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An innovative neural forecast of cumulative oil production from a petroleum reservoir employing higher-order neural networks (HONNs)

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A B S T R A C T

Precise and consistent production forecasting is indeed an important step for the management and planning of petroleum reservoirs. A new neural approach to forecast cumulative oil production using higher-order neural network (HONN) has been applied in this study. HONN overcomes the limitation of the conventional neural networks by representing linear and nonlinear correlations of neural input variables. Thus, HONN possesses a great potential in forecasting petroleum reservoir productions without sufficient training data. Simulation studies were carried out on a sandstone reservoir located in Cambay basin in Gujarat, India, to prove the efficacy of HONNs in forecasting cumulative oil production of the field with insufficient field data available. A pre-processing procedure was employed in order to reduce measurement noise in the production data from the oil field by using a low pass filter and optimal input variable selection using cross-correlation function (CCF). The results of these simulation studies indicate that the HONN models have good forecasting capability with high accuracy to predict cumulative oil production.

1. Introduction

An important phase in the field of petroleum reservoir engineering is concerned with the forecasting of oil production from the reservoir. This estimation of reserves involves massive investment of money, time and technology under a wide range of operating and maintenance scenarios such as well operations and completion, artificial lift, workover, production, and injection operations. A fairly precise estimation of oil quantity in the reservoir is in demand; however, the rock and fluid properties of the reservoirs are highly nonlinear and heterogeneous in nature. Therefore, it is difficult to estimate an accurate upcoming oil production. The oil production from a reservoir depends on many static and dynamic parameters such as porosity and permeability of rocks (static parameters), and fluid saturation and pressure in the reservoir (dynamic parameters). When these static and dynamic parameters are available, the forecasting of oil production of a reservoir would be more accurate. However, all the parameter data are not always available. This limited data access from the oil fields lessens the accuracy of forecasting.

In the past, several forecasting methods have been developed from decline curve analysis to soft computing techniques (Tamhane et al., 2000). Artificial intelligence tools such as neural computing, fuzzy inference systems and genetic algorithms have been extensively applied in petroleum industries because of their potential to handle the nonlinearities and time-varying situations (Mohaghegh, 2001). Neural networks (NN) is one of the most attractive methods of artificial intelligence to cope with the nonlinearities in production forecasting (Weiss et al., 2002) as well as in parameters estimation (Aminzadeh et al., 2000) due to its ability to learn and adapt to new dynamic environments. Numerous researches have shown successful implementation of NN in the field of oil exploration and development such as pattern recognition in well test analysis (Al-Kaabi and Lee, 1993), reservoir history matching (Maschio et al., 2010), prediction of phase behavior (Habiballah et al., 1996), prediction of natural gas production in the United States (Al-Fattah and Startzman, 2001) and reservoir characterization (Mohaghegh et al., 2001) by mapping the complex nonlinear input–output relationship. In conventional NN model, each neural unit (neuron) performs linear synaptic operation of neural inputs and synaptic weights. Later, extensive researches on NN have been made by Lee et al. (1986), Rumelhart and McClelland (1986), Giles and Maxwell (1987), Gosh and Shin (1992), and Homma and Gupta (2002) to capture the nonlinear synaptic operation of the input space.

As well, it has been reported that neural network models outperform any other conventional statistical model such as Autoregressive Integrated Moving Average (ARIMA), Autoregressive Moving Average (ARMA) and Autoregressive Conditioned Heteroskedasticity (ARCH). Castellano-Mendenz (2004) reported

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multi-layer NN perform better for single step-off prediction than linear ARMA (Box and Jenkins, 1976) model. A superior performance of NN is reported by Donaldson et al. (1993) when compared to specialized nonlinear finance models like ARCH. Donaldson et al. (1993) found that ARCH could only partially remove the leptokurtosis and symmetric/asymmetric heteroskedasticity from the data used to evaluate the fat-tailed and heteroskedasticity nature of the stock return. Nayak et al. (2004) and Tiwari et al. (2012) also reported superiority of NN model over ARMA model in river flow forecasting of hydrological model.

Although the conventional time series models have several advantages and are widely applied for forecasting, but these models have their own limitations while attempting to solve highly nonlinear time series data and also not perform well at times (Tokar and Johnson, 1999). More details on comparison between NN models and conventional statistical techniques for forecasting of time series data can be found in the research paper by Hill et al. (1994).

In order to overcome the constraints of the conventional NN models, numerous methods of modification and improvement of NN model have been carried out. One innovative neural structure embeds higher-order synaptic operations (HOSO) and a new NN model, named higher-order neural network (HONN), was developed employing the HOSO architecture (Gupta et al., 2003; Hou et al., 2006). The exclusive feature of HONN is the expression of the correlation of neural inputs by computing products of the inputs. It has been found that HONN has significant advantages over conventional NN such as faster training, reduced network size, and smaller forecasting errors (Redlapalli, 2004; Song et al., 2009; Gupta et al., 2010; Tiwari et al., 2012). The advantage of NN methods over conventional statistical techniques motivated us to employ HONN model for forecasting of highly nonlinear production data from petroleum reservoir.

HONN has been used for the first time to forecast cumulative oil production from a real oil field reservoir with limited dynamic parameter data: (i) oil production data and (ii) oil, gas and water production data (no data on pressure and fluid saturation available). Two case studies have been carried out to verify the potential of the proposed neural approach with limited available parameters from an oil field in Cambay basin, Gujarat, India. In case study-1, data on only one dynamic parameter, oil production, from five producing wells, are used for forecasting, whereas in case study-2, data on three dynamic parameters, oil, gas and water production from five producing wells, are used for forecasting. A pre-processing step is included for the preparation of neural inputs.

2. Neural networks (NN) and its extension to higher-order neural networks (HONN)

Neural networks (NN) are composed of several layers of neural units (neurons): input layer, hidden layers and output layer. A neural unit is structured mainly with two operations: synaptic operation for weighting, and somatic operation for mapping. In a conventional neural unit, the weighting process is operated with linear correlation of neural inputs, $x_a=(x_0, x_1, x_2, \ldots,x_n)\epsilon R^{n+1}$ (x_0 is the bias), and neural weights, $w_a=(w_0, w_1, w_2, \ldots, w_n)\epsilon R^{n+1}$ ($w_0=1$). The linear correlation can be expressed mathematically as

$$v=w_0x_0+\sum_{i=1}^{n} w_ix_i \tag{1}$$

However, in nature, the correlation of neural inputs and neural weights is not simply linear, but rather related nonlinearly. This observation introduced a nonlinear (higher-order) synaptic operation, and NN with the higher-order synaptic operation (HOSO) (see Fig. 1) was developed and named as higher-order neural networks (HONN) (Gupta et al., 2003; Song et al., 2009). HOSO of HONN embraces the linear correlation (conventional synaptic operation) as well as the higher-order correlation of neural inputs with synaptic weights (up to nth-order correlation).

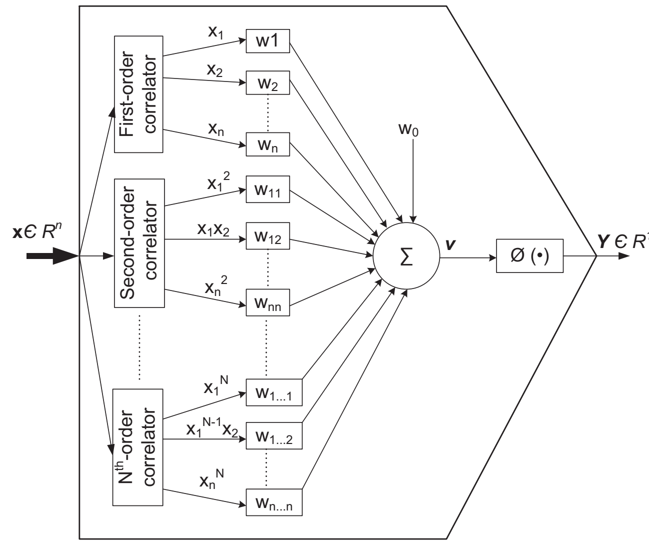

Fig. 1. A neural unit (neuron) with higher-order synaptic operation (HOSO) (Gupta et al., 2003).

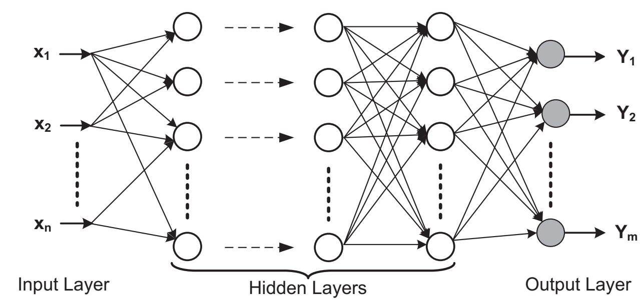

Fig. 2. A schematic diagram of HONN with multilayer.

An Nth order HOSO is defined as

$$v=w_0x_0+\sum_{i_1=1}^{n} w_{i_1}x_{i_1}+\sum_{i_1=1}^{n}\sum_{i_2=i_1}^{n} w_{i_1i_2}x_{i1}x_{i2}+\cdots$$
$$+\sum_{i_1=1}^{n}\sum_{i_2=i_1}^{n}\cdots\sum_{i_N=i_{N-1}}^{n} w_{i_1i_2\cdots i_N}x_{i_1}x_{i_2}\cdots x_{i_N} \tag{2}$$

and the somatic operation, which yields the neural output, is defined as

$$y=\phi(v) \tag{3}$$

In this paper, different HOSO have been applied up to third-order, and the first-order (conventional linear correlation), the second-order and the third-order synaptic operations are called linear synaptic operation (LSO), quadratic synaptic operation (QSO) and cubic synaptic operation (CSO), respectively.

The higher-order neural network (HONN), illustrated in Fig. 2, consists of multiple interconnected layers: input layer, hidden layers and output layer. The input layer conveys n number of input data to the first hidden layer. Each hidden layer includes different number of neurons, and the output layer contains m neurons, m being the number of desired outputs. The number of the hidden layers and the number of neurons in each hidden layer can be assigned after careful investigation for different applications.

HONN is trained by an error based algorithm in which synaptic weights (connection strength) are adjusted to minimize the error between desired and neural outputs (Gupta and Rao, 1993; Gupta, 2008; Gupta et al., 2010). Let $x(k) \in R^n$ be the neural input pattern at time step $k=1, 2,\ldots, n$ corresponding to desired output $y_d(k) \in R^1$ and neural output $y(k)$. The error of a pattern can be calculated as

$$e(k) = y(k) - y_d(k) \tag{4}$$

The overall error for an epoch $E(k)$ is defined as

$$E(k) = \frac{1}{2} e^2(k) \tag{5}$$

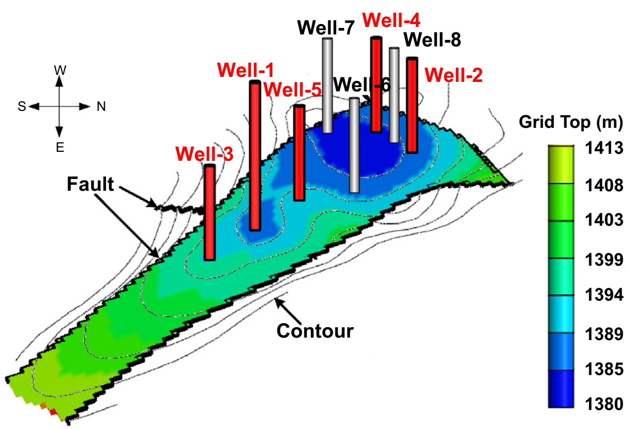

Fig. 3. The top structure map of the oil bearing reservoir with well locations. In this case study, the oil production from Well-1, Well-2, Well-3, Well-4 and Well-5 are forecasted.

