Petroleum 2 (2016) 49–53

Contents lists available at ScienceDirect

Petroleum

journal homepage: www.keaipublishing.com/en/journals/petlm

Original article

Fluvial facies reservoir productivity prediction method based on principal component analysis and artificial neural network

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ARTICLE INFO

Article history:
Received 3 July 2015
Received in revised form
31 December 2015
Accepted 31 December 2015

Keywords:
Fluvial facies reservoir
Productivity forecast
Principal component analysis
Artificial neural network

ABSTRACT

It is difficult to forecast the well productivity because of the complexity of vertical and horizontal developments in fluvial facies reservoir. This paper proposes a method based on Principal Component Analysis and Artificial Neural Network to predict well productivity of fluvial facies reservoir. The method summarizes the statistical reservoir factors and engineering factors that affect the well productivity, extracts information by applying the principal component analysis method and approximates arbitrary functions of the neural network to realize an accurate and efficient prediction on the fluvial facies reservoir well productivity. This method provides an effective way for forecasting the productivity of fluvial facies reservoir which is affected by multi-factors and complex mechanism. The study result shows that this method is a practical, effective, accurate and indirect productivity forecast method and is suitable for field application.

1. Introduction

Productivity indicates a dynamic equilibrium achieved in the mutual restraint process between the production potential of the reservoir and a variety of factors [1]. Considering the thin, varies in vertical and lateral and poor continuity features of the fluvial facies reservoir [2], the multilayer commingled production mode is often adopted to ensure the economic and efficient development. However, difficulties and uncertainties still exist in predicting the productivity of thin interbedded fluvial facies reservoirs [3–5]. Traditional percolation theory is venerable in forecasting the productivity due to the interference of vertical layers and the complexity of plane distribution. The productivity can be obtained by field test, but the test result is not representative since the test is limited by the test time, the changes in the reservoir and so on. In recent years, petroleum engineers gradually notice the importance of the artificial intelligence methods and apply the methods to petroleum geology and engineering researches [6–9] as well as to oil production prediction [10].

Principal Component Analysis (PCA) highlights the regularity of things by using a mathematical method which generates orthogonal principal components after combining the original features [11]. Artificial Neural Network (ANN) is a complex network system consists of a large number of connected neurons. ANN can theoretically achieve approximations of any arbitrary functions to meet the desirable accuracy requirement [12]. Principal component analysis can effectively solve the modeling problem under the situation where independent variables are severely multiple correlated or sample size is small. Neural network has the superiority in predicting nonlinear systems.

Representative samples are formed by analyzing the existing data of the wells and are used in the prediction model. The prediction model combines the advantages of the PCA and the ANN in that the principal components extracted by principal component analysis are imported as input variables to the artificial neural network to simulate data pattern and make

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Peer review under responsibility of Southwest Petroleum University.

Production and Hosting by Elsevier on behalf of KeAi

http://dx.doi.org/10.1016/j.petlm.2015.12.005

predictions. The combination shows an acceptable prediction result.

2. Model principle

(1) According to the real situation of reservoir and the well, various factors that impact production capacity are analyzed and organized and an appropriate set of factors is established. The sample set is divided into a training set and a testing set.

(2) The training set can be described as a sample matrix, with p dimensional vectors $x = (x_1, x_2, \ldots, x_p)^T$ and n samples $x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})^T$, $i = 1, 2, \ldots, n$. Then the following standardization processing is conducted on the set to get a standardized matrix.

$$Z_{ij} = \frac{x_{ij} - \overline{x}_j}{s_j}, i = 1, 2\cdots, n; j = 1, 2\cdots, p \tag{1}$$

where X_{ij} represent the j-th dimensional vector in the i-th sample, $\overline{x}_j = \frac{\sum_{i=1}^{n} x_{ij}}{n}, s_j^2 = \frac{\sum_{i=1}^{n} (x_{ij} - \overline{x}_j)^2}{n-1}$.

