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Forecasting Petroleum Production Using the Time-Series Prediction of Artificial Neural Network

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Abstract

The purpose of this paper is to present a special back-propagation neural network (BPNN) with two techniques of the optimal learning time count (OLTC) and the time-series prediction (TSP) for forecasting petroleum production in Chinese oilfields, as well as algorithm applicability. In general, when different algorithms are used to solve a real-world problem, they often produce different solution accuracies, and an algorithm is used to solve real-world problems, it often produces different solution accuracies. Toward this issue, the solution accuracy is expressed with the total mean absolute relative residual for all samples, $R(\%)$; and it is proposed that an algorithm is applicable if $R(\%) \leq 5$, otherwise this algorithm is inapplicable. Two case studies of China have been used to validate the proposed approach. The application results of this special BPNN are $R(\%) = 2.18$ in Case study 1 while $R(\%) = 2.05$ in Case study 2. From these results, it is concluded that: (a) this special BPNN for forecasting petroleum production in Chinese oilfields is feasible and practical; and (b) the definition of solution accuracy $R(\%)$, and the threshold of algorithm applicability ($R(\%) \leq 5$) for an algorithm, are feasible and practical, too.

Key words: Neural network; Optimal learning-count; Time-series prediction; Solution accuracy; Algorithm applicability; Production prediction

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INTRODUCTION

In the petroleum exploration and development, the popular three regression algorithms and three classification algorithms are applied[1-6]. The three regression algorithms are the support vector regression (SVR), the back-propagation neural network (BPNN), and the multiple regression analysis (MRA), while the three classification algorithms are the support vector classification (SVC), the naïve Bayesian (NBAY), and the Bayesian successive discrimination (BAYSD). But this used BPNN has no function of the time-series prediction (TSP). For the time-series forecasting petroleum production, literatures [7] and [8] applied the time-series prediction of BPNN to the Romashkino Oilfield of Russia. In this paper, we employ a special BPNN with two techniques of the optimal learning time count (OLTC) and TSP[8] to forecast petroleum production in Chinese oilfields.

In general, when different algorithms are used to solve a real-world problem, they often produce different solution accuracies, and an algorithm is used to solve real-world problems, it often produces different solution accuracies. Toward this issue, the solution accuracy is expressed with the total mean absolute relative residual for all samples, $R(\%)$; and it is proposed that an algorithm is applicable if $R(\%) \leq 5$, otherwise this algorithm is inapplicable. Two case studies of China below have been used to validate the proposed approach. The application results of this special BPNN are $R(\%) = 2.18$ in Case study 1 while $R(\%) = 2.05$ in Case study 2. From these results, it is concluded that: (a) this special BPNN for forecasting petroleum production in Chinese oilfields is feasible and practical; and (b) the definition of solution accuracy $R(\%)$, and the threshold of algorithm applicability ($R(\%) \le 5$) for an algorithm, are feasible and practical, too.

1. TIME-SERIES PREDICTION OF BPNN

The algorithm applied to the two case studies below is a special BPNN with two techniques of the optimal learning time count (OLTC) and the time-series prediction (TSP). These two techniques are detailedly described in [8]. In this paper, we only concisely introduce TSP, which is so-called as the time-series prediction of BPNN. Thus the following are definitions used by time-series prediction of BPNN, and method of time-series prediction (TSP).

1.1 Definitions Used by Time-Series Prediction of BPNN

Assume that there are n learning samples, each associated with two numbers (x_1, y^*) and a set of observed values (x_{i1}, y_i^*), with $i = 1, 2, \ldots, n$ for these numbers. The n samples associated with two numbers are defined as n vectors:

$$\boldsymbol{x}_i = (x_{i1}, y_i^*) \quad (i = 1, 2, \ldots, n), \tag{1}$$

where n is the number of learning samples; $\boldsymbol{x}_i$ is the i^{th} learning sample vector; x_{i1} is the value of the independent variable in the i^{th} learning sample; and y_i^* is the observed value of the i^{th} learning sample.

Equation 1 is the expression of learning samples.

Equation 2 is the expression of prediction samples:

$$\boldsymbol{x}_i = (x_{i1}) \quad (i = n+1, n+2, \ldots, n+k), \tag{2}$$

where k is the number of prediction samples; $\boldsymbol{x}_i$ is the i^{th} prediction sample vector; and the other symbols have been defined in Equation 1.