The overall error (squared error) is minimized by updating the weight matrix w_a as

$$w_a(k+1) = w_a(k) + \Delta w_a(k) \tag{6}$$

where the change in weight matrix is denoted by $\Delta w_a(k)$ which is proportional to the gradient of the error function $E(k)$ as

$$\Delta w_a(k) = -\alpha \frac{\partial E(k)}{\partial w_a(k)} \tag{7}$$

where $\alpha > 0$ is the learning rate which effects the performance of the algorithm during the updating process. The details can be found in the reference Gupta et al. (2003).

3. Model performance evaluation criteria

Several statistical methods have been used to evaluate the performance of neural networks in the literature. In these studies, the following performance measurements are applied to substantiate the statistical accuracy of the performance of HONNs: mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE). These performance measurements are commonly used evaluation criteria in assessing the model performance to predict the values that deviate from the mean value. They indicate the deviation of prediction of applied HONN models, and they are defined as

Mean Square Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i^{obs} - y_i^{pred})^2 \tag{8}$$

Table 1a
Raw monthly oil production ratios from Well-1, Well-2, Well-3, Well-4 and Well-5 and cumulative oil production ratio.

Months	Well-1 (C1)	Well-2 (C2)	Well-3 (C3)	Well-4 (C4)	Well-5 (C5)	Cumulative Oil (C6)	Months	Well-1 (C1)	Well-2 (C2)	Well-3 (C3)	Well-4 (C4)	Well-5 (C5)	Cumulative Oil (C6)
1	0.111	0.072	0.309	0.090	0.237	0.820	33	0.065	0.048	0.443	0.077	0.070	0.702
2	0.111	0.073	0.307	0.088	0.237	0.815	34	0.042	0.029	0.357	0.033	0.069	0.531
3	0.099	0.060	0.292	0.075	0.226	0.752	35	0.032	0.035	0.508	0.046	0.079	0.701
4	0.103	0.061	0.290	0.081	0.209	0.744	36	0.036	0.039	0.693	0.053	0.089	0.909
5	0.106	0.057	0.298	0.072	0.211	0.744	37	0.034	0.037	0.647	0.049	0.083	0.849
6	0.078	0.091	0.313	0.058	0.197	0.737	38	0.035	0.016	0.665	0.050	0.095	0.860
7	0.111	0.049	0.326	0.084	0.212	0.781	39	0.040	0.019	0.609	0.040	0.092	0.800
8	0.109	0.048	0.320	0.070	0.208	0.755	40	0.018	0.013	0.218	0.013	0.054	0.317
9	0.052	0.049	0.337	0.088	0.180	0.706	41	0.039	0.018	0.601	0.039	0.089	0.786
10	0.053	0.049	0.332	0.089	0.180	0.702	42	0.037	0.017	0.579	0.037	0.086	0.757
11	0.046	0.043	0.303	0.079	0.196	0.668	43	0.016	0.019	0.632	0.038	0.059	0.763
12	0.051	0.029	0.337	0.097	0.193	0.707	44	0.040	0.035	0.564	0.040	0.046	0.725
13	0.050	0.028	0.327	0.051	0.187	0.643	45	0.037	0.033	0.576	0.044	0.057	0.748
14	0.055	0.031	0.359	0.010	0.205	0.659	46	0.034	0.030	0.579	0.041	0.053	0.737
15	0.084	0.031	0.286	0.110	0.163	0.674	47	0.041	0.028	0.543	0.038	0.001	0.651
16	0.065	0.020	0.228	0.094	0.093	0.500	48	0.051	0.024	0.584	0.041	0.000	0.699
17	0.089	0.027	0.276	0.131	0.120	0.644	49	0.045	0.014	0.567	0.048	0.054	0.728
18	0.076	0.023	0.306	0.102	0.155	0.662	50	0.046	0.013	0.577	0.046	0.056	0.739
19	0.076	0.023	0.307	0.064	0.155	0.626	51	0.052	0.060	0.563	0.055	0.033	0.764
20	0.062	0.020	0.280	0.066	0.142	0.571	52	0.044	0.128	0.592	0.058	0.031	0.853
21	0.061	0.022	0.316	0.045	0.164	0.607	53	0.051	0.123	0.596	0.044	0.030	0.844
22	0.063	0.023	0.348	0.047	0.176	0.657	54	0.030	0.120	0.593	0.039	0.017	0.798
23	0.055	0.020	0.308	0.081	0.153	0.617	55	0.028	0.124	0.655	0.046	0.025	0.878
24	0.050	0.031	0.496	0.062	0.114	0.753	56	0.045	0.124	0.572	0.041	0.032	0.814
25	0.046	0.029	0.479	0.058	0.107	0.720	57	0.033	0.218	0.514	0.029	0.033	0.827
26	0.032	0.020	0.419	0.063	0.093	0.626	58	0.029	0.193	0.440	0.028	0.031	0.722
27	0.031	0.018	0.401	0.061	0.086	0.597	59	0.024	0.176	0.426	0.027	0.018	0.671
28	0.047	0.021	0.391	0.041	0.100	0.601	60	0.026	0.188	0.457	0.029	0.019	0.718
29	0.043	0.032	0.322	0.034	0.084	0.515	61	0.025	0.167	0.346	0.021	0.015	0.574
30	0.039	0.043	0.252	0.026	0.068	0.429	62	0.027	0.183	0.364	0.027	0.001	0.602
31	0.065	0.040	0.450	0.077	0.083	0.714	63	0.003	0.140	0.339	0.031	0.204	0.717
32	0.065	0.050	0.463	0.078	0.073	0.729							

Root mean square error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^{obs} - y_i^{pred})^2} \quad (9)$$

Mean absolute percentage error (MAPE) and mean absolute error (MAE):

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}}\right| \quad (10)$$

$$\text{Mean Absolute Error (MAE)} = \frac{\mathrm{MAPE}}{100} \quad (11)$$

where y^{obs} is the observed data, y^{pred} is the predicted data, and n is the number of data points.

In order to illustrate the consistency in performance of HONN model toward forecasting the production data, we have used three performance measurement metrics. The results obtained using all three metrics are different in their calculated values, but the significance of each metrics is similar in performance measurement of HONN model. Since the production data used as neural input, preprocessed data and raw data have different scales, it is preferable to use MAPE for estimating the relative error (Azadeh et al., 2006).

4. Pre-processing: optimal selection of input variables

Before performing a prediction by HONN, it is important and necessary to refine the available parameter data by applying pre-processing because of two main reasons: (i) noise reduction and (ii) proper selection of input variables.

The measured oil production data from the field include noise. It is not appropriate to use the raw production data for neural network training because NN requires extremely low learning rates. Thus, a preprocessing of the raw experimental production data was, therefore, incorporated in all cases. Moving average is a type of low pass filter that transforms the time series monthly production data into smooth trends. This filter does weighted averaging of past data points in the time series production data within the specified time span to generate a smoothed estimate of a time series. The time span of moving average depends on the analytical objectives of the problem. For case studies, we used moving average filter with a time span of five-points since it is found to be optimal for reducing the random noise by retaining the sharpest step response associated with production data. Moving average filter is the simplest and perhaps optimal filter that can be used for time domain signals as reported by Smith (1997).

After noise reduction process, cross-correlation analysis is carried out to find optimal input variables. Determining the significant input variables is an important task in the process of training HONN model for production forecasting. A thorough understanding of dynamics of petroleum reservoir is necessary to avoid missing key input variables and prevent introduction of spurious ones that create confusion in the training process. Currently, there are no defined rules for the selection of the input variables. Most of the heuristic methods for selecting the input variables are ad-hoc or have experimental basis. In this paper, significant input variables are selected by employing cross-correlation function (CCF) for multiple parameter data. Cross-correlation defines an interconnection between two or more variables in a time series and can be calculated using Eq. (12).

Consider two time series x_t and y_t, $t = 1, 2, \ldots, n$; the time series y_t may be related to the past lags of time series x_t and this can be calculated using Eq. (12). Here $r_{xy(k)}$ is the cross-correlation coefficient between x_t and y_t and k is the lag. This means

Table 1b
Smoothed monthly oil production ratios from Well-1, Well-2, Well-3, Well-4 and Well-5 and cumulative oil production ratio.

Months	Well-1 (C1)	Well–2 (C2)	Well–3 (C3)	Well–4 (C4)	Well-5 (C5)	Cumulative oil (C6)	Months	Well-1 (C1)	Well-2 (C2)	Well-3 (C3)	Well-4 (C4)	Well-5 (C5)	Cumulative oil (C6)
1	0.111	0.072	0.309	0.090	0.237	0.820	33	0.054	0.040	0.444	0.062	0.075	0.675
2	0.107	0.068	0.303	0.084	0.233	0.796	34	0.048	0.040	0.493	0.057	0.076	0.714
3	0.106	0.065	0.299	0.081	0.224	0.775	35	0.042	0.038	0.530	0.052	0.078	0.738
4	0.099	0.068	0.300	0.075	0.216	0.758	36	0.036	0.031	0.574	0.046	0.083	0.770
5	0.099	0.064	0.304	0.074	0.211	0.752	37	0.035	0.029	0.624	0.048	0.088	0.824
6	0.101	0.061	0.309	0.073	0.207	0.752	38	0.033	0.025	0.566	0.041	0.083	0.747
7	0.091	0.059	0.319	0.074	0.202	0.745	39	0.033	0.021	0.548	0.038	0.083	0.722
8	0.081	0.057	0.326	0.078	0.195	0.736	40	0.034	0.017	0.534	0.036	0.083	0.704
9	0.074	0.048	0.324	0.082	0.195	0.722	41	0.030	0.017	0.528	0.033	0.076	0.685
10	0.062	0.044	0.326	0.085	0.191	0.708	42	0.030	0.020	0.519	0.033	0.067	0.670
11	0.050	0.040	0.327	0.081	0.187	0.685	43	0.034	0.024	0.590	0.040	0.067	0.756
12	0.051	0.036	0.332	0.065	0.192	0.676	44	0.033	0.027	0.586	0.040	0.060	0.746
13	0.057	0.032	0.322	0.069	0.189	0.670	45	0.034	0.029	0.579	0.040	0.043	0.725
14	0.061	0.028	0.307	0.072	0.168	0.637	46	0.041	0.030	0.569	0.041	0.031	0.712
15	0.069	0.027	0.295	0.079	0.154	0.624	47	0.042	0.026	0.570	0.042	0.033	0.713
16	0.074	0.026	0.291	0.089	0.147	0.628	48	0.043	0.022	0.570	0.043	0.033	0.711
17	0.078	0.025	0.281	0.100	0.137	0.621	49	0.047	0.028	0.567	0.046	0.029	0.716
18	0.074	0.023	0.279	0.091	0.133	0.601	50	0.048	0.048	0.577	0.050	0.035	0.757
19	0.073	0.023	0.297	0.082	0.147	0.622	51	0.048	0.068	0.579	0.050	0.041	0.786
20	0.068	0.022	0.311	0.065	0.158	0.625	52	0.045	0.089	0.584	0.048	0.033	0.800
21	0.063	0.022	0.312	0.061	0.158	0.616	53	0.041	0.111	0.600	0.048	0.027	0.827
22	0.058	0.023	0.350	0.060	0.150	0.641	54	0.040	0.124	0.602	0.046	0.027	0.837
23	0.055	0.025	0.389	0.059	0.143	0.671	55	0.037	0.142	0.586	0.040	0.027	0.832
24	0.049	0.025	0.410	0.062	0.129	0.675	56	0.033	0.156	0.555	0.037	0.028	0.808
25	0.043	0.024	0.421	0.065	0.111	0.663	57	0.032	0.167	0.521	0.034	0.028	0.782
26	0.041	0.024	0.437	0.057	0.100	0.659	58	0.031	0.180	0.482	0.031	0.027	0.750
27	0.040	0.024	0.402	0.051	0.094	0.612	59	0.027	0.188	0.437	0.027	0.023	0.702
28	0.038	0.027	0.357	0.045	0.086	0.554	60	0.026	0.181	0.407	0.026	0.017	0.657
29	0.045	0.031	0.363	0.048	0.084	0.571	61	0.021	0.171	0.386	0.027	0.051	0.656
30	0.052	0.037	0.376	0.051	0.082	0.598	62	0.018	0.163	0.350	0.026	0.073	0.631
31	0.055	0.043	0.386	0.058	0.076	0.618	63	0.003	0.140	0.339	0.031	0.204	0.717
32	0.055	0.042	0.393	0.058	0.073	0.621							

measurements in the variable y are lagging or leading those in x by k time steps.

$$r_{xy(k)} = \frac{n\sum(x_t-\bar{x})(y_{t-}\bar{y})-\sum x_t\sum y_t}{\sqrt{n\sum x_t^2-(\sum x_t)^2}\sqrt{n\sum y_t^2-(\sum y_t)^2}} \tag{12}$$

In the present study only positive lags have been used. The presence of positive lag$k$ between x_t and y_t indicates that the relationship between these time series will be most significant when the data in x at time t are related to data in y at time $t+k$.

