with efficient selection of horizontal re-entry wells location in AB unit has been carried out with maintaining a reasonable accuracy. Sets of available input data were collected from the exploited grids and used in the training and testing of the used network.*

*A comparison between the calculated and observed cumulative oil production has been carried out through the testing steps of the constructed ANN, an absolute average percentage error of the used network was reached to 4.044%, and this is consider to be an acceptable limit within engineering applications, in addition to that, a good behavior was reached with (FFNNW) and suitable re-entry wells location were identified according to the reservoir configuration (pressure and saturation distribution) output from SRF simulation model at the end of 2005.*

**Keywords:** Horizontal re-entry well, neural network application, Cumulative production.

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### Introduction

The need of reservoir quantification and development can be achieved by more accurately reservoir performance with rigorous and complex full field reservoir models that is become basic requirement. Increasing of understanding and certainty of the information derived from advanced field scale simulation contributes the decision process reliability in comparison to the large capital expenditures required for the reservoir developments.

A variety of development options are under consideration by the Reservoirs and Field Development Directorate in South Oil Company that planning to execute. One of these development planning is to introduce a proposing

horizontal re-entry wells in AB production unit in the main pay reservoir. But before introducing the suggested wells, a full field reservoir study (1) has been carried out by constructed a SRF simulation model by using of simbest II simulator, that covered the time period spanned from 1954 to the end of 2005 according to the available information comprising all of the important data that related to the history matching of the concerning reservoir. The most important outputs for our reservoir unit concern are both of the pressure and saturation grid distribution for AB unit. Figures (1-2) show these output maps, and then a feed forward neural network has been used as decision making tool to investigate how much cumulative oil production can be gained from

unexploited AB grid unit, then inspect their adaptability with introducing re-entry horizontal well. Figures (3-4) present these elected and unexploited grid areas.

### **Review of the Field concern**

The Rumaila oil field is located in south of Iraq, 50 km west of Basra and 30 km to the west of the Zubair field. The northern part of the Rumaila is a marsh land and it plunges gradually below Hor Al-Hammar Lake. The South Rumaila oil field Extended from the south of the North Rumaila oil field to the southern boarder of Iraq. The dimensions of South Rumaila oil field are about 38 Km long and 14 Km a wide. The field is associated with large gentle anticline fold of submeridional trend; dip angles on the flanks do not exceed 3° whereas in the crestal parts they are about 1°. Figure (5) shows the geographical location of the Rumaila field.

Rumaila structure is consisting of three domes namely Southern, Northern domes. They are separated by small structural saddles. Accordingly, the field which is geologically and hydrodynamically uniform is subdivided into two parts, namely North Rumaila and South Rumaila. The South Rumaila oil field / Main pay reservoir is mainly composed of sandstone with some of the interbedded shale and siltstone. In general, the reservoir has very good properties.

Also the main pay consists of five production units according to the differences between the porosity and the permeability. Geographical and petrophysical description of these production units are presented in the reference (1). The South Rumaila field is surrounded by a large aquifer (2) and the predominate production driving force is the natural water drive which is very active as driving force and contribute to 90% of the production.

### **Neural Network Application**

Inspection, identification and prediction reservoir characteristics are the main application of ANN in petroleum engineering in addition to another application (3,4). The present research deals with the ANN as a decision tool when prediction cumulative oil production. The property of a reservoir is controlled by many non-linear parameters. A reservoir is usually made up of layered sedimentary rocks, which were defined after a long period of sedimentation and millions of years of diagenesis as well as structural evolution. These sedimentation, diagenesis and structural evolution processes are dominated by a series of nonlinear time-varying dynamic systems existing in the geological history. Each layer or zone in a layered reservoir, corresponding to a particular geological period in the geological history, is usually controlled simultaneously by more than one non-linear dynamic system (time varying or time invariant) which have quite different controlling parameters from those for another layer or zone.