To express the calculation accuracies of the predicted dependent variable y for learning and prediction samples when the special BPNN is used, the following four types of residuals are defined.

The absolute relative residual for each sample, $R(\%)_i$ ($i = 1, 2, \ldots, n, n+1, n+2, \ldots, n+k$), is defined as

$$R(\%)_i = |(y_i - y_i^*) / y_i^*| \times 100, \tag{3}$$

where y_i is the calculation result of the dependent variable y in the i^{th} sample; and the other symbols have been defined in Equations 1 and 2. $R(\%)_i$ is the fitting residual to express the fitness for a sample in learning or prediction process.

It is noted that zero must not be taken as a value of y_i^* to avoid floating-point overflow. Therefore, for the special BPNN, delete the sample if its $y_i^* = 0$.

The mean absolute relative residual for all learning samples, $R_1(\%)$, is defined as

$$R_1(\%) = \sum_{i=1}^{n} R(\%)_i \,/\, n, \tag{4}$$

where all symbols have been defined in Equations 1 and 3. $R_1(\%)$ is the fitting residual to express the fitness of learning process.

The mean absolute relative residual for all prediction samples, $R_2(\%)$, is defined as

$$R_2(\%) = \sum_{i=n+1}^{k} R(\%)_i \,/\, k, \tag{5}$$

where all symbols have been defined in Equations 2 and 3. $R_2(\%)$ is the fitting residual to express the fitness of prediction process.

The total mean absolute relative residual for all samples, $R(\%)$, is defined as

$$R(\%) = \sum_{i=1}^{n+k} R(\%)_i \,/\, (n+k), \tag{6}$$

where all symbols have been defined in Equations 1, 2 and 3. If there are no prediction samples, $k = 0$, then $R(\%) = R_1(\%)$. $R(\%)$ is the fitting residual to express the fitness of learning and prediction processes.

When the special BPNN is used to solve real-world problems, it often produces different solution accuracies. Toward this issue, the solution accuracy is expressed with $R(\%)$ shown in Equation 6; and it is proposed that an algorithm is applicable if $R(\%) \le 5$, otherwise this algorithm is inapplicable.

1.2 Method of Time-Series Prediction (TSP)

The method of BPNN is not detailedly described here because readers can refer to [8].

If x_{i1} and y_i^* shown in Equation 1 are directly introduced in BPNN, this is a very simple network structure: Only one node (x_1) on input layer, and only one node (y) on output layer. It is proved from practice that this network structure is not easily converged, mainly due to the fact that only one node on input layer causing no enough information provided for network learning. To solve this problem, a way of changing one-dimensional input space to multi-dimensional input space was proposed[7-8]. Concretely, we consider x_{i1} as the 1st node on input layer, then take x_{i1}^2 as the 2nd node on input layer, …, and x_{i1}^m as the m^{th} node on input layer. In this case, the 1-D input space becomes m-D input space, i.e., the number of independent variables for samples is increased from 1 to m. Obviously, these independent variables $x_{i1}, x_{i1}^2, \ldots,$ and x_{i1}^m are mutually independent, because these m independent variables constitute an orthogonal set.

Excepting the aforementioned special way of changing one-dimensional input space to multi-dimensional input space, there is no change in BPNN. It is noted that the bigger the m, the higher the accuracy of calculation results, but the longer the time consuming. In the two case studies below, m is taken as 6.

Through the learning process, BPNN constructs its own function $y = y(\boldsymbol{x})$. It is noted that $y = y(\boldsymbol{x})$ created by BPNN is an implicit expression, i.e., which cannot be expressed as a usual mathematical formula.

In the two case studies below, $N_{\text{hidden}} = 2(N_{\text{input}}+N_{\text{output}})-1$ where N_{hidden} is the number of hidden nodes, N_{input} is the number of input nodes and N_{output} is the number of output nodes; the termination of calculation accuracy TCA is fixed to 10^{-4}; and in each iteration, the error takes the root mean square error[8-9] is

$$\text{RMSE}(\%)=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-y_i^*)^2}\times 100, \tag{7}$$

where y_i and y^* are under the conditions of normalizations in the learning process. RMSE(%) is used in the conditions for terminating network learning.