5. The reservoir under study

The simulation studies are carried out with the production data from a real oil field reservoir which has 63 months (from 2004 to 2009) of production history. The oil field is located in south-western part of Tarapur Block of Cambay Basin and to the west of Cambay Gas Field in India. This field consists of total eight oil producing wells. The structure of the field trends NNW–SSE in direction and bounded by a fault on either side, which separates the structure from the adjoining lows. The reservoir structure is controlled by East–West trending normal fault in the north, and it narrows down toward south. The field is composed of three sandstone layers (L-1, L-2, and L-3) having varying thickness up to 25 m, and these layers are separated by thin shales with thickness between the range of 1 m and 2 m. The graphical presentation of oil field reservoir for this study is shown in Fig. 3.

The initial reservoir pressure was recorded as 144 kg/cm^2 at 1397 m. The quantity of reserved oil inplace was 2.47 MMt, and the cumulative oil production until September 2009 was 0.72 MMt which is 29.1% of the inplace reserve and 64.5% of ultimate reserve. The marginal drop in reservoir pressure against cumulative oil production of 0.72 MMt indicates that the reservoir is operating under active water drive. Most of the wells are producing gas to oil ratio (GOR) in the range of 30–35 v/v as wells are flowing above the bubble point pressure. Hence the model shows constant producing GOR.

The field started producing oil from February 2000 through Well-1 and December 2000 through Well-2. Well-1 produces oil at 58 m^3/d through 6 mm bean. The initial reservoir pressure recorded at Well-1 was 144.6 kg/cm^2 at 1385 m. The cumulative productions of oil, gas and water from Well-1 till September 2009 are 0.156 MMt, 8.1 MMm^3, and 7.2 Mm^3, respectively. Later, other wells (Well-3–Well-8) were drilled and put on production in different years until 2009. In this study, we are interested in forecasting cumulative oil production from the five wells having continuous production history, Well-1, Well-2, Well-3, Well-4 and Well-5. Two cases are studied for cumulative oil production

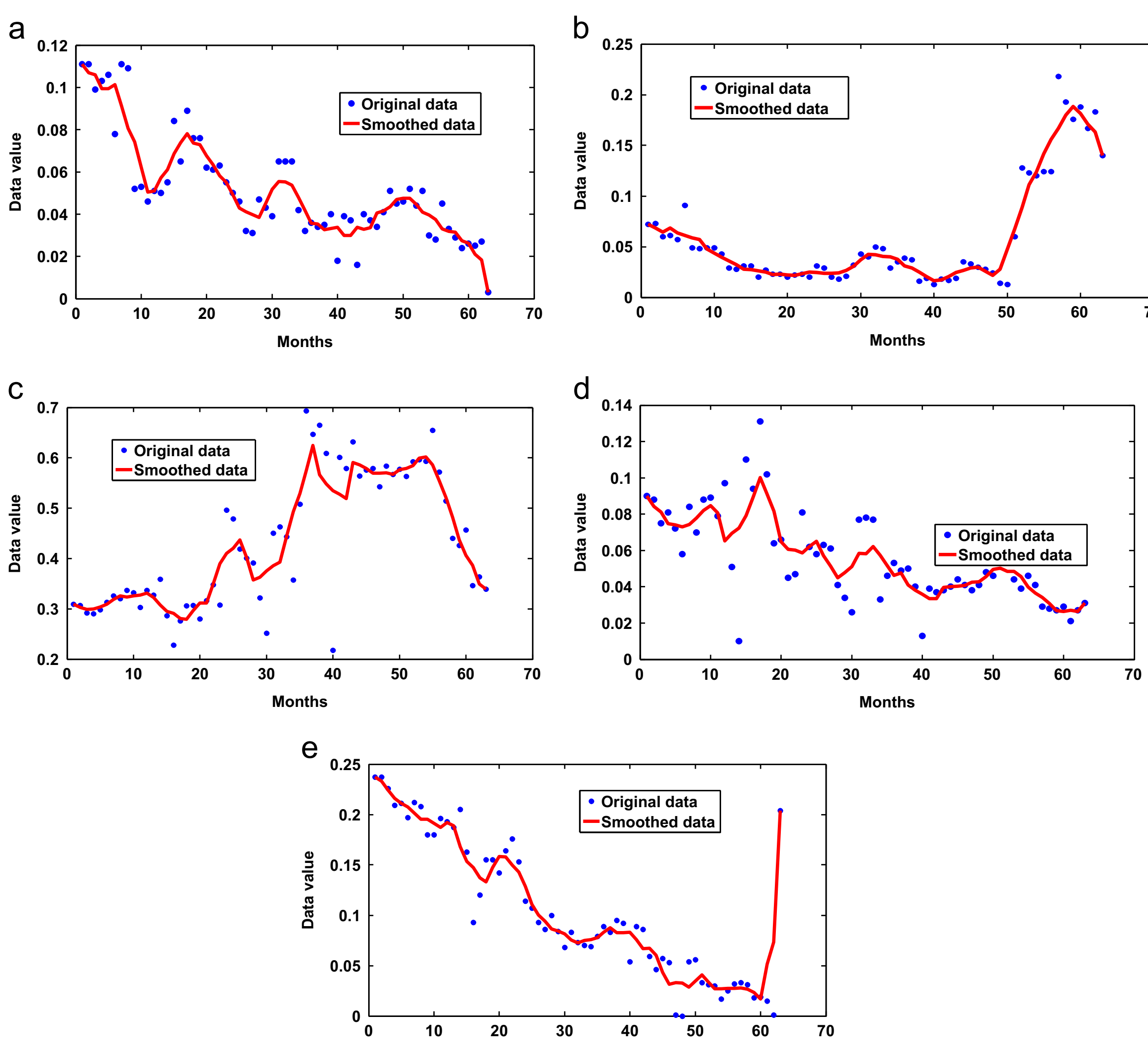

Fig. 4. Oil production history from 2004 to 2009 before and after smoothing of (a) Well-1, (b) Well-2, (c) Well-3, (d) Well-4, and (e) Well-5.

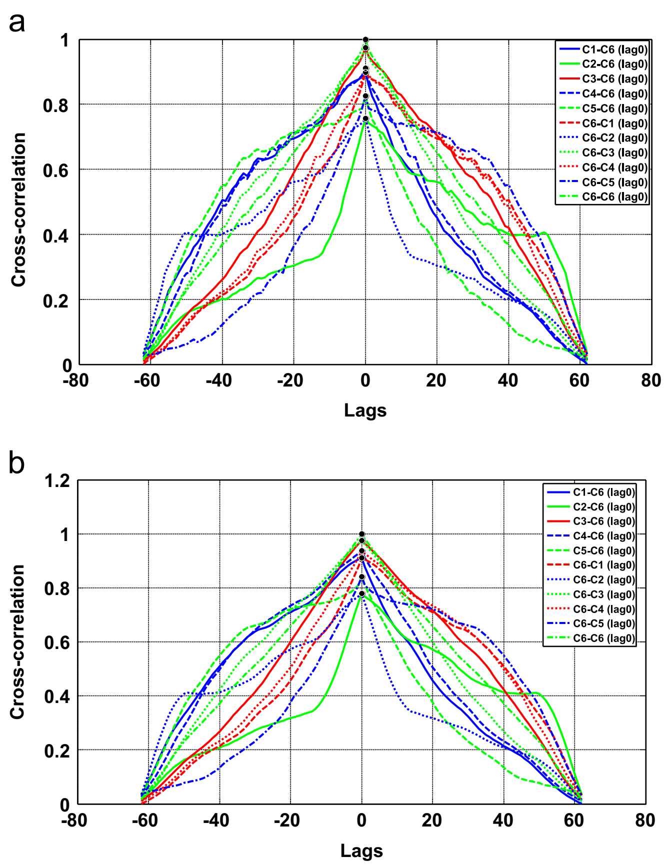

Fig. 5. Cross-correlation of cumulative oil production to five wells. The legend represents the correlation between two parameters. The dark circles on the plot indicate the highest correlation between two parameters. (a) CCF of original oil production data and (b) CCF of smoothed oil production data.

forecasting using (i) only oil production data from five wells and (ii) oil, water and gas production data from five wells.

5.1. Structure of HONN

In this study, a number of design factors for HONN were considered such as selection of neural structure (order of synaptic operation), numbers of neurons and hidden layers. Also, different mapping functions (somatic operation) were selected after careful investigation in each layer: a sigmoidal (hyperbolic tangent) function for hidden layers and a linear function for the output layer. In HONN, three synaptic operations were applied for HONN modeling: linear synaptic operation (LSO), quadratic synaptic operation (QSO) and cubic synaptic operation (CSO). It should be noted that LSO represents the synaptic operation of the conventional NN. Only one hidden layer was used since it resulted in the best output for time sequence applications such as forecasting (Tiwari et al., 2012) and different number of neurons (1–10 for case-1, and 1–5 for case-2) in the hidden layer were applied. Each HONN model was run with learning rate of 0.01 and different initial synaptic weights. The learning rate was dynamically updated by multiplying with 0.7 for increasing error and with 1.05 for reducing error. After pre-processing, the data were divided into three segments for training, validation and test. Thirty-five data sets were used for training, 17 for validation and remaining 10 data for testing. Each model was trained and updated for 200 epochs for training and validation before test.

5.2. Case study-1

In this case study, for training HONN, the monthly oil production ratios from month one to month 63 (6 years) were used for cumulative oil production forecasting as shown in Table 1a. The monthly production ratios were calculated using the maximum

Table 2
The training, validation and target data used to train HONN models for scenario 1 (lag1).