In addition to the geologic parameters (5), reservoir modeling and characterization always involve a high degree of uncertainty due to the following factors:

1. Experimental errors resulted from different procedures or the equipment used
2. Lack of information
3. Disagreement between experts
4. Poor identification of the model attributes
5. Inappropriate definitions of the problem and their domain
6. Errors involved in the translation from natural language to a formal or machine language.

Because of these factors, a powerful tool is required to deal with the fuzziness, incompleteness, poorly defined nonlinear systems, and uncertainties that exist in reservoir studies. Neural networks are well suited for these problems.

According to Jacek M. Zurada (1992) (6), ANNs have essential qualities in:

- Learning
- Association ability
- Real-time capability
- Self-organization
- Robustness against noise
- Ability to generalize.

In the present research, the above qualities were reflected by the results of the testing and simulation steps, where a noise data were used and recognized by the neural. Thus it seems that neural networks are quite suitable to solve reservoir problems.

The application of neural networks to reservoir studies (7) has become a hot topic in today's oil and gas industry. In recent years, ANNs have been successfully used in various aspects of reservoir studies, such as geology, geophysics, drilling and completion, formation evaluation, production and simulation and reservoir engineering (8-11).

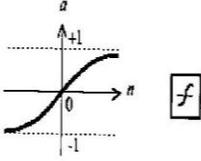
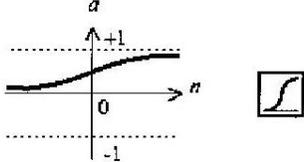
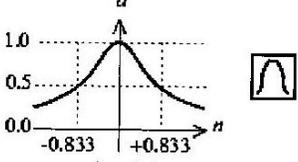
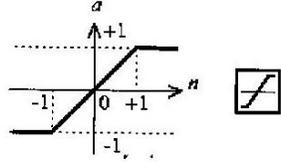
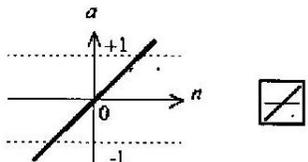
ANN are developed by creating artificial neurons, which are simple processing elements (PE) massively interconnected in order to mimic a small portion of the serial- and parallel-information processing ability of the biological neural network. There are many different types of ANN, each of which has different strengths particular to its applications. The abilities of different networks can be related to their structure, dynamics, and learning methods. ANN can be used for pattern recognition, signal filtering, data segmentation, and so on. They offer the advantages of learning from examples, self-organization, fast data processing and ease of insertion into existing and newly developed systems.

ANN provides a powerful tool to perform nonlinear, multidimensional interpolations. This feature of ANN makes it possible to capture the existing nonlinear

relationships that are most of the time not well understood between the input and output parameters. Thus ANN can be effectively used to implicitly incorporate the controlling mechanisms and parameters into the models which are developed for.

Usually, the activation functions of the nodes at each layer are the same. The input layer activation function is usually the identity function, while the hidden layer activation function is usually non-linear for non-linear systems and that of the output layer may be linear or non-linear. The following are briefly description of the some of activation function that are using within neural networks ( 12 )

The multilayer FFNNW (12) is an important ANN architecture. Typically, this network consists of an input layer, one or more hidden layers and one output layer Figure (6) shows the schematic at each node, a function (activation function) is applied to the node input.

Function Name	Diagram	Mathematical Expression
1- Tan sigmoid	 <p style="text-align: center;"><math>a = \text{tansig}(n)</math></p>	$\text{Tansig}(n) = \frac{2}{(1 + \exp^{-2n}) - 1}$
2- Log sigmoid	 <p style="text-align: center;"><math>a = \text{logsig}(n)</math></p> <p style="text-align: center;">Log-Sigmoid Transfer Function</p>	$\text{Logsig}(n) = \frac{1}{(1 + \text{Exp}^{-n})}$
3- Radial basis	 <p style="text-align: center;"><math>a = \text{radbas}(n)</math></p> <p style="text-align: center;">Radial Basis Function</p>	$\text{Rad bas}(n) = \left( \text{Exp}^{-n^2} \right)$
4- Sat lines	 <p style="text-align: center;"><math>a = \text{satlins}(n)</math></p> <p style="text-align: center;">Satlins Transfer Function</p>	$\text{Satlins}(n) = \begin{cases} -1 & \text{if } n < -1 \\ 1 & \text{if } n > 1 \\ n & -1 \leq n \leq 1 \end{cases}$
5- Pure Line	 <p style="text-align: center;"><math>a = \text{purelin}(n)</math></p> <p style="text-align: center;">Linear Transfer Function</p>	$\text{Purelin}(n) = n$

