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The Application of BP Neural Network in Oil-Field

Pei-Ying ZHANG[1*], Meng-Meng ZHAO[2]
[1]College of Computer and Communication Engineering/ China University of Petroleum (East China) QingDao, ShanDong China
[2]School of Petroleum engineering, China University of Petroleum (East China), QingDao, China QingDao, ShanDong China
*Corresponding author, e-mail: 25640521@qq.com

Abstract

Aiming at the situation that many techniques of production performance analysis acquire lots of data and are expensive considering the computational and human resources, and their applications are limited, this paper puts forward a new method to analyze the production performance of oil-field based on the BP neural network. It builds a dataset with some available measured data such as well logs and production history, then, builds a field-wide production model by neural network technique, a model will be used to predict. The technique is verified, which shows that the predicted results are consistent with the maximum error of rate of oil production lower than 7% and maximum error of rate of water production lower than 5%, having certain application and research value.

Keywords*: neural network, production performance, dataset, mesh delineation*

1. Introduction

Production performance analysis is one of the main aspects of the reservoir engineering research and important ways of understanding, improving, effectively developing reservoir. At present, there are more than one hundred techniques of production performance analysis in home and abroad. According to the usage of production practice, the technique is mainly divided into two types. (1) One type is the technique which doesn't need production data: synectics, empirical formula method, chart method, laboratory procedure and hydrodynamic method. These five kinds of method are only adapted to the period before reservoir development or early development. (2) The other type is the technique which needs production data: material balance method, numerical simulation [1], water drive characteristic curve [2-3], successive subtraction method, forecasting model method and resultant method. These methods have a wide range of applications. Nevertheless, they have lots of limitations in some aspects. For instance, material balance method [4] needs large amount of parameters, and many of them can not be obtained easily and are along with inconvenient errors in measuring and calculating; numerical simulation method are expensive in measurements because of its acquiring such data; successive subtraction method [5-6] is mainly applied to oil-field of production decline period, limited to some certain development stage; water drive characteristic curve method is main applied to water-drive field, limiting to certain producing method.

Production performance analysis of oil-field based on the BP neural network [7] is one technique which builds a field-wide production forecast model using the widely available measured data such as well logs and production history of existing wells.

Compiling a spatial-temporal dataset by evolving static data of reservoir, dynamic data of oil well and associated data together, then building a coupling model by BP neural network technique which can predict the future production behavior. This technique not only overcomes the shortcoming of needing much data but also can be applied to field during any development period and adopting any development method, therefore it has a wide range of application.

2. Production Performance Analysis based on the BP Neural Network

A brief flowchart of production analysis based on the BP neural network is illustrated in Figure 1. The first step is building a dataset; the second step is building a network model as

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approximation of function by BP neural network after preparing dataset. Training a series of neural networks, putting them together, and then the technique of production performance analysis comes into being. So there is a field-field coupling model based on single well history, then, it will be used to forecast future performance.

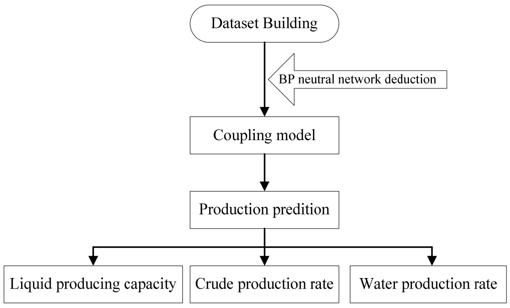

Figure 1. Brief Flowchart of Production Analysis Method

2.1. Dataset Building

Dataset which including the data of a well and COWs (Closet Offset Wells') can be divided into three portions: static data of reservoir, dynamic data of oil wells and the spatio-temporal dependencies (associated data). Static data itself includes lots of reservoir information, once reservoir information is commingled with the available static and dynamic information of the reservoir, it can bring out a cohesive full field model that represents the reservoir in a predictive way.