Months	Input-1	Input-2	Input-3	Input-4	Input-5	Target
1	0.111	0.072	0.309	0.09	0.237	0.796
2	0.107	0.068	0.303	0.084	0.233	0.775
3	0.106	0.065	0.299	0.081	0.224	0.758
4	0.099	0.068	0.3	0.075	0.216	0.752
5	0.099	0.064	0.304	0.074	0.211	0.752
6	0.101	0.061	0.309	0.073	0.207	0.745
7	0.091	0.059	0.319	0.074	0.202	0.736
8	0.081	0.057	0.326	0.078	0.195	0.722
9	0.074	0.048	0.324	0.082	0.195	0.708
10	0.062	0.044	0.326	0.085	0.191	0.685
11	0.05	0.04	0.327	0.081	0.187	0.676
12	0.051	0.036	0.332	0.065	0.192	0.67
13	0.057	0.032	0.322	0.069	0.189	0.637
14	0.061	0.028	0.307	0.072	0.168	0.624
15	0.069	0.027	0.295	0.079	0.154	0.628
16	0.074	0.026	0.291	0.089	0.147	0.621
17	0.078	0.025	0.281	0.1	0.137	0.601
18	0.074	0.023	0.279	0.091	0.133	0.622
19	0.073	0.023	0.297	0.082	0.147	0.625
20	0.068	0.022	0.311	0.065	0.158	0.616
21	0.063	0.022	0.312	0.061	0.158	0.641
22	0.058	0.023	0.35	0.06	0.15	0.671
23	0.055	0.025	0.389	0.059	0.143	0.675
24	0.049	0.025	0.41	0.062	0.129	0.663
25	0.043	0.024	0.421	0.065	0.111	0.659
26	0.041	0.024	0.437	0.057	0.1	0.612
27	0.04	0.024	0.402	0.051	0.094	0.554
28	0.038	0.027	0.357	0.045	0.086	0.571
29	0.045	0.031	0.363	0.048	0.084	0.598

Table 2 (*continued*)

Months	Input-1	Input-2	Input-3	Input-4	Input-5	Target
30	0.052	0.037	0.376	0.051	0.082	0.618
31	0.055	0.043	0.386	0.058	0.076	0.621
32	0.055	0.042	0.393	0.058	0.073	0.675
33	0.054	0.04	0.444	0.062	0.075	0.714
34	0.048	0.04	0.493	0.057	0.076	0.738
35	0.042	0.038	0.53	0.052	0.078	0.77
36	0.036	0.031	0.574	0.046	0.083	0.824
37	0.035	0.029	0.624	0.048	0.088	0.747
38	0.033	0.025	0.566	0.041	0.083	0.722
39	0.033	0.021	0.548	0.038	0.083	0.704
40	0.034	0.017	0.534	0.036	0.083	0.685
41	0.03	0.017	0.528	0.033	0.076	0.67
42	0.03	0.02	0.519	0.033	0.067	0.756
43	0.034	0.024	0.59	0.04	0.067	0.746
44	0.033	0.027	0.586	0.04	0.06	0.725
45	0.034	0.029	0.579	0.04	0.043	0.712
46	0.041	0.03	0.569	0.041	0.031	0.713
47	0.042	0.026	0.57	0.042	0.033	0.711
48	0.043	0.022	0.57	0.043	0.033	0.716
49	0.047	0.028	0.567	0.046	0.029	0.757
50	0.048	0.048	0.577	0.05	0.035	0.786
51	0.048	0.068	0.579	0.05	0.041	0.8
52	0.045	0.089	0.584	0.048	0.033	0.827

Table 3
Performance measure of HONNs using single lag1.

Synaptic operation	Number of hidden layers	Number of neurons	MSE		RMSE		MAPE (%)	
			Mean	SD	Mean	SD	Mean	SD
Linear synaptic operation (LSO)	1	1	0.003	0.001	0.057	0.010	6.777	1.302
		2	0.003	0.001	0.054	0.011	5.954	1.181
		3	0.003	0.001	0.052	0.010	6.042	0.956
		4	0.002	0.000	0.047	0.004	5.425	0.489
		5	0.002	0.000	0.043	0.006	4.717	0.721
		6	0.002	0.000	0.044	0.004	5.041	0.599
		7	0.002	0.001	0.043	0.006	5.276	0.776
		8	0.002	0.001	0.049	0.006	5.979	0.799
		9	0.004	0.001	0.061	0.008	6.771	0.768
		10	0.002	0.000	0.041	0.004	4.055	0.620
Quadratic synaptic operation (QSO)	1	1	0.003	0.001	0.055	0.008	6.610	0.711
		2	0.001	0.000	0.038	0.003	3.943	0.383
		3	0.003	0.001	0.050	0.008	5.464	0.902
		4	0.001	0.000	0.038	0.005	4.355	0.852
		5	0.003	0.001	0.051	0.012	5.248	1.454
		6	0.001	0.000	0.038	0.004	4.081	0.781
		7	0.002	0.001	0.044	0.006	5.268	0.822
		8	0.001	0.000	0.036	0.006	4.131	0.831
		9	0.002	0.001	0.041	0.010	3.898	0.590
		10	0.003	0.001	0.052	0.010	5.663	1.127
Cubic synaptic operation (CSO)	1	1	0.003	0.001	0.056	0.005	6.517	0.481
		2	0.002	0.001	0.044	0.009	4.920	0.813
		3	0.002	0.001	0.047	0.006	5.368	0.981
		4	**0.001**	**0.001**	**0.035**	**0.010**	**3.459**	**0.452**
		5	0.003	0.001	0.050	0.007	5.758	1.001
		6	0.003	0.002	0.049	0.016	5.373	1.845
		7	0.002	0.000	0.041	0.003	4.044	0.741
		8	0.003	0.000	0.055	0.005	6.610	0.706
		9	0.001	0.001	0.033	0.009	3.634	0.930
		10	0.002	0.000	0.047	0.005	5.087	0.493

The numbers in bold represent best results from HONN.

production of products (approximately 9500 m^3/month for oil) through the 6 year production history of Well-1, Well-2, Well-3, Well-4 and Well-5. For example, C1, the production ratio for Well-1, is calculated by dividing the first month's oil production from this well by 9500.

In the pre-processing stage, the oil production ratio data were smoothed using a five point moving average filter. Table 1b shows the smoothed oil production data for this case study. The graphical representation of original oil production versus smoothed production data for Well-1 to Well-5 is shown in Fig. 4. As seen in this figure, the high peaks of the data were smoothed. After the smoothing process, the cross-correlations of the cumulative oil production data for the five wells were calculated by the cross-correlation function (CCF). The CCF plots of oil production before and after smoothing are presented in Fig. 5. In Fig. 5, notations; C1, C2, C3, C4, and C5, in the legend box corresponds to the each wells oil production from Well-1–Well-5 and C6 corresponds to cumulative oil production. C1–C6, in Fig. 5, represents the cross-correlation between the oil productions from Well-1 to cumulative oil production from all the wells. As shown, the highest correlation occurs at lag0. Since lag0 represents current time step (no step ahead), lag0 can be neglected for forecasting methods. From the CCF plot, it was identified that lag1 and lag2 have the most significant correlation which means that the input variables in these lags are the optimal to train HONN. HONN was trained to forecast cumulative oil production based on three scenarios: (1) using only lag1 (single lag1) for training; (2) using only lag2 (single lag2) for training; and (3) using lag1 and lag2 (accumulated lag2) for training.

5.2.1. HONN using single Lag1

In scenario 1, first 35 months data were used for training and next 17 months data for validation, and the data were randomly rearranged as presented in Table 2 after the pre-processing. In Table 2, Input-1, Input-2, Input-3, Input-4, and Input-5 correspond to oil productions rates from Well-1, Well-2, Well-3, Well-4 and Well-5. It may be noted that to account for this lag1, the cumulative oil production has been advanced by one time step.

The simulation results from HONN model in terms of RMSE, MSE and MAPE are shown in Table 3, comparing the performances with different number of neurons in the hidden layer. The selection criteria for a better model are lower values of MAPE, MSE and RMSE. From simulation results, the best model was HONN with CSO having four neurons in the hidden layer. The performance indices show that the best model is the HONN with CSO resulted in MAPE=3.459%, MSE=0.001, and RMSE=0.035. In case of HONN with LSO, MAPE=4.055% was achieved having 10

Table 4
The training, validation and target data used to train HONN models for scenario 2 (lag2).

Months	Input 1	Input-2	Input -3	Input -4	Input-5	Target
1	0.111	0.072	0.309	0.09	0.237	0.775
2	0.107	0.068	0.303	0.084	0.233	0.758
3	0.106	0.065	0.299	0.081	0.224	0.752
4	0.099	0.068	0.3	0.075	0.216	0.752
5	0.099	0.064	0.304	0.074	0.211	0.745
6	0.101	0.061	0.309	0.073	0.207	0.736
7	0.091	0.059	0.319	0.074	0.202	0.722
8	0.081	0.057	0.326	0.078	0.195	0.708
9	0.074	0.048	0.324	0.082	0.195	0.685
10	0.062	0.044	0.326	0.085	0.191	0.676
11	0.05	0.04	0.327	0.081	0.187	0.67
12	0.051	0.036	0.332	0.065	0.192	0.637
13	0.057	0.032	0.322	0.069	0.189	0.624
14	0.061	0.028	0.307	0.072	0.168	0.628
15	0.069	0.027	0.295	0.079	0.154	0.621
16	0.074	0.026	0.291	0.089	0.147	0.601
17	0.078	0.025	0.281	0.1	0.137	0.622
18	0.074	0.023	0.279	0.091	0.133	0.625
19	0.073	0.023	0.297	0.082	0.147	0.616
20	0.068	0.022	0.311	0.065	0.158	0.641
21	0.063	0.022	0.312	0.061	0.158	0.671
22	0.058	0.023	0.35	0.06	0.15	0.675
23	0.055	0.025	0.389	0.059	0.143	0.663
24	0.049	0.025	0.41	0.062	0.129	0.659
25	0.043	0.024	0.421	0.065	0.111	0.612
26	0.041	0.024	0.437	0.057	0.1	0.554
27	0.04	0.024	0.402	0.051	0.094	0.571
28	0.038	0.027	0.357	0.045	0.086	0.598
29	0.045	0.031	0.363	0.048	0.084	0.618
30	0.052	0.037	0.376	0.051	0.082	0.621
31	0.055	0.043	0.386	0.058	0.076	0.675
32	0.055	0.042	0.393	0.058	0.073	0.714
33	0.054	0.04	0.444	0.062	0.075	0.738
34	0.048	0.04	0.493	0.057	0.076	0.77
35	0.042	0.038	0.53	0.052	0.078	0.824
36	0.036	0.031	0.574	0.046	0.083	0.747
37	0.035	0.029	0.624	0.048	0.088	0.722
38	0.033	0.025	0.566	0.041	0.083	0.704
39	0.033	0.021	0.548	0.038	0.083	0.685
40	0.034	0.017	0.534	0.036	0.083	0.67
41	0.03	0.017	0.528	0.033	0.076	0.756
42	0.03	0.02	0.519	0.033	0.067	0.746
43	0.034	0.024	0.59	0.04	0.067	0.725
44	0.033	0.027	0.586	0.04	0.06	0.712
45	0.034	0.029	0.579	0.04	0.043	0.713
46	0.041	0.03	0.569	0.041	0.031	0.711
47	0.042	0.026	0.57	0.042	0.033	0.716
48	0.043	0.022	0.57	0.043	0.033	0.757
49	0.047	0.028	0.567	0.046	0.029	0.786
50	0.048	0.048	0.577	0.05	0.035	0.8
51	0.048	0.068	0.579	0.05	0.041	0.827

Table 5
Performance measure of HONNs using single lag2.