2. CASE STUDY 1: PREDICTION OF MONTHLY PETROLEUM PRODUCTION FOR AN OILFIELD IN CHINA

The objective of this case study is to predict the monthly petroleum production (MPP), which has practical value for making future MPP plan in oilfields.

Using data of 174 samples from an oilfield in China[10], and each sample contains one independent variable (x_1 = month) and one variable (y^* = MPP). Among these 174 samples, taking the former168 samples as learning samples and the latter 6 samples as prediction samples, Liu & Xie (2006) adopted a self-adaptation wavelet neural network for the prediction of MPP[10]. In this case study, among the 174 samples, the former 144 are taken as learning samples and the latter 30 as prediction samples (Table 1) for the prediction of MPP, using BPNN with OLTC and TSP.

Table 1
Input Data and Prediction Results for Prediction of Monthly Petroleum Production in an Oilfield in China (Modified From [10])

No.[a]	Month[b]	MPP (10^4 Ton)[c]		$R(\%)_i$	No.[a]	Month[b]	MPP (10^4 Ton)[c]		$R(\%)_i$
	x_1	y^*	y^*			x_1	y^*	y^*	
1	1990.083	1.15×10^3	1.13×10^3	2.41	88	1997.3	1.35×10^3	1.35×10^3	2.06×10^{-2}
2	1990.167	1.06×10^3	1.13×10^3	6.63	89	1997.417	1.39×10^3	1.35×10^3	2.89
3	1990.25	1.18×10^3	1.14×10^3	2.72	90	1997.5	1.34×10^3	1.35×10^3	3.98×10^{-1}
4	1990.3	1.13×10^3	1.15×10^3	2.16	91	1997.583	1.38×10^3	1.35×10^3	2.16
5	1990.417	1.17×10^3	1.16×10^3	8.45×10^{-1}	92	1997.67	1.36×10^3	1.35×10^3	5.48×10^{-1}
6	1990.5	1.14×10^3	1.16×10^3	1.88	93	1997.75	1.34×10^3	1.35×10^3	9.70×10^{-1}
7	1990.583	1.16×10^3	1.16×10^3	5.14×10^{-1}	94	1997.83	1.38×10^3	1.35×10^3	1.78
8	1990.67	1.17×10^3	1.16×10^3	5.30×10^{-1}	95	1997.917	1.33×10^3	1.35×10^3	1.94
9	1990.75	1.14×10^3	1.17×10^3	1.96	96	1998	1.35×10^3	1.35×10^3	1.21×10^{-1}
10	1990.83	1.18×10^3	1.17×10^3	1.25	97	1998.083	1.37×10^3	1.35×10^3	1.41
11	1990.917	1.15×10^3	1.17×10^3	1.27	98	1998.167	1.19×10^3	1.35×10^3	1.41×10
12	1991	1.17×10^3	1.17×10^3	4.42×10^{-1}	99	1998.25	1.34×10^3	1.35×10^3	7.55×10^{-1}
13	1991.083	1.17×10^3	1.17×10^3	2.37×10^{-1}	100	1998.3	1.29×10^3	1.35×10^3	5.03
14	1991.167	1.07×10^3	1.17×10^3	9.29	101	1998.417	1.36×10^3	1.35×10^3	2.87×10^{-1}
15	1991.25	1.18×10^3	1.17×10^3	7.01×10^{-1}	102	1998.5	1.34×10^3	1.35×10^3	8.87×10^{-1}
16	1991.3	1.15×10^3	1.17×10^3	2.52	103	1998.583	1.37×10^3	1.35×10^3	9.46×10^{-1}
17	1991.417	1.19×10^3	1.18×10^3	1.03	104	1998.67	1.35×10^3	1.35×10^3	3.13×10^{-1}
18	1991.5	1.15×10^3	1.18×10^3	2.58	105	1998.75	1.32×10^3	1.35×10^3	2.74
19	1991.583	1.18×10^3	1.18×10^3	2.10×10^{-1}	106	1998.83	1.36×10^3	1.35×10^3	5.37×10^{-1}
20	1991.67	1.18×10^3	1.18×10^3	1.31×10^{-1}	107	1998.917	1.35×10^3	1.36×10^3	3.13×10^{-1}
21	1991.75	1.15×10^3	1.18×10^3	2.32	108	1999	1.39×10^3	1.36×10^3	2.26
22	1991.83	1.19×10^3	1.18×10^3	7.58×10^{-1}	109	1999.083	1.36×10^3	1.36×10^3	6.03×10^{-1}
23	1991.917	1.15×10^3	1.18×10^3	3.01	110	1999.167	1.23×10^3	1.36×10^3	9.96
24	1992	1.19×10^3	1.18×10^3	3.61×10^{-1}	111	1999.25	1.36×10^3	1.36×10^3	4.88×10^{-2}
25	1992.083	1.20×10^3	1.19×10^3	1.21	112	1999.3	1.32×10^3	1.36×10^3	2.75
26	1992.167	1.13×10^3	1.19×10^3	4.68	113	1999.417	1.39×10^3	1.36×10^3	2.06
27	1992.25	1.20×10^3	1.19×10^3	1.09	114	1999.5	1.32×10^3	1.36×10^3	2.61
28	1992.3	1.17×10^3	1.19×10^3	1.57	115	1999.583	1.38×10^3	1.36×10^3	1.30
29	1992.417	1.20×10^3	1.19×10^3	9.62×10^{-1}	116	1999.67	1.36×10^3	1.36×10^3	2.71×10^{-1}
30	1992.5	1.16×10^3	1.19×10^3	2.68	117	1999.75	1.29×10^3	1.36×10^3	5.54
31	1992.583	1.20×10^3	1.19×10^3	4.39×10^{-1}	118	1999.83	1.34×10^3	1.36×10^3	1.42
32	1992.67	1.19×10^3	1.19×10^3	9.87×10^{-2}	119	1999.917	1.34×10^3	1.36×10^3	1.85
33	1992.75	1.17×10^3	1.19×10^3	1.84	120	2000	1.36×10^3	1.36×10^3	5.86×10^{-2}
34	1992.83	1.22×10^3	1.20×10^3	1.88	121	2000.083	1.35×10^3	1.36×10^3	1.06
35	1992.917	1.17×10^3	1.20×10^3	2.57	122	2000.167	1.30×10^3	1.36×10^3	4.76
36	1993	1.18×10^3	1.20×10^3	1.44	123	2000.25	1.41×10^3	1.36×10^3	3.22
37	1993.083	1.22×10^3	1.20×10^3	1.82	124	2000.3	1.34×10^3	1.36×10^3	1.81