Table 1. The Composition of dataset

<table>
<tr><td colspan="4">Dataset</td></tr>
<tr><td colspan="2">Well's</td><td colspan="2">Closest Offset Well's</td></tr>
<tr><td rowspan="5">Static Data</td><td>Porosity</td><td rowspan="4">Static Data</td><td>Porosity</td></tr>
<tr><td>Formation Thickness</td><td>Formation Thickness</td></tr>
<tr><td>Initial Water Saturation</td><td>Initial Water Saturation</td></tr>
<tr><td>Formation Top</td><td>Formation Top</td></tr>
<tr><td>Location's Lat and Long</td><td rowspan="3">Dynamic Data</td><td>Drainage Area</td></tr>
<tr><td rowspan="2">Dynam ic Data</td><td>Drainage Area</td><td>Initial Production Rate</td></tr>
<tr><td>Initial Production Rate</td><td>Current Production Rate</td></tr>
<tr><td colspan="2" rowspan="2"></td><td rowspan="2">Dynamic Data</td><td>Production Days</td></tr>
<tr><td>Distance to the Well</td></tr>
</table>

The composition of the dataset is shown in Table 1, the parameters except drainage area can be gotten easily.

There are two dependencies between production histories and reservoir characteristics. One is the temporal dependency which is defined by the dependency of each well's performance to the history of the production of its own and other wells. The other is the spatial defining the dependency of reservoir heterogeneity [12-13], which can be interpreted by putting distance between wells and drainage area into the dataset.

In order to introduce the concept of temporal and spatial dependency, adding the information (including static and dynamic data) of one well's three COWs into the dataset, as shown in Figure 2, CTH1-P3, CTH1-P10 and CTH1-P11 are the three COWs of CTH1-P38. Voronoi graph theory can integrate single-well models into a field-wide comprehension of the reservoir. Using the theory, a Voronoi diagram is generated for the entire field. By a sweeping technique over the entire grid blocks, the Euclidean distance of the block to all the wells are calculated for each grid, each block would belong to the Voronoi cell of the well which is closest to it. That well will be called the “Parent well” for that grid block. The area of Voronoi cell of the blocks is its own parent well’s Ultimate Drainage Area. As seen in Figure 2, every cell is marked by different color.

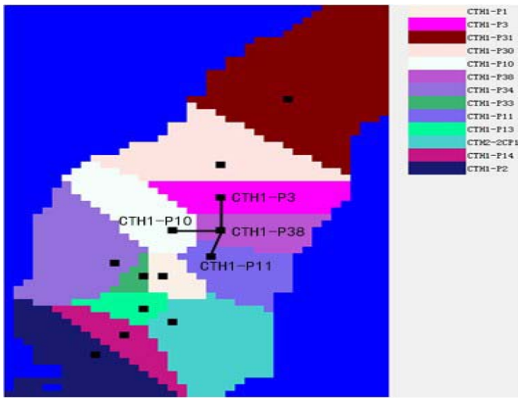

Figure 2. Voronoi Delineation of One Certain Real Reservoir

Because of production rate’s recording monthly, a new data record for each well is produced at each month which is included in the dataset. Once the data set is generated for an enough length of time, it can be put into use to train a neural network which then learn to forecast the well’s future performance.

2.2. Neural Network Training

Training process of the neural networks is done by back-propagation technique (BP algorithm) [14-17]. Dataset is divided into three portions. The first portion which is the largest of them is used to train the network. The second portion of the dataset is taken for calibration for the purpose of preventing the memorizing and over training effect in neural network training process. In the calibration process, the best network is to be selected. This part of the data is not introduced into the network for training but every step of training the network is tested for this set and the best network is selected based on the calibration set prediction error.

The third portion of the dataset is the verification part. It is only used to test the precision of the neural network. If the results are satisfactory after training and calibrating, the network is acceptable to be part of the entire prediction system.

2.3. Initial Rate Prediction Model

The first step of production prediction is the initial production rate (initial oil, water or gas production rate) estimation. The initial production rate depends on the production history of the wells surrounding it and the reservoir characteristics at that location. It is better to understand the future production behavior by integrating the information of production history of the wells surrounding it into reservoir information.

The input data of this model is the same with the input data in Table 1. The first rate prediction model which is trained, calibrated and verified to predict the initial production rate of new drilled well’s is designed using a dataset built based on the production history of the numerical reservoir model, described in previous sections.