Synaptic operation	Number of hidden layers	Number of neurons	MSE		RMSE		MAPE (%)	
			Mean	SD	Mean	SD	Mean	SD
Linear synaptic operation (LSO)	1	1	0.004	0.001	0.065	0.010	7.562	0.831
		2	0.003	0.001	0.058	0.006	6.392	0.894
		3	0.003	0.001	0.055	0.006	6.169	0.793
		4	0.005	0.001	0.070	0.004	7.695	0.210
		5	0.002	0.001	0.049	0.006	5.925	0.821
		6	0.004	0.001	0.060	0.005	6.473	0.382
		7	0.003	0.001	0.054	0.007	6.110	0.722
		8	0.003	0.001	0.058	0.006	6.702	0.740
		9	0.004	0.000	0.060	0.004	6.884	0.667
		10	0.003	0.001	0.057	0.008	6.242	0.919
Quadratic synaptic operation (QSO)	1	1	0.003	0.001	0.057	0.007	6.220	0.699
		2	0.003	0.001	0.054	0.010	5.859	0.843
		3	0.002	0.001	0.047	0.011	5.216	1.057
		4	0.003	0.000	0.056	0.004	6.279	0.624
		5	0.003	0.001	0.051	0.008	5.358	1.124
		6	0.003	0.001	0.052	0.010	5.649	1.145
		7	0.002	0.000	0.043	0.004	5.127	0.694
		8	0.003	0.001	0.057	0.005	6.614	0.606
		9	0.002	0.001	0.049	0.008	5.445	1.431
		10	0.002	0.001	0.046	0.008	5.381	1.017
Cubic synaptic operation (CSO)	1	1	0.002	0.001	0.049	0.005	5.650	0.761
		2	**0.002**	**0.000**	**0.045**	**0.005**	**4.882**	**0.791**
		3	0.002	0.000	0.048	0.005	5.665	0.978
		4	0.003	0.001	0.052	0.006	5.818	0.862
		5	0.002	0.001	0.048	0.009	5.413	1.369
		6	0.003	0.000	0.055	0.003	6.222	0.577
		7	0.003	0.002	0.057	0.016	6.573	2.033
		8	0.002	0.001	0.049	0.007	5.276	0.614
		9	0.004	0.001	0.060	0.008	6.623	1.030
		10	0.008	0.005	0.083	0.030	9.662	2.979

The numbers in bold represent best results from HONN.

Table 6
The training, validation and target data used to train HONN models for scenario 3 (accumulated lag2).

Months	Input-1	Input-2	Input-3	Input-4	Input-5	Input-6	Input-7	Input-8	Input-9	Input-10	Target
1	0.107	0.068	0.303	0.084	0.233	0.111	0.072	0.309	0.09	0.237	0.775
2	0.106	0.065	0.299	0.081	0.224	0.107	0.068	0.303	0.084	0.233	0.758
3	0.099	0.068	0.3	0.075	0.216	0.106	0.065	0.299	0.081	0.224	0.752
4	0.099	0.064	0.304	0.074	0.211	0.099	0.068	0.3	0.075	0.216	0.752
5	0.101	0.061	0.309	0.073	0.207	0.099	0.064	0.304	0.074	0.211	0.745
6	0.091	0.059	0.319	0.074	0.202	0.101	0.061	0.309	0.073	0.207	0.736
7	0.081	0.057	0.326	0.078	0.195	0.091	0.059	0.319	0.074	0.202	0.722
8	0.074	0.048	0.324	0.082	0.195	0.081	0.057	0.326	0.078	0.195	0.708
9	0.062	0.044	0.326	0.085	0.191	0.074	0.048	0.324	0.082	0.195	0.685
10	0.05	0.04	0.327	0.081	0.187	0.062	0.044	0.326	0.085	0.191	0.676
11	0.051	0.036	0.332	0.065	0.192	0.05	0.04	0.327	0.081	0.187	0.67
12	0.057	0.032	0.322	0.069	0.189	0.051	0.036	0.332	0.065	0.192	0.637
13	0.061	0.028	0.307	0.072	0.168	0.057	0.032	0.322	0.069	0.189	0.624
14	0.069	0.027	0.295	0.079	0.154	0.061	0.028	0.307	0.072	0.168	0.628
15	0.074	0.026	0.291	0.089	0.147	0.069	0.027	0.295	0.079	0.154	0.621
16	0.078	0.025	0.281	0.1	0.137	0.074	0.026	0.291	0.089	0.147	0.601
17	0.074	0.023	0.279	0.091	0.133	0.078	0.025	0.281	0.1	0.137	0.622
18	0.073	0.023	0.297	0.082	0.147	0.074	0.023	0.279	0.091	0.133	0.625
19	0.068	0.022	0.311	0.065	0.158	0.073	0.023	0.297	0.082	0.147	0.616
20	0.063	0.022	0.312	0.061	0.158	0.068	0.022	0.311	0.065	0.158	0.641
21	0.058	0.023	0.35	0.06	0.15	0.063	0.022	0.312	0.061	0.158	0.671
22	0.055	0.025	0.389	0.059	0.143	0.058	0.023	0.35	0.06	0.15	0.675
23	0.049	0.025	0.41	0.062	0.129	0.055	0.025	0.389	0.059	0.143	0.663
24	0.043	0.024	0.421	0.065	0.111	0.049	0.025	0.41	0.062	0.129	0.659
25	0.041	0.024	0.437	0.057	0.1	0.043	0.024	0.421	0.065	0.111	0.612
26	0.04	0.024	0.402	0.051	0.094	0.041	0.024	0.437	0.057	0.1	0.554
27	0.038	0.027	0.357	0.045	0.086	0.04	0.024	0.402	0.051	0.094	0.571
28	0.045	0.031	0.363	0.048	0.084	0.038	0.027	0.357	0.045	0.086	0.598
29	0.052	0.037	0.376	0.051	0.082	0.045	0.031	0.363	0.048	0.084	0.618
30	0.055	0.043	0.386	0.058	0.076	0.052	0.037	0.376	0.051	0.082	0.621
31	0.055	0.042	0.393	0.058	0.073	0.055	0.043	0.386	0.058	0.076	0.675

Table 6 (*continued*)

Months	Input-1	Input-2	Input-3	Input-4	Input-5	Input-6	Input-7	Input-8	Input-9	Input-10	Target
32	0.054	0.04	0.444	0.062	0.075	0.055	0.042	0.393	0.058	0.073	0.714
33	0.048	0.04	0.493	0.057	0.076	0.054	0.04	0.444	0.062	0.075	0.738
34	0.042	0.038	0.53	0.052	0.078	0.048	0.04	0.493	0.057	0.076	0.77
35	0.036	0.031	0.574	0.046	0.083	0.042	0.038	0.53	0.052	0.078	0.824
36	0.035	0.029	0.624	0.048	0.088	0.036	0.031	0.574	0.046	0.083	0.747
37	0.033	0.025	0.566	0.041	0.083	0.035	0.029	0.624	0.048	0.088	0.722
38	0.033	0.021	0.548	0.038	0.083	0.033	0.025	0.566	0.041	0.083	0.704
39	0.034	0.017	0.534	0.036	0.083	0.033	0.021	0.548	0.038	0.083	0.685
40	0.03	0.017	0.528	0.033	0.076	0.034	0.017	0.534	0.036	0.083	0.67
41	0.03	0.02	0.519	0.033	0.067	0.03	0.017	0.528	0.033	0.076	0.756
42	0.034	0.024	0.59	0.04	0.067	0.03	0.02	0.519	0.033	0.067	0.746
43	0.033	0.027	0.586	0.04	0.06	0.034	0.024	0.59	0.04	0.067	0.725
44	0.034	0.029	0.579	0.04	0.043	0.033	0.027	0.586	0.04	0.06	0.712
45	0.041	0.03	0.569	0.041	0.031	0.034	0.029	0.579	0.04	0.043	0.713
46	0.042	0.026	0.57	0.042	0.033	0.041	0.03	0.569	0.041	0.031	0.711
47	0.043	0.022	0.57	0.043	0.033	0.042	0.026	0.57	0.042	0.033	0.716
48	0.047	0.028	0.567	0.046	0.029	0.043	0.022	0.57	0.043	0.033	0.757
49	0.048	0.048	0.577	0.05	0.035	0.047	0.028	0.567	0.046	0.029	0.786
50	0.048	0.068	0.579	0.05	0.041	0.048	0.048	0.577	0.05	0.035	0.8
51	0.045	0.089	0.584	0.048	0.033	0.048	0.068	0.579	0.05	0.041	0.827

Table 7
Performance measure of HONNs using accumulated lag2.

Synaptic operation	Number of hidden layers	Number of neurons	MSE		RMSE		MAPE (%)	
			Mean	SD	Mean	SD	Mean	SD
Linear synaptic operation (LSO)	1	1	0.004	0.001	0.059	0.008	6.715	1.261
		2	0.004	0.001	0.063	0.008	7.134	0.563
		3	0.003	0.001	0.055	0.010	6.362	0.834
		4	0.004	0.001	0.059	0.010	6.670	1.081
		5	0.003	0.000	0.051	0.003	5.711	0.150
		6	0.003	0.000	0.054	0.004	6.266	0.565
		7	0.003	0.001	0.051	0.007	5.167	1.024
		8	0.002	0.000	0.042	0.003	4.748	0.802
		9	0.003	0.001	0.056	0.007	6.695	0.578
		10	0.002	0.001	0.047	0.005	5.134	0.671
Quadratic synaptic operation (QSO)	1	1	0.003	0.000	0.055	0.004	6.583	0.534
		2	0.002	0.000	0.041	0.003	4.465	0.547
		3	0.002	0.000	0.040	0.003	4.320	0.407
		4	0.003	0.001	0.051	0.011	5.438	1.413
		5	0.002	0.001	0.045	0.006	5.184	0.717
		6	0.002	0.001	0.045	0.010	5.289	1.534
		7	0.002	0.001	0.047	0.009	4.984	0.847
		8	0.003	0.001	0.055	0.005	5.525	0.576
		9	0.003	0.001	0.054	0.007	6.199	1.087
		10	0.005	0.002	0.070	0.015	7.320	1.138
Cubic synaptic operation (CSO)	1	1	0.003	0.000	0.056	0.003	6.456	0.516
		2	0.002	0.001	0.046	0.008	5.214	1.181
		3	**0.002**	**0.000**	**0.039**	**0.003**	**4.045**	**0.462**
		4	0.003	0.001	0.053	0.008	5.474	1.168
		5	0.003	0.001	0.058	0.009	6.141	1.016
		6	0.002	0.001	0.045	0.011	5.362	1.508
		7	0.004	0.001	0.063	0.007	7.013	0.853
		8	0.003	0.001	0.054	0.012	6.045	1.748
		9	0.004	0.001	0.063	0.008	7.293	0.901
		10	0.005	0.002	0.072	0.013	7.620	1.191

The numbers in bold represent best results from HONN.

neural units in the hidden layer, and MAPE=3.89% was achieved by HONN with QSO having nine neurons in the hidden layer.

5.2.2. *HONN using single Lag2*

In scenario 2, first 34 months data were used for training and next 17 months data for validation were selected applying single lag2 after pre-processing and the data were randomly rearranged as listed in Table 4. Here again, the first number in C6 has been advanced by two time steps.

Table 5 lists the simulation results using single lag2 for HONN. The performance indices show that the best model is HONN with CSO resulting in MAPE=4.882%, MSE=0.002, and RMSE=0.045 with two neurons in the hidden layer. HONN with QSO also resulted in low error having MAPE=5.127, MSE=0.002, RMSE=0.043 with seven neurons in the hidden layer. However, the HONNs LSO resulted in higher errors compared to CSO and QSO with single lag2.

5.2.3. HONN using accumulated Lag2

In this scenario, after the pre-processing, the data were selected applying accumulated lag2 (lag1 and lag2), and the data were randomly rearranged for training and validation as shown in

Table 8
Smoothed monthly oil, gas and water production data ratios of 5 wells and cumulative oil production ratio.

