PETROLEUM EXPLORATION AND DEVELOPMENT
Volume 43, Issue 4, August 2016
Online English edition of the Chinese language journal

Available online at www.sciencedirect.com
ScienceDirect

**Cite this article as:** PETROL. EXPLOR. DEVELOP., 2016, 43(4): 611–615.

RESEARCH PAPER

# Physical properties modeling of reservoirs in Mansuri oil field, Zagros region, Iran

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**Abstract:** The porosity and permeability distribution in four layers of the Cretaceous Ilam Formation was simulated using optimized artificial intelligent algorithms based on conventional logging data of 50 wells in Mansuri oil field in Iran. First, the neutron porosity, interval transit time and density wireline logs in five key wells with core data were used as input parameters to calculate porosity and permeability of the reservoirs using backpropagation artificial neural network (BP neural network) and Support Vector Regression methods, and based on the correlation between the calculated results and the core tested results, BP neural network method was taken to do the physical property calculation. Then, the porosity and permeability distribution of the four layers were modeled using kriging geostatistical algorithms. The results show that Layers 2.1 and 2.2 are high in porosity, Layers 1, 2.1 and 2.2 are high in permeability, while Layer 3 is not reservoir; and the porosity and permeability are higher in the north and lower in the south on the whole.

**Key words:** reservoir; physical property modeling; BP neural network; Support Vector Regression; Mansuri oil field; Zagros region

## Introduction

Reservoir property prediction is one of the most complicated and significant affairs for oilfield exploration and development[1–2]. Artificial neural network, especially back-propagation artificial neural network (BP neural network) is widely used in predicting porosity and permeability, whereas support vector regression is another reservoir porosity and permeability estimation method suggested recently[3]. In this paper, based on conventional log data, BP neural network and support vector regression methods were used to predict the porosity and permeability of Cretaceous Ilam Formation in the Mansuri Oilfield of the Zagros Region, Iran; the algorithm with higher accuracy was adopted to calculate the reservoir porosity and permeability of all wells; and then, the Kriging algorithm was used to build a reservoir attribute model.

## 1. Geological setting

Based on tectonic style and sedimentary history, the Zagros Region in Iran can be divided into such zones as Dezful Embayment, Lurestan and Fars[4–7], among which, the Dezful Embayment zone is controlled by three major faults, i.e., Kzerun fault, mountain front fault and Balarud fault respectively. The Mansuri Oilfield is located in the south of the Dezful Embayment zone, with structural trend the same as the Zagros fold-thrust belt (Fig. 1); Ilam Formation composed of Upper Cretaceous Santonian - Campanian carbonate rocks is studied in the paper, which is considered as the third important reservoir in the southwest of Iran[8–10], and it is also a high yield reservoir in the oilfield.

## 2. Porosity and permeability distribution modeling

The conventional log data of 50 wells in the Mansuri Oilfield were used for modeling, five of them with core analysis derived physical property (porosity and permeability) data. BP neural network and support vector regression methods were used to build the correlation between log parameters and physical property parameters (porosity and permeability) of cores of cored wells. Firstly, for the purpose of using the BP neural network to estimate outputs, the network was trained and tested, and the accuracy of structuring network was evaluated. Secondly, a support vector regression model was built to estimate the reservoir property characteristics of the study area. Thirdly, the calculation accuracy of the two methods was correlated and analyzed, so as to select more accurate method and apply its results in physical property modeling. And fourthly, the Kriging algorithm was used to build a 3D attribute (porosity and permeability) model of reservoir to realize visualization and separate the reservoir interval from the nonreservoir interval. Because the 50 wells selected in the paper distribute evenly