To be continued

Continued

No.[a]	Month[b] x_1	MPP (10^4 Ton)[c]		$R(\%)_i$	No.[a]	Month[b] x_1	MPP (10^4 Ton)[c]		$R(\%)_i$
		y^*	y^*				y^*	y^*	
38	1993.167	1.10×10^3	1.20×10^3	9.33	125	2000.417	1.37×10^3	1.36×10^3	5.15×10^{-1}
39	1993.25	1.22×10^3	1.21×10^3	1.25	126	2000.5	1.34×10^3	1.37×10^3	1.54
40	1993.3	1.19×10^3	1.21×10^3	2.03	127	2000.583	1.37×10^3	1.37×10^3	1.07×10^{-1}
41	1993.417	1.24×10^3	1.22×10^3	1.27	128	2000.67	1.36×10^3	1.37×10^3	8.93×10^{-1}
42	1993.5	1.21×10^3	1.23×10^3	1.42	129	2000.75	1.34×10^3	1.37×10^3	2.41
43	1993.583	1.24×10^3	1.23×10^3	6.26×10^{-1}	130	2000.83	1.36×10^3	1.37×10^3	4.74×10^{-1}
44	1993.67	1.21×10^3	1.24×10^3	2.11	131	2000.917	1.32×10^3	1.37×10^3	4.07
45	1993.75	1.19×10^3	1.24×10^3	4.25	132	2001	1.38×10^3	1.37×10^3	1.43×10^{-1}
46	1993.83	1.26×10^3	1.24×10^3	1.80	133	2001.083	1.35×10^3	1.38×10^3	1.69
47	1993.917	1.21×10^3	1.24×10^3	2.55	134	2001.167	1.28×10^3	1.38×10^3	7.83
48	1994	1.23×10^3	1.24×10^3	9.87×10^{-1}	135	2001.25	1.43×10^3	1.38×10^3	3.85
49	1994.083	1.33×10^3	1.24×10^3	6.48	136	2001.3	1.36×10^3	1.38×10^3	1.67
50	1994.167	1.16×10^3	1.24×10^3	7.42	137	2001.417	1.41×10^3	1.38×10^3	1.65
51	1994.25	1.24×10^3	1.24×10^3	3.64×10^{-1}	138	2001.5	1.36×10^3	1.39×10^3	1.73
52	1994.3	1.19×10^3	1.24×10^3	4.48	139	2001.583	1.39×10^3	1.39×10^3	1.17×10^{-1}
53	1994.417	1.26×10^3	1.24×10^3	1.16	140	2001.67	1.40×10^3	1.39×10^3	9.53×10^{-1}
54	1994.5	1.22×10^3	1.25×10^3	1.75	141	2001.75	1.35×10^3	1.39×10^3	2.98
55	1994.583	1.26×10^3	1.25×10^3	8.15×10^{-1}	142	2001.83	1.41×10^3	1.39×10^3	9.60×10^{-1}
56	1994.67	1.24×10^3	1.25×10^3	5.55×10^{-1}	143	2001.917	1.36×10^3	1.40×10^3	2.43
57	1994.75	1.18×10^3	1.25×10^3	5.75	144	2002	1.39×10^3	1.40×10^3	6.09×10^{-1}
58	1994.83	1.26×10^3	1.25×10^3	9.13×10^{-1}	145	2002.083	(1.43×10^3)	1.40×10^3	2.03
59	1994.917	1.25×10^3	1.25×10^3	1.69×10^{-1}	146	2002.167	(1.28×10^3)	1.40×10^3	9.79
60	1995	1.28×10^3	1.25×10^3	2.71	147	2002.25	(1.42×10^3)	1.40×10^3	1.29
61	1995.083	1.24×10^3	1.25×10^3	1.11	148	2002.3	(1.37×10^3)	1.41×10^3	2.58