(3) Calculate the correlation matrix R based on the Standardized matrix Z as:

$$R = [r_{ij}]_p xp = \frac{Z^T Z}{n-1} \tag{2}$$

where $r_{ij} = \frac{\sum z_{ki} \cdot z_{kj}}{n-1}, i, j = 1, 2\cdots, p$.

(4) Obtain the eigenvalue of the correlation matrix R by solving the characteristic equation $|R - \lambda I_p| = 0$, $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0$. The respective unit feature vectors are $T_1, T_2, \ldots, T_p$. λ_i stands for the i-th eigenvalue of the i-th component Y_i which the variance equals to R.

(5) Calculate the contribution θ and the cumulative contribution ξ of each of the main components in the original variables:

$$\theta_i = \frac{\lambda_i}{\sum_{i=1}^{p} \lambda_i}, \quad i = 1, 2\cdots, p \tag{3}$$

$$\xi_k = \sum_{i=1}^{k} \theta_i, \quad k = 1, 2\cdots, p \tag{4}$$

where θ_i represent the contribution of the main components in the original variables, ξ_k represent the cumulative contribution of the main components in the original variables.

(6) Select m (m < p) principal components, so that the ξ_m is greater than 95% and transfer information extracted by principle component analysis to the neural network.

(7) The widely used BP neural network is adopted in the method. The network automatically divides the extracted sample into training and testing parts [13]. In this paper, a BP neural network with only one hidden layer is used. The hidden layer and output layer in the network are:

$$z_k = f_1\left(\sum_{i=0}^{n} v_{ki} x_i\right), \quad k = 1, 2\cdots, q \tag{5}$$

$$y_j = f_2\left(\sum_{k=0}^{q} w_{jk} z_k\right), \quad j = 1, 2\cdots, m \tag{6}$$

where n, q and m are the number of nodes in the input layer, hidden layer and output layer respectively; v_{ki} stands for the weights between input layer and hidden layer; w_{jk} denotes the weights between the hidden layer and the output layer; $f_1()$ and $f_2()$ are the transfer functions of the hidden layer and the output layer.

(8) Based on the actual productivity of the wells and classification principles, optimize the parameters of the transfer function and the network and eventually form a principal component analysis and artificial neural network combined productivity prediction method.

3. Case study

Data is collected from the actual data of a fluvial facies reservoir X in a certain sea in China. The above forecasting method is applied and the method is evaluated from the effectiveness and the applicability aspects.

3.1. Parameters preprocessing and principal component analysis

The mechanism of fluvial facies reservoirs is complex. Well productivity is affected many factors, of which can be summarized to two categories: One is the reservoir factor, the other is the engineering factor [14]. The parameters for the productivity prediction should contain as much information to better cover the reservoir factors and engineering factors, including reservoir conditions, fluid properties and the characteristics of the well, etc.

According to the theory of percolation mechanics, the production of a vertical well in the center of a circular reservoir with a constant pressure boundary is:

$$q_o = \frac{0.543kh\left(\overline{p}_r - p_{wf}\right)}{\mu_o B_o\left(\ln\frac{r_e}{r_w} - \frac{1}{2} + S\right)} \tag{7}$$

Where q_o is output of oil well ground, m^3/d; k is permeability, $10^{-3}\ \mu m^2$; h is reservoir thickness, m; μ_o is viscosity, mPa·s; B_o is oil volume factor; $\overline{p}_r$ is reservoir pressure, MPa; p_{wf} is bottom hole flowing pressure, MPa; r_e is drainage region radius, m; r_w is wellbore radius, m; S is skin factor.

Generally, the productivity index per meter is the key indicators of evaluation and analysis of the production capacity. From the above equation, the productivity index per meter of a vertical well in the center of a circular reservoir with a constant pressure boundary is:

$$J_o = \frac{0.543k}{\mu_o B_o\left(\ln\frac{r_e}{r_w} - \frac{1}{2} + S\right)} \tag{8}$$

Based on the theory of percolation mechanics, for the oil well with the actual non circular closed seepage area center need to be amended, even:

$$\frac{r_e}{r_w} = \frac{C_A\sqrt{A}}{r_w} \tag{9}$$