Months	Well-1			Well-2			Well-3			Well-4			Well-5			Cumulative oil
	Oil (C1)	Gas (C2)	Water (C3)	Oil (C4)	Gas (C5)	Water (C6)	Oil (C7)	Gas (C8)	Water (C9)	Oil (C10)	Gas (C11)	Water (C12)	Oil (C13)	Gas (C14)	Water (C15)	
1	0.111	0.107	0.184	0.072	0.050	0.203	0.309	0.256	0.029	0.090	0.047	0.210	0.237	0.217	0.080	0.820
2	0.107	0.103	0.188	0.068	0.047	0.210	0.303	0.251	0.016	0.084	0.044	0.217	0.233	0.214	0.077	0.796
3	0.106	0.107	0.190	0.065	0.045	0.215	0.299	0.248	0.012	0.081	0.042	0.229	0.224	0.205	0.072	0.775
4	0.099	0.103	0.205	0.068	0.049	0.197	0.300	0.256	0.008	0.075	0.040	0.243	0.216	0.203	0.070	0.758
5	0.099	0.106	0.210	0.064	0.047	0.195	0.304	0.266	0.006	0.074	0.041	0.261	0.211	0.204	0.067	0.752
6	0.101	0.110	0.211	0.061	0.046	0.189	0.309	0.277	0.006	0.073	0.043	0.268	0.207	0.205	0.062	0.752
7	0.091	0.098	0.196	0.059	0.046	0.162	0.319	0.295	0.007	0.074	0.046	0.287	0.202	0.206	0.059	0.745
8	0.081	0.085	0.184	0.057	0.046	0.137	0.326	0.312	0.009	0.078	0.051	0.297	0.195	0.207	0.056	0.736
9	0.074	0.078	0.155	0.048	0.039	0.133	0.324	0.314	0.012	0.082	0.055	0.300	0.195	0.210	0.048	0.722
10	0.062	0.067	0.138	0.044	0.037	0.127	0.326	0.323	0.015	0.085	0.056	0.302	0.191	0.210	0.041	0.708
11	0.050	0.054	0.123	0.040	0.034	0.121	0.327	0.327	0.018	0.081	0.058	0.287	0.187	0.208	0.035	0.685
12	0.051	0.058	0.122	0.036	0.031	0.135	0.332	0.330	0.015	0.065	0.048	0.222	0.192	0.215	0.026	0.676
13	0.057	0.065	0.144	0.032	0.029	0.142	0.322	0.320	0.020	0.069	0.058	0.161	0.189	0.211	0.023	0.670
14	0.061	0.068	0.156	0.028	0.025	0.145	0.307	0.302	0.022	0.072	0.067	0.106	0.168	0.187	0.049	0.637
15	0.069	0.076	0.182	0.027	0.025	0.142	0.295	0.286	0.025	0.079	0.082	0.047	0.154	0.170	0.088	0.624
16	0.074	0.081	0.211	0.026	0.024	0.141	0.291	0.281	0.033	0.089	0.093	0.041	0.147	0.163	0.121	0.628
17	0.078	0.086	0.242	0.025	0.023	0.140	0.281	0.271	0.048	0.100	0.104	0.062	0.137	0.151	0.160	0.621
18	0.074	0.082	0.231	0.023	0.021	0.140	0.279	0.271	0.053	0.091	0.095	0.082	0.133	0.147	0.189	0.601
19	0.073	0.082	0.234	0.023	0.022	0.145	0.297	0.296	0.053	0.082	0.086	0.106	0.147	0.168	0.190	0.622
20	0.068	0.079	0.221	0.022	0.021	0.141	0.311	0.321	0.048	0.065	0.070	0.128	0.158	0.187	0.178	0.625
21	0.063	0.076	0.203	0.022	0.021	0.134	0.312	0.327	0.041	0.061	0.068	0.155	0.158	0.190	0.172	0.616
22	0.058	0.070	0.187	0.023	0.023	0.125	0.350	0.366	0.039	0.060	0.067	0.162	0.150	0.182	0.188	0.641
23	0.055	0.067	0.191	0.025	0.024	0.122	0.389	0.404	0.045	0.059	0.065	0.167	0.143	0.173	0.208	0.671
24	0.049	0.059	0.199	0.025	0.023	0.112	0.410	0.420	0.049	0.062	0.069	0.163	0.129	0.154	0.238	0.675
25	0.043	0.050	0.207	0.024	0.022	0.101	0.421	0.426	0.053	0.065	0.071	0.158	0.111	0.129	0.269	0.663
26	0.041	0.047	0.207	0.024	0.022	0.088	0.437	0.440	0.057	0.057	0.062	0.130	0.100	0.115	0.287	0.659
27	0.040	0.046	0.200	0.024	0.023	0.074	0.402	0.408	0.056	0.051	0.056	0.127	0.094	0.109	0.285	0.612
28	0.038	0.045	0.193	0.027	0.026	0.058	0.357	0.366	0.053	0.045	0.050	0.119	0.086	0.101	0.289	0.554
29	0.045	0.052	0.184	0.031	0.029	0.065	0.363	0.372	0.046	0.048	0.053	0.117	0.084	0.099	0.293	0.571
30	0.052	0.060	0.175	0.037	0.035	0.069	0.376	0.382	0.045	0.051	0.056	0.114	0.082	0.095	0.294	0.598
31	0.055	0.064	0.178	0.043	0.040	0.078	0.386	0.391	0.048	0.058	0.064	0.107	0.076	0.088	0.310	0.618
32	0.055	0.064	0.175	0.042	0.039	0.086	0.393	0.398	0.040	0.058	0.063	0.102	0.073	0.084	0.306	0.621
33	0.054	0.062	0.179	0.040	0.038	0.084	0.444	0.446	0.029	0.062	0.067	0.108	0.075	0.086	0.299	0.675
34	0.048	0.055	0.181	0.040	0.037	0.067	0.493	0.484	0.033	0.057	0.061	0.114	0.076	0.086	0.288	0.714
35	0.042	0.047	0.185	0.038	0.034	0.054	0.530	0.506	0.040	0.052	0.054	0.123	0.078	0.087	0.280	0.738
36	0.036	0.040	0.186	0.031	0.028	0.049	0.574	0.533	0.042	0.046	0.048	0.129	0.083	0.092	0.261	0.770
37	0.035	0.039	0.192	0.029	0.026	0.057	0.624	0.572	0.054	0.048	0.049	0.138	0.088	0.098	0.267	0.824
38	0.033	0.036	0.169	0.025	0.022	0.065	0.566	0.515	0.059	0.041	0.042	0.121	0.083	0.093	0.241	0.747
39	0.033	0.038	0.163	0.021	0.019	0.084	0.548	0.505	0.078	0.038	0.040	0.120	0.083	0.096	0.234	0.722
40	0.034	0.039	0.161	0.017	0.016	0.104	0.534	0.504	0.101	0.036	0.039	0.121	0.083	0.099	0.232	0.704
41	0.030	0.036	0.167	0.017	0.017	0.116	0.528	0.516	0.110	0.033	0.038	0.119	0.076	0.093	0.222	0.685
42	0.030	0.037	0.168	0.020	0.020	0.096	0.519	0.517	0.111	0.033	0.038	0.119	0.067	0.084	0.206	0.670
43	0.034	0.042	0.182	0.024	0.024	0.093	0.590	0.589	0.116	0.040	0.046	0.140	0.067	0.086	0.223	0.756
44	0.033	0.041	0.175	0.027	0.027	0.080	0.586	0.587	0.106	0.040	0.046	0.143	0.060	0.077	0.218	0.746
45	0.034	0.041	0.171	0.029	0.029	0.065	0.579	0.581	0.084	0.040	0.046	0.141	0.043	0.066	0.209	0.725
46	0.041	0.050	0.160	0.030	0.030	0.049	0.569	0.569	0.079	0.041	0.047	0.139	0.031	0.066	0.213	0.712
47	0.042	0.051	0.154	0.026	0.026	0.050	0.570	0.569	0.078	0.042	0.048	0.132	0.033	0.068	0.212	0.713
48	0.043	0.053	0.159	0.022	0.022	0.039	0.570	0.570	0.082	0.043	0.049	0.124	0.033	0.068	0.206	0.711
49	0.047	0.058	0.159	0.028	0.028	0.030	0.567	0.570	0.086	0.046	0.053	0.114	0.029	0.063	0.206	0.716
50	0.048	0.059	0.158	0.048	0.049	0.019	0.577	0.584	0.087	0.050	0.058	0.106	0.035	0.059	0.207	0.757
51	0.048	0.060	0.153	0.068	0.069	0.012	0.579	0.590	0.078	0.050	0.059	0.107	0.041	0.053	0.207	0.786
52	0.045	0.056	0.154	0.089	0.091	0.005	0.584	0.596	0.062	0.048	0.057	0.108	0.033	0.043	0.210	0.800
53	0.041	0.051	0.154	0.111	0.112	0.010	0.600	0.607	0.042	0.048	0.057	0.112	0.027	0.035	0.210	0.827
54	0.040	0.049	0.153	0.124	0.124	0.013	0.602	0.604	0.033	0.046	0.053	0.118	0.027	0.034	0.193	0.837
55	0.037	0.046	0.155	0.142	0.142	0.022	0.586	0.586	0.049	0.040	0.046	0.125	0.027	0.034	0.182	0.832
56	0.033	0.041	0.157	0.156	0.160	0.033	0.555	0.563	0.076	0.037	0.043	0.127	0.028	0.035	0.176	0.808
57	0.032	0.039	0.156	0.167	0.165	0.040	0.521	0.514	0.116	0.034	0.039	0.133	0.028	0.035	0.172	0.782
58	0.031	0.038	0.158	0.180	0.174	0.043	0.482	0.467	0.166	0.031	0.034	0.138	0.027	0.033	0.172	0.750
59	0.027	0.032	0.168	0.188	0.177	0.049	0.437	0.411	0.191	0.027	0.029	0.146	0.023	0.028	0.180	0.702
60	0.026	0.029	0.169	0.181	0.166	0.048	0.407	0.372	0.192	0.026	0.028	0.147	0.017	0.020	0.145	0.657
61	0.021	0.022	0.147	0.171	0.147	0.045	0.386	0.333	0.188	0.027	0.027	0.142	0.051	0.057	0.112	0.656
62	0.018	0.019	0.137	0.163	0.142	0.049	0.350	0.304	0.163	0.026	0.026	0.140	0.073	0.082	0.063	0.631
63	0.003	0.003	0.046	0.14	0.13	0.054	0.339	0.301	0.159	0.031	0.031	0.11	0.204	0.230	0.011	0.717

Table 6. The Input-1 to Input-5 in Table 6 corresponds to oil production from Well-1 to Well-5 at time lag1, and Input-6 to Input-10 in the table corresponds to oil production from Well-1 to Well-5 at time lag2. Hence, both lag1 and lag2 are combined to form the training data for accumulated lag2.

The simulation results from HONN models are presented in Table 7 with their performance accuracy. The performance indices show that the best model is HONN with CSO having three neurons in the hidden layer which resulted in MAPE = 4.045%, MSE = 0.002, and RMSE = 0.039.