62	1995.167	1.16×10^3	1.25×10^3	7.52	149	2002.417	(1.43×10^3)	1.41×10^3	1.60
63	1995.25	1.28×10^3	1.25×10^3	2.35	150	2002.5	(1.48×10^3)	1.41×10^3	4.85
64	1995.3	1.22×10^3	1.25×10^3	2.75	151	2002.583	(1.44×10^3)	1.41×10^3	2.24
65	1995.417	1.24×10^3	1.25×10^3	9.72×10^{-1}	152	2002.67	(1.48×10^3)	1.41×10^3	4.70
66	1995.5	1.24×10^3	1.25×10^3	1.01	153	2002.75	(1.41×10^3)	1.41×10^3	1.97×10^{-1}
67	1995.583	1.28×10^3	1.25×10^3	2.06	154	2002.83	(1.46×10^3)	1.41×10^3	3.41
68	1995.67	1.28×10^3	1.26×10^3	1.74	155	2002.917	(1.39×10^3)	1.42×10^3	1.69
69	1995.75	1.26×10^3	1.26×10^3	2.27×10^{-1}	156	2003	(1.43×10^3)	1.42×10^3	1.11
70	1995.83	1.31×10^3	1.26×10^3	4.01	157	2003.083	(1.43×10^3)	1.42×10^3	1.22
71	1995.917	1.26×10^3	1.26×10^3	3.94×10^{-3}	158	2003.167	(1.31×10^3)	1.42×10^3	8.03
72	1996	1.21×10^3	1.26×10^3	4.27	159	2003.25	(1.46×10^3)	1.42×10^3	2.63
73	1996.083	1.27×10^3	1.27×10^3	1.18×10^{-1}	160	2003.3	(1.42×10^3)	1.42×10^3	1.35×10^{-1}
74	1996.167	1.27×10^3	1.29×10^3	1.30	161	2003.417	(1.46×10^3)	1.42×10^3	2.66
75	1996.25	1.34×10^3	1.31×10^3	2.14	162	2003.5	(1.42×10^3)	1.42×10^3	3.32×10^{-2}
76	1996.3	1.27×10^3	1.32×10^3	4.45	163	2003.583	(1.44×10^3)	1.42×10^3	1.22
77	1996.417	1.35×10^3	1.34×10^3	9.85×10^{-1}	164	2003.67	(1.44×10^3)	1.42×10^3	1.36
78	1996.5	1.33×10^3	1.34×10^3	9.83×10^{-1}	165	2003.75	(1.39×10^3)	1.42×10^3	2.51
79	1996.583	1.36×10^3	1.35×10^3	1.07	166	2003.83	(1.44×10^3)	1.42×10^3	1.29
80	1996.67	1.33×10^3	1.35×10^3	1.12	167	2003.917	(1.39×10^3)	1.42×10^3	2.07
81	1996.75	1.30×10^3	1.35×10^3	3.78	168	2004	(1.46×10^3)	1.42×10^3	2.64
82	1996.83	1.37×10^3	1.35×10^3	1.80	169	2004.083	(1.45×10^3)	1.42×10^3	2.18
83	1996.917	1.33×10^3	1.35×10^3	9.93×10^{-1}	170	2004.167	(1.38×10^3)	1.42×10^3	2.97
84	1997	1.34×10^3	1.35×10^3	2.15×10^{-1}	171	2004.25	(1.44×10^3)	1.42×10^3	1.35
85	1997.083	1.37×10^3	1.35×10^3	1.95	172	2004.3	(1.41×10^3)	1.42×10^3	6.60×10^{-1}
86	1997.167	1.24×10^3	1.35×10^3	9.09	173	2004.417	(1.47×10^3)	1.42×10^3	3.56
87	1997.25	1.39×10^3	1.35×10^3	2.72	174	2004.5	(1.44×10^3)	1.42×10^3	1.36