2.4. Production Profile Prediction Model

After estimating a new well's initial production rate, the production rate is modeled in a time successive fashion. In other words, the production rate is predicted based on previous production rates and offset wells' information at each time step.

In order to improve the accuracy of the prediction each time, we decided to use the past three months' production rates as input values for the neural network. This can be applied for modeling the production at month four through. Different models should be created to predict second and third month of the production [18].

Wells in a mature field have been producing for a long time and been depleted at most locations, the production rate of new well is predicted by initial rate prediction model. Then, the past production rate can be added into the dataset since the second month. Therefore, the second and the third month prediction models are built, so with every month prediction model since the fourth month. Once all the four models are trained and verified, a field-wide production prediction comes into being. Once new well is drilled and begin produce, its information would be integrated into the dataset.

It is worth noting that OWs are determined dynamically, meaning that new wells are added to the reservoir each well's OWs are changing during the reservoir's lifetime. In order to address this offset wells for each well are recalculated at each time step. Implementing this step is done using Visual C# environment. A controller program is designed and tested.

3. Application to a Real Reservoir

Take one certain real reservoir for example, it has thirteen wells: CTH1-P1, CTH1-P2, CTH1-P3, CTH1-P10, CTH1-P11, CTH1-P13, CTH1-P14, CTH1-P30, CTH1-P31, CTH1-P33, CTH1-P34, CTH1-P38, CTH1-2CP1, and has been producing for thirteen months from July 1st 2009 to July 31st 2010, therefore, the dataset contains 169 samples. Appendix shows section of the first month data of CTH1-P1, CTH1-P2 and CTH1-P3, and parameters that contain porosity, formation thickness, initial water saturation, formation top, location's lat and long, drainage area, initial oil production rate, current oil production rate and porosity, formation thickness, initial water saturation, formation top, drainage area, initial oil production rate, current oil production rate, production days, distance to the well of three COWs. Appendix lists the parameters of the three COWs. So far, the dataset is ready, the next step is to build a prediction model by BP neural network which is used to predict oil production rate.

Dataset is divided into three section, 130 samples are selected randomly as training sample, 21 samples as calibrating sample, and 18 samples as verification sample. The output parameter is current oil production rate while building the prediction model, and all the other parameters are input parameter. In the model, TRAINDX is the default training function because it is fast; LEARNGDM is the learning function. Parameters associated with training function TRAINDX contain epochs (max training time), goal (training goal), show (show iteration), lr (learning rate), min_grad (min gradient) and so on, which shows bellow in MATLAB software.

```
Net.trainParam.epochs=5000;
Net.trainParam.goal=1e-5;
Net.trainParam.show=100;
Net.trainParam.lr=0.4;
Net.trainParam.min_grad=1e-9;
```

As shown in Figure 3, the most training error is almost 0.8% in this application, and most of training errors are lower than 0.4%, hence we can conclude that it is reliable for this neural network model.

Predicted result of CTH1-P1 which has been producing for 12 months since August 2010 is shown as Figure 4, the real oil production rate is shown in blue and the production prediction is in red. The most likely prediction stays very close to the real production profile while the predicted error is lower than 7%.

While the model is used to predict water production rate, the output parameter changes to current water production rate, all the other parameters are input parameter similarly. This prediction model is built in the same way. As it can be seen in the Figure 5, the predicted error of water production rate is within 5% after 12 months prediction. Therefore the prediction stays very close to the real production profile while the minimum and maximum range is showing the extent of possible output values from this technique, and this technique has a certain application and reference value.