A frequently used network is the multi-layer feed forward network that is trained by the back-propagation (BP) learning algorithm, which is extensively used in this work. BP networks typically operate in two modes, a learning mode and a testing mode. In the learning or training mode, ANN modifies its internal representation by changing the values of its weights in an attempt to improve the required outputs. In the testing or recall mode, the network is fed new inputs and utilizes the representation it had previously learned to generate associated outputs without changing the values of its weights. If this is done properly, superior performance and more accurate forecasts can be achieved over rule based technical analysis methods.

**Used of ANN to Identify Cumulative Production.**The neural network used in this research is the standard back propagation feed forward neural network (FFNNW) that was developed through the back propagation training algorithm which allow the ANN to learn it by its self according to the input data sets of input and output results. This kind of networks classified as supervised network that required training data sets with known inputs and outputs.

The used ANN was developed through the back propagation training of feed forward neural network, which allow the ANN to predict the cumulative production for AB unit grids that were un exploited (virgin grids). Once the network has learned by exposed it to such information in the training phase, a testing phase has been applied to the network for verification which coverage a range of input data sets of input parameters with different variety from training range. It is important to note that although the user has the desired output of the test set; it has seen by the network with some of difference. This ensures the integrity and robustness of the trained network.

The first step of applying the neural network is how to process the input data sets by coding them, because of their variety in values range. Inorder to prevent the noise effect that disturbs the learning of the network or it may prevent the network to reach its goal at all.

The second step is the training network inorder to help the network to adjust the weights among it's neurons or processing elements (supervised training), section A of table (1) presents input data sets for this step, whenever the ANN is good trained for a specific reservoir configuration, it forms a fast predictive tool for checking the location of the new wells in the reservoir, therefore this step has taken more time than other steps.

The connection elements (weights) are initialized with random numbers and are iteratively updated using the algorithm until the total error between calculated and known outputs of the entire training pattern is minimizing as indicated by the figure (7) of the used network.

The third step is testing of the trained network inorder to check the network validity or in other words, how is the generality of neural network in the problem space. So it is necessary to expose the network to sufficient data sets for both processes learning and adjusting. New sets of input data will be provided to the neural network and the difference between the actual and real output at this step is check. High error rate mean the network didn't learn the general solution of the problem, and then further learning will be needed. Section B of table (1) presents the input data sets and output results.

The fourth step that followed with the trained and tested neural network is to simulate the new un exploiting grid areas with AB unit to check how much oil can be gained. According to the training step, good and encourage results were obtained. Table (2) shows these data input and output sets for the neural network simulation step.

## Results and Discussion

It is clear from the output trend behavior of the used FFNNW through the training phase as shown in figure (7), the network has very good training and reaching its goal where the calculated difference is specify. This trend was reached according to the powerful training algorithm used with the network which is an advanced version of standard gradient descent algorithm that introduces momentum and dynamic learning factor as good factors to enhance the behavior of the algorithm according to the following weight adaptation equation :-

$$\Delta W_{(t+1)} = mc * \Delta W_{(t)} + Lr * mc * (Dperf/Dx)$$

Where:-

$\Delta W_{(t+1)}$  = The new weight adjustment

$\Delta W_{(t)}$  = The previous weight adjustment

mc = momentum constant

(D perf /Dx) = Derivative of performance with respect to weight and bias.

