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# LSTM Based EFAST Global Sensitivity Analysis for Interwell Connectivity Evaluation Using Injection and Production Fluctuation Data

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**ABSTRACT** In petroleum production system, interwell connectivity evaluation is a significant process to understand reservoir properties comprehensively, determine water injection rate scientifically, and enhance oil recovery effectively for oil and gas field. In this paper, a novel long short-term memory (LSTM) neural network based global sensitivity analysis (GSA) method is proposed to analyse injector-producer relationship. LSTM neural network is employed to build up the mapping relationship between production wells and surrounding injection wells using the massive historical injection and production fluctuation data of a synthetic reservoir model. Next, the extended Fourier amplitude sensitivity test (EFAST) based GSA approach is utilized to evaluate interwell connectivity on the basis of the generated LSTM model. Finally, the presented LSTM based EFAST sensitivity analysis method is applied to a benchmark test and a synthetic reservoir model. Experimental results show that the proposed technique is an efficient method for estimating interwell connectivity.

**INDEX TERMS** Interwell connectivity, long short-term memory, global sensitivity analysis, extended Fourier amplitude sensitivity test, oil and gas field.

## I. INTRODUCTION

Accurate evaluation of interwell connectivity is an important process to know communication barriers, flow conduits and injection imbalance properties among multiple producers and injectors. In oil and gas (O&G) field, the petroleum production system is a very complicated and collaborative system:

1) The production wells influence each other because they use the same surface production system and gathering pipe system.
2) The injection wells also impact each other because of the sharing of the surface production system and water injection pipe system.
3) The production wells and injection wells strongly interact with each other due to the underground reservoir system.

Therefore, it is a difficult and challenging task to evaluate interwell connectivity precisely.

Waterflooding is a major method that is widely used in secondary phase of oil production after the crude oil has been partly produced from a underground reservoir with its natural energy [1]. Water injection can effectively increase the yield of producers, implemented as shown in Fig. 1, where "P" and "I" represent producer and injector, respectively, connected to a reservoir with two production wells and one injection well. The vertical producers are connected with the vertical injector by complex reservoir system. The petroleum can be further pushed out of the producers with the continuous increase of bottom-hole pressure (BHP) after water is injected from the connected injector into the reservoir. However, if there is no correlation between production wells and injection wells, the operation of water injection has no effect on the increase of oil production, which means resource-wasting and cost-increasing.

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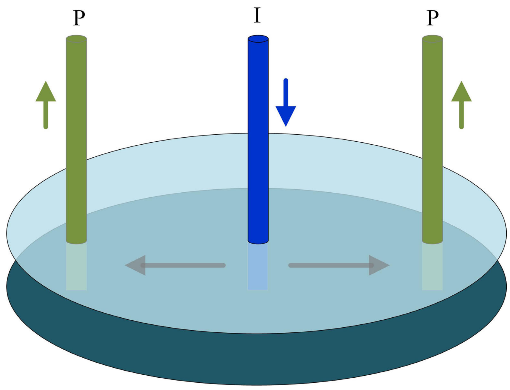


**FIGURE 1.** Illustration on the interwell connectivity.

Oil production is a highly complex, strongly coupled and nonlinear process with multiple objectives and constraints. It involves complicated seepage variation in reservoir, and multiple objectives and constraints, and multiple parameters are associated with production process. In oilfield, production wells and injection wells are distributed spatially across the whole field, production data is collected from all sorts of isolated sites in an oilfield using various instruments, and the data distributes across all the reservoirs and spans over decades of the field history [1].

Traditionally, the oilfield data is processed manually by engineers according to their past experience or calculated based on numerical simulations to get reservoirs and wells information. All kinds of geological properties in oilfield are carefully considered and seriously analysed by petroleum researchers and experts [2]. However, this work is tedious and time-consuming. The real challenge is how to transform these massive historical production data into valuable information and knowledge to assist researchers and engineers in making quick, reliable and informed decisions.

When the interwell connectivity is determined, petroleum researchers and engineers can effectively achieve some significant information, such as the reasonable rate of water injection, and the effective prediction of oil production. The production optimization can be realized when all the information is confirmed. The precondition of optimization process is field data, especially injection data, production data, and geological information.