**Received date:** 14 Dec. 2015; **Revised date:** 31 May 2016.
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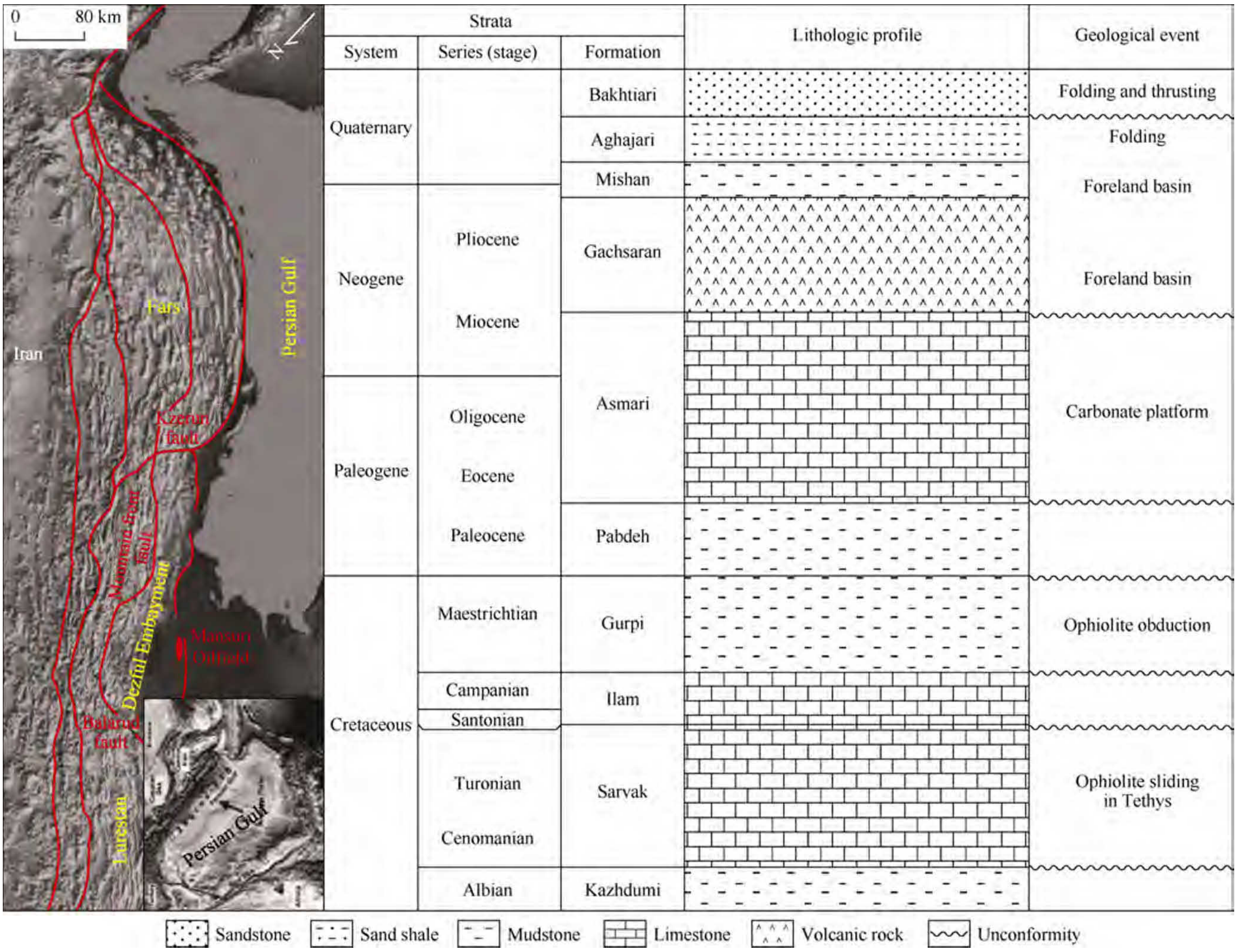


**Fig. 1. Position and stratigraphic column of Mansuri Oilfield (modified from references[4–7]).**

over the whole Mansuri Oilfield, the smooth effect of the Kriging algorithm has been obviously reduced, and the modeling results are reliable. Finally, the attribute model obtained from modeling was used to analyze the reservoir property of four zones in the Ilam Formation of Mansuri Oilfield.

### 2.1. Neural network modeling

Firstly, the core porosity and permeability data of four wells were used to train the artificial neural network, and the physical property data of cores taken from the fifth well were used to test the network, so as to guarantee the accuracy. At the time of training the network, the conventional log parameters having the best correlativity to porosity and permeability were screened out. The correlation coefficient of some conventional log parameters and physical property data is listed as in Table 1, showing that the neutron porosity, sonic differential time and density log value have the highest correlativity to porosity and permeability, therefore, the neutron porosity, sonic differential time and density log are selected as the input parameters in the paper. All the data used in artificial nueral network training and the statistics of them are listed as in Table 2, showing that about 70% input data are placed in training set to ensure the trained network to be reliable.

**Table 1. Correlation coefficient between conventional log parameters and porosity and permeability**

| Conventional logs | W/porosity | W/permeability |
|---|---|---|
| Sonic differential time | 0.73 | 0.60 |
| Density wireline log | 0.69 | 0.58 |
| Neutron porosity | 0.65 | 0.63 |
| Gamma Ray | 0.54 | 0.45 |
| Photoelectric | 0.50 | 0.48 |
| Conductivity temperature | 0.43 | 0.39 |

**Table 2. Statistics of data used in artificial neural network**

| Data set | Number of porosity data | Number of permeability data |
|---|---|---|
| Training set | 712 | 356 |
| Validation set | 152 | 76 |
| Testing set | 152 | 76 |
| All data | 1 016 | 508 |

### 2.2. Support vector regression modeling

The input data set of support vector regression modeling is