Lr = Learning Factor.

Learning factor will change as following:-

$$Lr_{(t+1)} = \begin{cases} Lr_{(t)} + Lr - Inc \\ Lr_{(t)} - Lr - Dec \end{cases}$$

Where :-

Inc. = Increase factor (1.05 ratio), if performance increase toward goal.

Dec. = Decreasing Factor (0.7 ratio), if performance increase more than max performance.

In addition to that , the following table explain the structure of the constructed ANN. For more details on can refer to reference ( 12 ).

Input Layer	4
Hidden Layer	
Output Layer	1
Learning Factor	Start with
Momentum Factor	7%
Epoches	200
Acceptable Goal Error	1E-04

The absolute average percentage error indicated by the used network is 4.044 %.

In respect to the results of simulation phase of the used network, which had been trained and tested according to the data available and included in table (1) previously, it is note that the output column (Cumulative Oil Production) represents the main objective of the research in the application of selected network in the present research. Also it is note that there is a clear trend in the results, while here is a disparity among the studied grids location which are called virgin grids. These grids areas unused or un exploited even by vertical wells that were operating in the concerning field , therefore these grids still reserve with high oil saturation that can exploited by either vertical or horizontal wells according to the future development planes by the Reservoir and Field Development Directorate in South Oil company. In addition to that the method was easy and accurate in the investigation of those grid areas in the field under study, also it is good way of identification for new field locations before switching to reservoir simulator in comparison with the conventional method in the field of inspection and prediction manner according to the type of relationship between input variables in calculation involved. The calculated error percentage by this application falling with the acceptable range that is indicating good results obtain and give us more convenience when use this application in ANN simulation phase. Also this is good crediting for calling this method rather than using of prolong regression or convention calculations.

## Conclusions

1. Artificial neural network models can provide a better description of relationships and dependencies among datasets; also it has also proven to be a valuable tool in cases where adequate engineering data are not available but where a large amount of historical data can be acquired.

2. Best behavior was obtained and reaching to the desired goal with 178 epochs after many trials during the training of the used network.
3. Good Indication were obtained were whenever horizontal re-entry wells location identified by the used (FFNNW).

## Nomenclature

FFNNW = Feed Forward Neural Network  
 ANN = Artificial Neural Network  
 SOC = South Oil Company  
 SRF = South Rumail Field  
 Kx = horizontal permeability (md)  
 H = Layer thickness (ft)  
 Sw = water saturation (percentage)  
 P = Pressure (Pisa).