In case study-1, overall, the performance measure of HONN models show that HONN with CSO is the best model for forecasting cumulative oil production by yielding a stable value between the range of MSE = 0.002–0.005, RMSE =

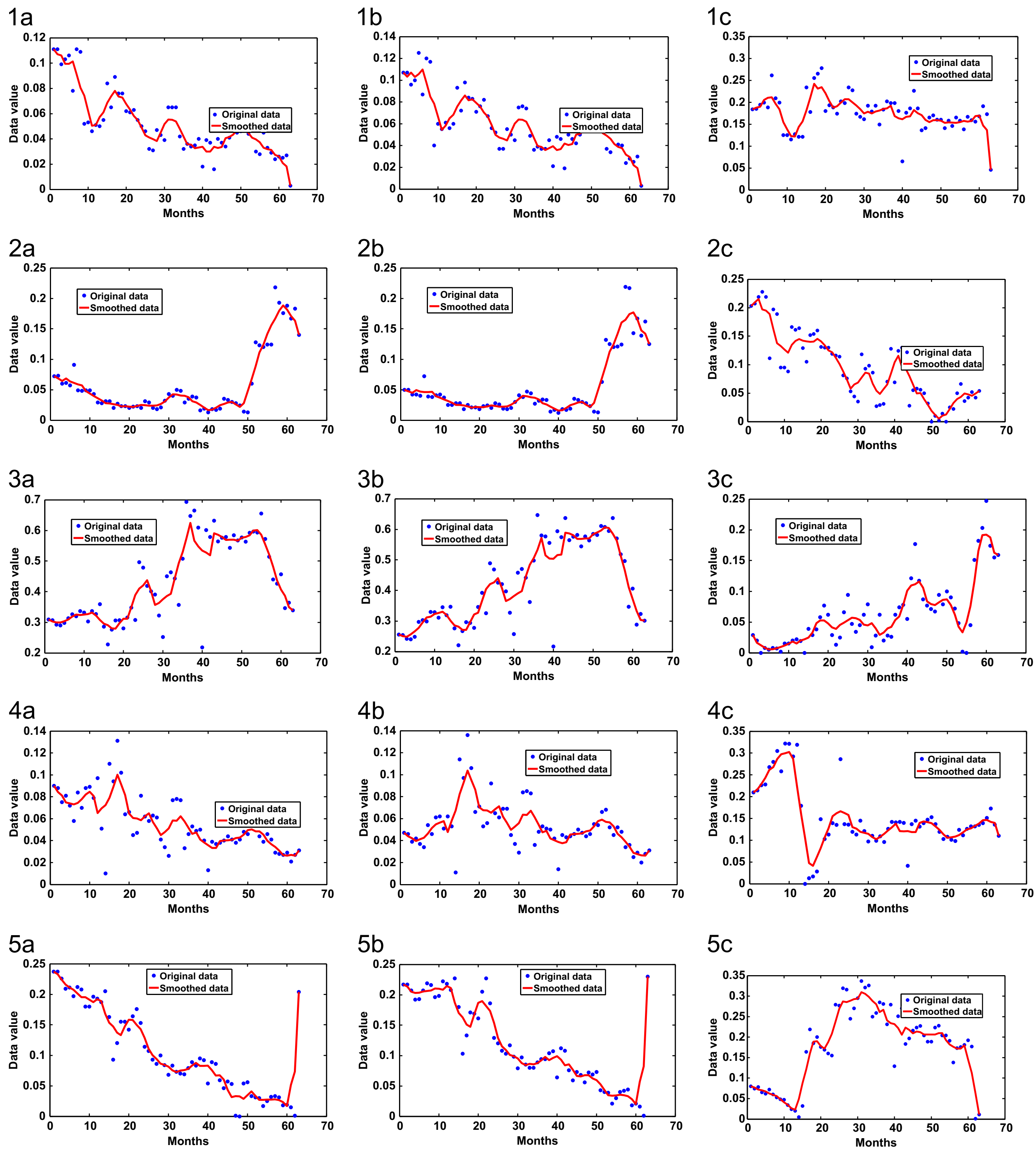

Fig. 6. Before and after smoothing process of oil, gas and water productions from five wells. (1a) oil from well-1, (1b) water from well-1, (1c) gas from well-1; (2a) oil from well-2, (2b) water from well-2, (2c)gas from well-2; (3a) oil from well-3, (3b) water from well-3, (3c) gas from well-3; (4a) oil from well-4, (4b) water from well-4, (4c) gas from well-4; and (5a) oil from well-5, (5b) water from well-5, (5c) gas from well-5.

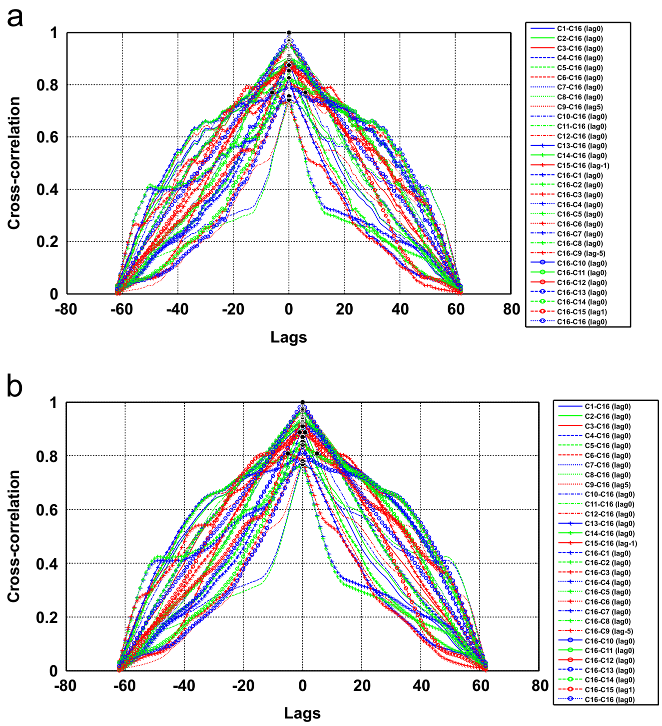

Fig. 7. (a) CCF of original oil, gas and water production data and (b) CCF of smoothed oil, gas and water production data. The dark circles on the plot indicate the highest correlation between two parameters.

0.039–0.072 and MAPE=4–7.6% with few neurons in the hidden layer.

5.3. Case study-2

For this simulation study, monthly oil, gas and water production ratios from Well-1, Well-2, Well-3, Well-4 and Well-5 for 63 months were used for forecasting of cumulative oil production. The production ratios used for this simulation were obtained by dividing the production of oil, gas and water with maximum cumulative productions (through 63 months) of oil, gas and water, approximately 9500 m^3, 275,000 m^3, and 5200 m^3, respectively. Table 8 presents the smoothed monthly oil, gas and water production data ratios of five wells for 63 months.

This case study shows how additional input parameters (gas and water production) influence the efficiency of HONN model in forecasting cumulative oil production. The production data were preprocessed by applying smoothing process and cross-correlation. The smoothing process was carried out by a moving averaging filter with five sequence data points to reduce noise. Oil, gas and water production ratios of five producing wells before and after smoothing are graphically represented in Fig. 6. After that, the smoothed data were used to find correlation between the cumulative oil production and oil, gas, and water production from each well by cross-correlation function (CCF) as shown in Fig. 7. The notations C1, C2, and C3 in the legend box of Fig. 7 indicates the oil, gas and water production of Well-1. Similarly, C4, C5, and C6 corresponds to oil, gas and water production from Well-2 and

Table 9
The training, validation and test data sets used for training HONN model for case study-2.

Months	Input-1	Input-2	Input-3	Input-4	Input-5	Input-6	Input-7	Input-8	Input-9	Input-10	Input-11	Input-12	Input-13	Input-14	Target
1	0.111	0.107	0.184	0.072	0.05	0.203	0.309	0.256	0.09	0.047	0.21	0.237	0.217	0.08	0.796
2	0.107	0.103	0.188	0.068	0.047	0.21	0.303	0.251	0.084	0.044	0.217	0.233	0.214	0.077	0.775
3	0.106	0.107	0.19	0.065	0.045	0.215	0.299	0.248	0.081	0.042	0.229	0.224	0.205	0.072	0.758
4	0.099	0.103	0.205	0.068	0.049	0.197	0.3	0.256	0.075	0.04	0.243	0.216	0.203	0.07	0.752
5	0.099	0.106	0.21	0.064	0.047	0.195	0.304	0.266	0.074	0.041	0.261	0.211	0.204	0.067	0.752
6	0.101	0.11	0.211	0.061	0.046	0.189	0.309	0.277	0.073	0.043	0.268	0.207	0.205	0.062	0.745
7	0.091	0.098	0.196	0.059	0.046	0.162	0.319	0.295	0.074	0.046	0.287	0.202	0.206	0.059	0.736
8	0.081	0.085	0.184	0.057	0.046	0.137	0.326	0.312	0.078	0.051	0.297	0.195	0.207	0.056	0.722
9	0.074	0.078	0.155	0.048	0.039	0.133	0.324	0.314	0.082	0.055	0.3	0.195	0.21	0.048	0.708
10	0.062	0.067	0.138	0.044	0.037	0.127	0.326	0.323	0.085	0.056	0.302	0.191	0.21	0.041	0.685
11	0.05	0.054	0.123	0.04	0.034	0.121	0.327	0.327	0.081	0.058	0.287	0.187	0.208	0.035	0.676
12	0.051	0.058	0.122	0.036	0.031	0.135	0.332	0.33	0.065	0.048	0.222	0.192	0.215	0.026	0.67
13	0.057	0.065	0.144	0.032	0.029	0.142	0.322	0.32	0.069	0.058	0.161	0.189	0.211	0.023	0.637
14	0.061	0.068	0.156	0.028	0.025	0.145	0.307	0.302	0.072	0.067	0.106	0.168	0.187	0.049	0.624
15	0.069	0.076	0.182	0.027	0.025	0.142	0.295	0.286	0.079	0.082	0.047	0.154	0.17	0.088	0.628
16	0.074	0.081	0.211	0.026	0.024	0.141	0.291	0.281	0.089	0.093	0.041	0.147	0.163	0.121	0.621
17	0.078	0.086	0.242	0.025	0.023	0.14	0.281	0.271	0.1	0.104	0.062	0.137	0.151	0.16	0.601
18	0.074	0.082	0.231	0.023	0.021	0.14	0.279	0.271	0.091	0.095	0.082	0.133	0.147	0.189	0.622
19	0.073	0.082	0.234	0.023	0.022	0.145	0.297	0.296	0.082	0.086	0.106	0.147	0.168	0.19	0.625
20	0.068	0.079	0.221	0.022	0.021	0.141	0.311	0.321	0.065	0.07	0.128	0.158	0.187	0.178	0.616
21	0.063	0.076	0.203	0.022	0.021	0.134	0.312	0.327	0.061	0.068	0.155	0.158	0.19	0.172	0.641
22	0.058	0.07	0.187	0.023	0.023	0.125	0.35	0.366	0.06	0.067	0.162	0.15	0.182	0.188	0.671
23	0.055	0.067	0.191	0.025	0.024	0.122	0.389	0.404	0.059	0.065	0.167	0.143	0.173	0.208	0.675
24	0.049	0.059	0.199	0.025	0.023	0.112	0.41	0.42	0.062	0.069	0.163	0.129	0.154	0.238	0.663
25	0.043	0.05	0.207	0.024	0.022	0.101	0.421	0.426	0.065	0.071	0.158	0.111	0.129	0.269	0.659
26	0.041	0.047	0.207	0.024	0.022	0.088	0.437	0.44	0.057	0.062	0.13	0.1	0.115	0.287	0.612
27	0.04	0.046	0.2	0.024	0.023	0.074	0.402	0.408	0.051	0.056	0.127	0.094	0.109	0.285	0.554
28	0.038	0.045	0.193	0.027	0.026	0.058	0.357	0.366	0.045	0.05	0.119	0.086	0.101	0.289	0.571
29	0.045	0.052	0.184	0.031	0.029	0.065	0.363	0.372	0.048	0.053	0.117	0.084	0.099	0.293	0.598
30	0.052	0.06	0.175	0.037	0.035	0.069	0.376	0.382	0.051	0.056	0.114	0.082	0.095	0.294	0.618
31	0.055	0.064	0.178	0.043	0.04	0.078	0.386	0.391	0.058	0.064	0.107	0.076	0.088	0.31	0.621
32	0.055	0.064	0.175	0.042	0.039	0.086	0.393	0.398	0.058	0.063	0.102	0.073	0.084	0.306	0.675
33	0.054	0.062	0.179	0.04	0.038	0.084	0.444	0.446	0.062	0.067	0.108	0.075	0.086	0.299	0.714
34	0.048	0.055	0.181	0.04	0.037	0.067	0.493	0.484	0.057	0.061	0.114	0.076	0.086	0.288	0.738
35	0.042	0.047	0.185	0.038	0.034	0.054	0.53	0.506	0.052	0.054	0.123	0.078	0.087	0.28	0.77
36	0.036	0.04	0.186	0.031	0.028	0.049	0.574	0.533	0.046	0.048	0.129	0.083	0.092	0.261	0.824
37	0.035	0.039	0.192	0.029	0.026	0.057	0.624	0.572	0.048	0.049	0.138	0.088	0.098	0.267	0.747
38	0.033	0.036	0.169	0.025	0.022	0.065	0.566	0.515	0.041	0.042	0.121	0.083	0.093	0.241	0.722