[a] No. = the sample number; No. 1~144 are learning samples, while No. 145~174 are prediction samples.
[b] x_1 = the real number expression of year and month, e.g., 1990.083 is January of 1990, 1990.167 is February of 1990, …, 1990.917 is November of 1990, 1991 is December of 1990.
[c] MPP = the monthly petroleum production. y^* is measured by well test, number in parenthesis is not input data, but is used for calculating $R(\%)_i$; y is calculated by BPNN.

Using the 144 learning samples with y^* (Table 1) and by the BPNN with OLTC and TSP[8], the following function of y with respect to 6 independent variables (x_1, x_1^2, x_1^3, x_1^4, x_1^5, x_1^6) has been constructed (see Equation 8). This BPNN used consists of 6 input layer nodes, 1 output layer node and 13 hidden layer nodes. Equation 8 is an implicit nonlinear function:

$$y = \text{BPNN}(x_1, x_1^2, x_1^3, x_1^4, x_1^5, x_1^6), \quad (8)$$

with OLTC = 199,988, and RMSE(%) = 0.946×10^{-1}.

Substituting the values of 6 independent variables (x_1, x_1^2, x_1^3, x_1^4, x_1^5, x_1^6) given by the 144 learning samples and 30 prediction samples (Table 1) in Equation 8, the y of each sample is obtained (Table 1).

3. CASE STUDY 2: PREDICTION OF ANNUAL PETROLEUM PRODUCTION FOR JIANGHAN OILFIELD IN CHINA

The objective of this case study is to predict the annual petroleum production (APP), which has practical value for making future APP plan in oilfields.

Using data of 23 samples from the Jianghan Oilfield in China[11], and each sample contains one independent variable (x_1 = year) and one variable (y^* = APP). Among these 23 samples, taking the former 21 samples as learning samples and the latter 2 samples as prediction samples Diao et al. (2007) adopted a Markov model based on nearest neighbor radial basis for the prediction of APP[11]. In this case study, among the 23 samples, the former 18 are taken as learning samples and the latter 5 as prediction samples (Table 2) for the prediction of APP, using BPNN with OLTC and TSP.