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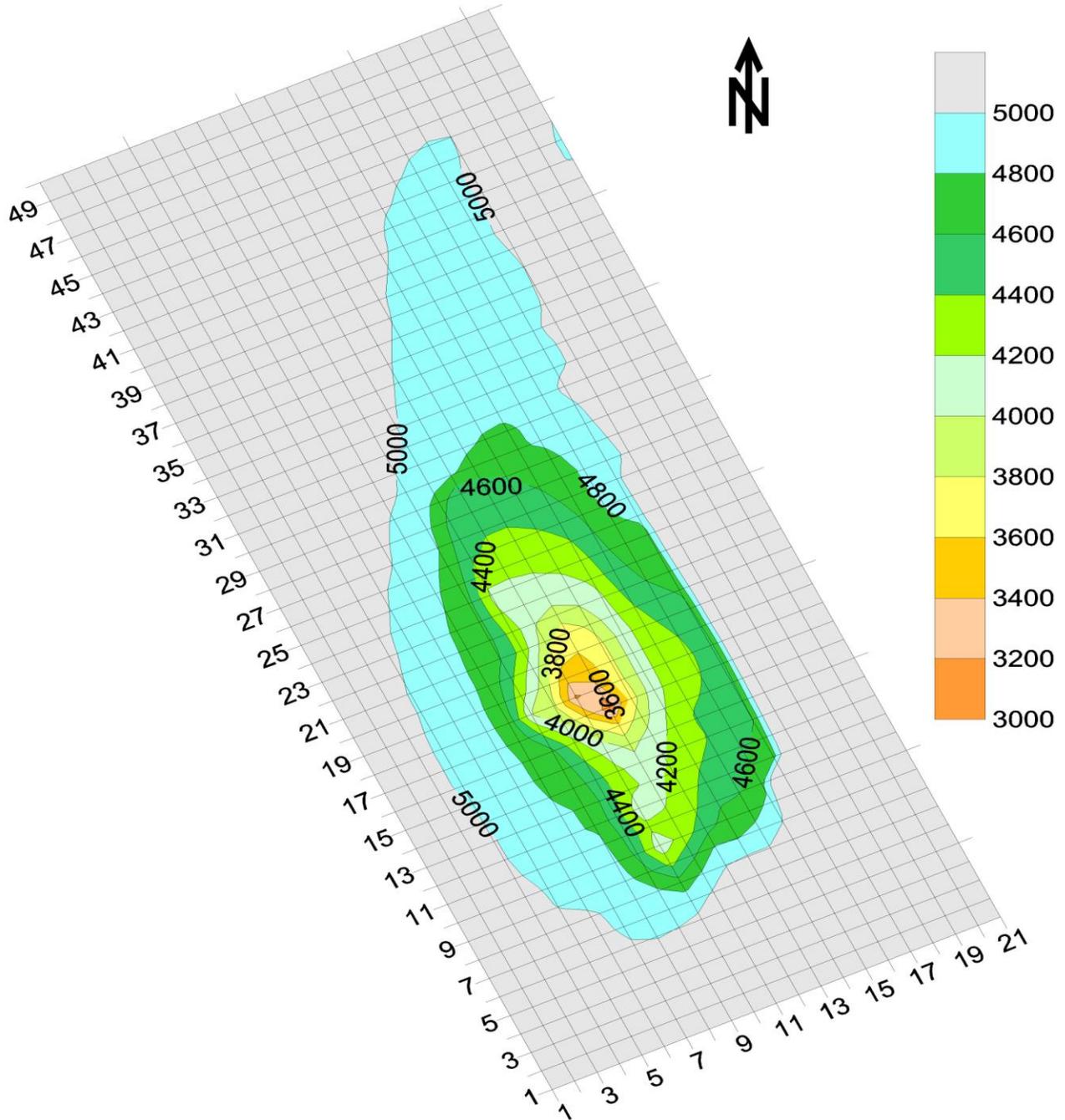


Figure (1) – Final Pressure distribution of AB unit at the end of 2005, (Psia)