Table 9 (*continued*)

Months	Input-1	Input-2	Input-3	Input-4	Input-5	Input-6	Input-7	Input-8	Input-9	Input-10	Input-11	Input-12	Input-13	Input-14	Target
39	0.033	0.038	0.163	0.021	0.019	0.084	0.548	0.505	0.038	0.04	0.12	0.083	0.096	0.234	0.704
40	0.034	0.039	0.161	0.017	0.016	0.104	0.534	0.504	0.036	0.039	0.121	0.083	0.099	0.232	0.685
41	0.03	0.036	0.167	0.017	0.017	0.116	0.528	0.516	0.033	0.038	0.119	0.076	0.093	0.222	0.67
42	0.03	0.037	0.168	0.02	0.02	0.096	0.519	0.517	0.033	0.038	0.119	0.067	0.084	0.206	0.756
43	0.034	0.042	0.182	0.024	0.024	0.093	0.59	0.589	0.04	0.046	0.14	0.067	0.086	0.223	0.746
44	0.033	0.041	0.175	0.027	0.027	0.08	0.586	0.587	0.04	0.046	0.143	0.06	0.077	0.218	0.725
45	0.034	0.041	0.171	0.029	0.029	0.065	0.579	0.581	0.04	0.046	0.141	0.043	0.066	0.209	0.712
46	0.041	0.05	0.16	0.03	0.03	0.049	0.569	0.569	0.041	0.047	0.139	0.031	0.066	0.213	0.713
47	0.042	0.051	0.154	0.026	0.026	0.05	0.57	0.569	0.042	0.048	0.132	0.033	0.068	0.212	0.711
48	0.043	0.053	0.159	0.022	0.022	0.039	0.57	0.57	0.043	0.049	0.124	0.033	0.068	0.206	0.716
49	0.047	0.058	0.159	0.028	0.028	0.03	0.567	0.57	0.046	0.053	0.114	0.029	0.063	0.206	0.757
50	0.048	0.059	0.158	0.048	0.049	0.019	0.577	0.584	0.05	0.058	0.106	0.035	0.059	0.207	0.786
51	0.048	0.06	0.153	0.068	0.069	0.012	0.579	0.59	0.05	0.059	0.107	0.041	0.053	0.207	0.8
52	0.045	0.056	0.154	0.089	0.091	0.005	0.584	0.596	0.048	0.057	0.108	0.033	0.043	0.21	0.827

Table 10
Performance measure of HONN models with oil, gas and water production ratios.

Synaptic operation	Number of hidden layers	Number of neurons	MSE		RMSE		MAPE (%)	
			Mean	SD	Mean	SD	Mean	SD
Linear synaptic operation	1	1	0.004	0.001	0.065	0.011	7.480	1.104
		2	0.004	0.001	0.060	0.008	6.687	1.008
		3	0.003	0.001	0.052	0.006	6.199	0.631
		4	0.002	0.001	0.048	0.009	5.562	0.748
		5	0.003	0.000	0.054	0.005	6.187	0.435
Quadratic synaptic operation	1	1	0.002	0.001	0.046	0.006	5.147	0.734
		2	0.001	0.000	0.038	0.004	4.196	0.434
		3	0.003	0.001	0.054	0.008	6.004	0.964
		4	0.002	0.001	0.048	0.007	5.553	0.396
		5	0.003	0.001	0.054	0.005	6.046	0.855
Cubic synaptic operation	1	1	0.003	0.001	0.050	0.007	5.359	0.874
		2	0.002	0.001	0.049	0.006	5.627	0.393
		3	**0.001**	**0.000**	**0.036**	**0.004**	**3.990**	**0.450**
		4	0.003	0.001	0.054	0.008	6.238	1.013
		5	0.002	0.001	0.044	0.010	4.568	0.961

so on and C16 corresponds to cumulative oil production from all the wells. The C16–C1 in legend box corresponds to cross-correlation of cumulative oil production to oil production of Well-1. Similarly for notations C16–C2, C16–C3, C16–C5 etc. represent the correlation of cumulative oil production to each production data from corresponding five wells.

The significant input variables were determined using the CCF plot. It is observed from the CCF plot (Fig. 7) that the correlations between oil, gas, and water of five producing wells are the most significant at lag0. Since lag0 does not represent step ahead, lag1 was selected as the highest cross-correlation. Also, since the CCF for two parameters were calculated twice (i.e., Cx–C16 and C16–Cx, $x=1, 2,\ldots, 16$), one of them was dropped. C16–C16 CCF was also dropped because it represented auto-correlation. A closer look at Fig. 7 showed that the water production from Well-3 was negatively correlated with cumulative oil production and hence C9 was dropped from HONN input. Thus, overall 14 input vectors were rearranged for HONN models as listed in Table 9. Input 1 to input 14 represents the correlation of oil, gas and water productions from each well at lag1 to the cumulative field oil production. First 35 months data were used for training and next 17 months data for validation

Table 10 presents the results from HONN models with its performance measure in terms of MSE, RMSE, and MAPE for different configurations of neurons in the hidden layer and synaptic operation. In this case study, the best model resulted in MAPE=3.990%, MSE=0.001, RMSE=0.036 by HONN with CSO having three neurons in the hidden layer.

6. Discussions

From the case studies, the performance evaluation criteria indicate that the better cumulative oil production forecasting can be achieved from HONN with CSO using oil, gas and water production data. The simulation results from three different lag scenarios also present that HONN with CSO gives best agreement between simulation results and observed data. In this study, the selection of lag time is an important factor that influences the forecasting results.

In case study-1, cross-correlation function (CCF) indicates that the most significant lag for oil production forecasting with only oil production data from five producing well is lag1, and HONN with CSO yields the best forecasting cumulative oil production in this case. This can be explained by recalling that five input parameters (oil productions from five wells) generate complex correlation for target parameter (oil production to be predicted). Thus, in this case, nonlinear combination of synaptic operations could result in better prediction. The oil production forecasting from HONN with CSO with single lag1 for next 10 months, from month 53 to 63, is

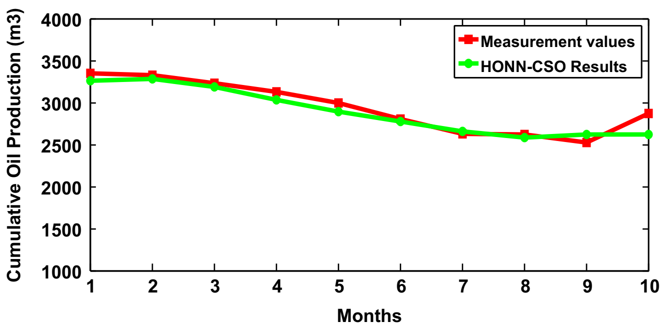

Fig. 8. Comparison between the measured cumulative oil production and the forecast results from HONN with CSO using single lag-1 for case study-1.

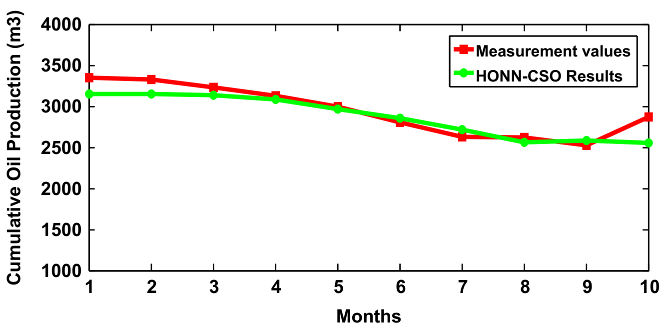

Fig. 9. Comparison between the measured cumulative oil production and the forecast results from HONN with CSO from case study-2.

compared with measurement production data in Fig. 8. The figure indicates a good match between the measured production data and forecast results within the overall testing error of 0.025.

In case study-2, the 14 input parameters, namely oil, gas and water production from five oil producing wells generates non-linearity and heterogeneity between input and target parameters. In this case, the higher-order synaptic operations, QSO and CSO, fit more to forecast the oil production as presented in the performance measure table (Table 10). It is also observed from simulation results that the HONN with QSO and CSO provide better agreement between observed and predicted production data even with fewer number of neural units than the best results of HONN with LSO. Fig. 9 illustrates the comparison between the measured oil production data and the forecast results from HONN with CSO for 10 months from month 53 to 63 within the overall testing error of 0.035. Again the match is reasonably satisfactory.

Through these case studies, it is observed that the performance of HONN with CSO in the case study-1 shows less MAPE than that in the case study-2. This is because the number of input parameters for training HONN in the case study-2 is higher than that in the case study-1. It should be noted that for the application of HONN for forecasting, the number of input variables is one of the significant factors to determine the order of synaptic operation in the neuron. The results indicate that by increasing the order of combination of neural inputs, the capability of an HONN model increases; however, the uncertainty in input data also gets multiplied resulting in higher MAPE. The performance of HONN with HOSO is very susceptible to higher number of neurons in the hidden layer, which induces longer computational time.

7. Conclusion

In this paper, an innovative neural approach has been attempted for forecasting cumulative oil production using higher-order neural network (HONN) for the first time. Two case studies were carried out with the data from an oil field situated at Cambay basin, Gujarat, India, in order to prove the capability of forecasting of HONN.

The simulation study indicates that HONN has high potential for application in cumulative oil production prediction with limited available parameters of petroleum reservoirs. The HONN methodology applied to forecasting of oil production yielded 3.459% and 3.990% of MAPE in the two cases examined. In order to perform more effective HONN models, two pre-processing procedures were performed: (i) noise reduction and (ii) selection of optimal input variables. Since the measuring process of oil production in the oil field cannot avoid noise during the measurement, it is essential to perform a noise reduction step. Furthermore, in order to enhance the accuracy of prediction of HONN, it is important to select and group optimal input variables. Cross-correlation function for multiple input parameters was employed to determine the most significant correlation between the parameters. Considering the limited available inputs for forecasting, the performance indicates that HONN has a high potential to overcome this limitation. Also, for complicated input patterns, such as in the case study-2, the higher combination of the input products reduces the computational cost, which yields faster results.

In summary, HONN appears to be a satisfactory tool for long-term and short term oil production forecasting. However, a careful selection of time lag and number of neurons in the hidden layer are required to achieve accurate oil production forecasting. Further research is being carried out to evaluate the effectiveness of HONN in forecasting hydrocarbon production by incorporating static and dynamic parameters of the reservoir.

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