Using the 18 learning samples with y^* (Table 2) and by the BPNN with OLTC and TSP[8], the following function of y with respect to 6 independent variables (x_1, x_1^2, x_1^3, x_1^4, x_1^5, x_1^6) has been constructed (see Equation 9). This BPNN used consists of 6 input layer nodes, 1 output layer node and 13 hidden layer nodes. Equation 9 is an implicit nonlinear function:

$$y = \text{BPNN}(x_1, x_1^2, x_1^3, x_1^4, x_1^5, x_1^6), \quad (9)$$

with OLTC = 199,994, and RMSE(%) = 0.340×10^{-1}.

Substituting the values of 6 independent variables (x_1, x_1^2, x_1^3, x_1^4, x_1^5, x_1^6) given by the 18 learning samples and 5 prediction samples (Table 2) in Equation 9, the y of each sample is obtained (Table 2).

From Tables 1 and 2, Table 3 summarizes the applicability of BPNN applied in the two case studies.

Table 2
Input Data and Prediction Results for Prediction of Annual Petroleum Production in Jianghan Oilfield in China (Modified From [11])

No.[a]	Year[b] x_1	APP (Ton)[c] y^*	APP (Ton)[c] y	$R(\%)_i$	No.[a]	Year[b] x_1	APP (Ton)[c] y^*	APP (Ton)[c] y	$R(\%)_i$
1	1983	2.80×10^3	2.80×10^3	0.00	13	1995	2.33×10^3	2.27×10^3	2.63
2	1984	2.78×10^3	2.80×10^3	5.00×10^{-1}	14	1996	2.36×10^3	2.28×10^3	3.76
3	1985	2.74×10^3	2.75×10^3	3.80×10^{-1}	15	1997	2.25×10^3	2.18×10^3	2.89
4	1986	2.79×10^3	2.77×10^3	5.62×10^{-1}	16	1998	2.05×10^3	2.05×10^3	2.99×10^{-1}
5	1987	2.77×10^3	2.79×10^3	8.07×10^{-1}	17	1999	2.15×10^3	2.05×10^3	4.61
6	1988	2.79×10^3	2.77×10^3	5.22×10^{-1}	18	2000	2.06×10^3	2.06×10^3	5.65×10^{-2}
7	1989	2.55×10^3	2.50×10^3	2.09	19	2001	(2.12×10^3)	2.06×10^3	2.58
8	1990	2.28×10^3	2.21×10^3	2.73	20	2002	(2.15×10^3)	2.06×10^3	3.82
9	1991	2.01×10^3	2.05×10^3	2.21	21	2003	(2.12×10^3)	2.07×10^3	2.80
10	1992	2.09×10^3	2.05×10^3	1.85	22	2004	(2.14×10^3)	2.07×10^3	3.34
11	1993	2.22×10^3	2.18×10^3	1.91	23	2005	(2.14×10^3)	2.07×10^3	3.45
12	1994	2.38×10^3	2.30×10^3	3.36					

[a] No. = the sample number; No.1~18 are learning samples, while No.18~23 are prediction samples.
[b] x_1 = year.
[c] APP = the annual petroleum production. y^* is measured by well test, number in parenthesis is not input data, but is used for calculating $R(\%)_i$; y is calculated by BPNN.

Table 3
The Applicability of BPNN Applied in the Two Case Studies

Case study	Mean absolute relative residual $R_1(\%)$	Mean absolute relative residual $R_2(\%)$	Mean absolute relative residual $R(\%)$	Time consuming on PC (Intel Core 2)	Algorithm applicability
Case study 1	2.12	2.45	2.18	8 min 20 s	Applicable
Case study 2	1.73	3.20	2.05	58 s	Applicable

From Table 3, this BPNN applied in the two case studies is applicable because its $R(\%)$ values are 2.18 and 2.05, respectively.

CONCLUSION

The purpose of this paper is to present a special BPNN with two techniques of OLTC and TSP for forecasting petroleum production in Chinese oilfields, as well as algorithm applicability. Two case studies of China have been used to validate the proposed approach. From the application results of the two case studies, two major conclusions can be drawn as follows:

(a) The special BPNN with two techniques of OLTC and TSP for forecasting petroleum production in Chinese oilfields is feasible and practical;

(b) And the definition of solution accuracy $R(\%)$, and the threshold of algorithm applicability ($R(\%) \leq 5$) for an algorithm, are feasible and practical, too.

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