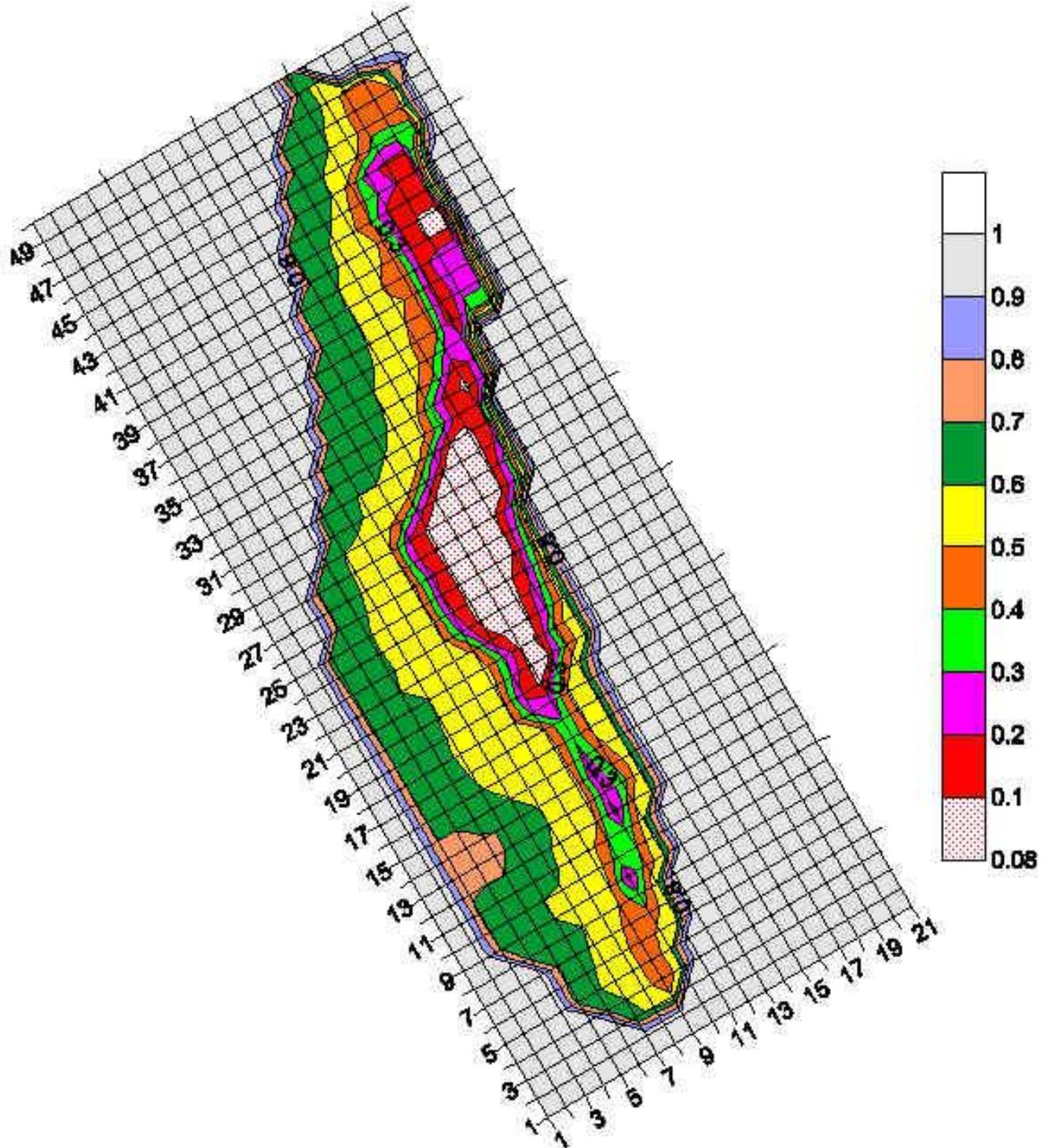


Figure (2) – Water saturation distribution of AB unit at the end of 2005





Figure (4)- Demons. of Different Grids Area Within South Rumaila Oil field

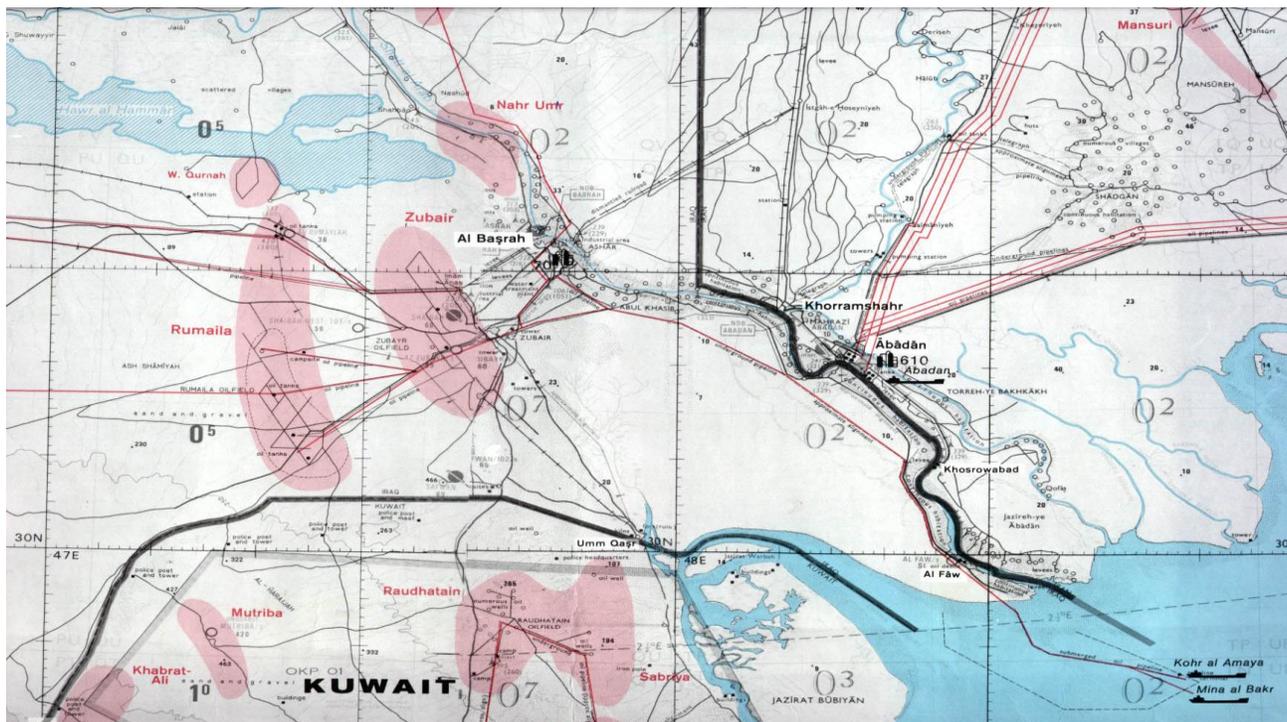