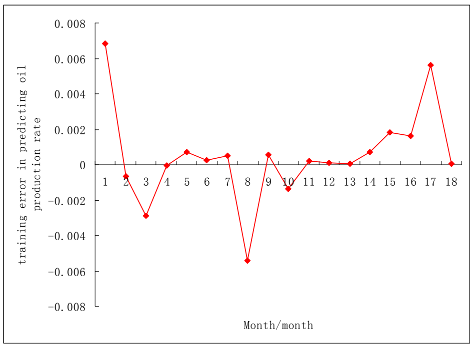

Figure 3. Neural Network Training Error in Oil Production Rate

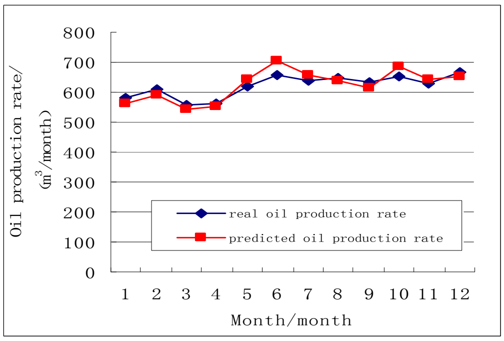

Figure 4. Real Oil Production Rate and Predicted Oil Production Rate

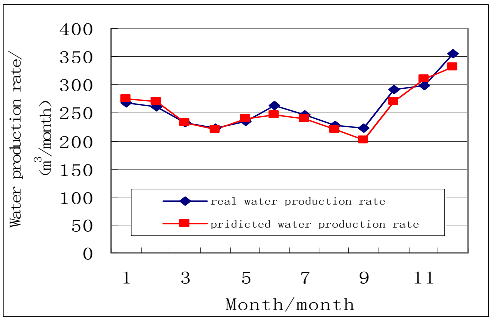

Figure 5. Real Water Production Rate and Predicted Water Production Rate

In addition to the production forecast, the technique can be used in predicting other dynamic indicators (such as BHFP, dissolved gas and so on) and can be used as a reference or with other techniques.

4. Conclusion

Technique by neural network has some advantages [19-24] that don't exist in other techniques. This technique can build a field-wide production model when it applies to production prediction in real reservoir. Its cost is not high and has a wide application range and can be used in oilfield in any production period or with any producing method. Therefore, this model can provide technical support for decision-making engineers instead of real reservoir. Also, this model is defective and we should pay attention to the following points.

(1) Parameters of dataset is the key to have a accurate prediction of this technique, so parameters differ in different situation such as different reservoir or different prediction purpose.

(2) By incorporating the information of heterogeneity of reservoir characteristics into the Voronoi delineation, the prediction error of this technique would decrease conspicuously.

(3) It is necessary to normalize the dataset before training process. An adverse operation is obligatory after prediction accordingly.

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Appendix

The dataset of one certain real reservoir, here only list section of the first month data of CTH1-P1, CTH1-P2 and CTH1-P3.

Well name /Month	CTH1 -P1 /2009.07	CTH1 -P2 /2009.07	CTH1 -P3 /2009.07
Porosity	0.15215	0.17208	0.21933
Formation Thickness/m	9.721	12.436	19.166
Initial water saturation	0.15	0.15	0.15
Formation top/m	1196.49	1205.22	1246.26
Well location X	567669.3	567635.9	566050.3
Well location Y	-420279	-420092	-420247
Drainage area/m2	58596.31	545919.7	917365
Initial oil production rate/(m3/month)	580.32	577.51	214.27
Current oil production rate/(m3/month)	580.32	577.51	214.27
Porosity of COW1	0.172085	0.152158	0.204975
Formation thickness of COW1/m	12.436	9.721	21.914
Initial water saturation of COW1	0.15	0.15	0.15
Formation top of COW1/m	1205.223	1196.496	1260.335
Drainage area of COW1/m3	545919.7	58596.31	324914.5
Initial oil production rate of COW1/(m3/month)	577.51	580.32	680.68
Current oil production rate of COW1/(m3/month)	577.51	580.32	680.68
Production days of COW1/day	484	537	420
Distance to the well of COW1/m	189.944	189.944	237.631
Porosity of COW2	0.212285	0.204975	0.249937
Formation thickness of COW2/m	18.154	21.914	23.560
Initial water saturation of COW2	0.15	0.15	0.15
Formation top of COW2/m	1227.095	1260.335	1275.424
Drainage area of COW2/m3	4906916	324914.5	884740.3
Initial oil production rate of COW2/(m3/month)	1017.33	680.68	848.19
Current oil production rate of COW2/(m3/month)	1017.33	680.68	848.19
Production days of COW2/day	534	448	410
Distance to the well of COW2/m	410.08	237.63	690.12

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