Figure (5) – Geographical location of Rumaila Field

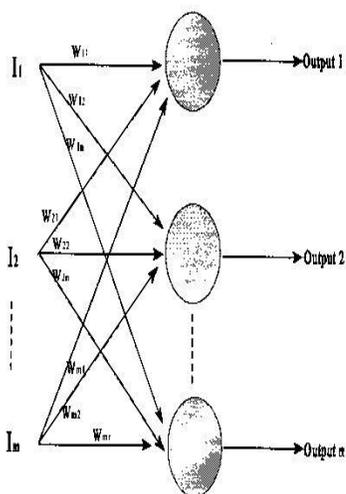


Figure (6) - Basic structure for multilayer perceptron network

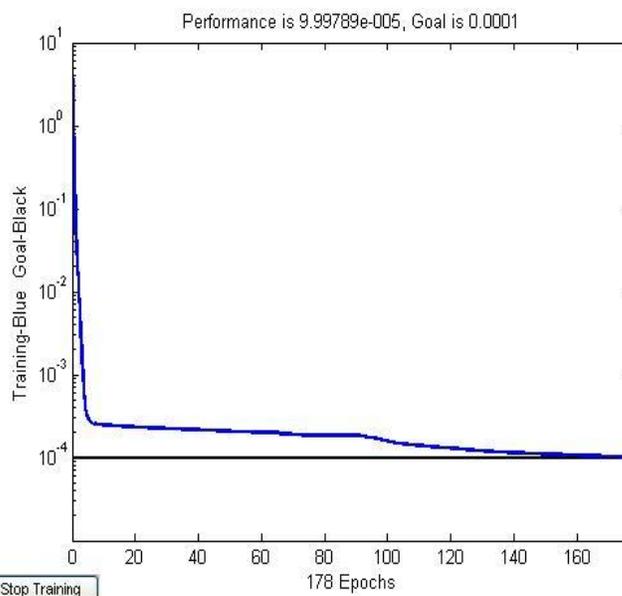


Figure (7) - FFNNW Training Performance ( Training stopped at 178 epochs )