Currently, the majority of existing implementation methodologies for interwell connectivity analysis are mainly based on the long-term accumulated work experience of oilfield researchers and engineers, and numerical simulation techniques. These methods are always cumbersome, time-consuming and error-prone because the influence of non-linear interactions between various factors is often overlooked in the process.

In this paper, a long short-term memory (LSTM) based global sensitivity analysis (GSA) algorithm is proposed to estimate interwell connectivity index based on a large amount of historical injection and production data. LSTM network is used to build up the relationship between production wells and surrounding injection wells based on the massive historical liquid production and water injection data. Because neural network is widely used method to employ historical data to establish the complex non-linear relationship between multiple input and output factors without knowing the system characteristics. Therefore, LSTM neural network-based method is developed to build the non-linear reservoir model. Extended Fourier amplitude sensitivity test (EFAST) is a model-form independent GSA method, which can globally and quantitatively evaluate the impact of input factors on output factors across the whole input parameters space. Therefore, EFAST method can be utilized to evaluate total sensitivity index for interwell connectivity analysis based on the generated LSTM network reservoir model.

The rest of this paper is organized as follows. Section II introduces the related works on evaluation of interwell connectivity. Section III describes the proposed LSTM-EFAST algorithm for reservoir modeling and total sensitivity index analysis. The experimental results are given in Section IV, and two additional tests are executed to verify the correctness and validity of the proposed LSTM-EFAST method. Finally, Section V concludes with a short summary and an outlook for future work.

## II. RELATED WORKS

In the last few decades, some effective methods have been developed to evaluate interwell connectivity using massive historical injection and production data, as shown in Fig. 2. The main and most widely used approaches are Spearman Rank Correlation (SRC) technique [3]–[5], Multivariate Linear Regression (MLR) technique [6]–[10] and Capacitance Model (CM) technique [1], [11]–[21].

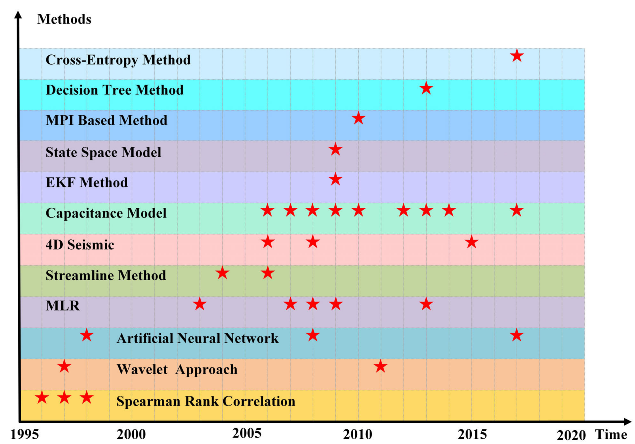


**FIGURE 2.** Main interwell connectivity analysis methods.

SRC is a primitive method to evaluate the relations between injectors and producers in 1990s. It is easy to use to infer interwell relations. However, it does not always create correct relations between well pairs because of the existence of negative coefficient values, which are inconsistent with real condition.

MLR is an applicable method to solve this problem, but many qualification should be satisfied, such as high diffusivity, constant permeability and non-waterflooding production, and new wells production and old wells shut-in have huge effect on desired results. In MLR method, the authors assumed the relation between production rate of each production well and the filtered injection rates of surrounding injection wells is a linear. The weight factors are considered as the measurement of connectivity, and a higher value indicates a stronger connection between well pair.

CM is a famous and widely used method to estimate interwell connectivity, which is an effectively analytical tool to infer interwell connectivity based on historical rates and BHP data in waterflood reservoir. It is a material balance equation with compression coefficient, and superposition principle is applied to express the interaction of multiple wells. Because CM model is a reduced-physics model, it can provide deep insight into reservoir properties when combined with other methods, such as tracer test.

There are some other methods to analyse interwell connectivity apart from the above main approaches, such as Wavelet approach [22], [23], Artificial Neural Network (ANN) approach [1], [24], [25], Streamline method [26], [27], 4D Seismic [28]–[30], Extended Kalman Filter (EKF) method [31], State Space [32], Multiwell Productivity Index (MPI) method [33], Decision Tree [34], and Cross-Entropy method [2]. All of these approaches provide some new thoughts to solve this important and significant problem. For ANN and Cross-Entropy methods, researchers do not need to know the specialized reservoir engineering knowledge. The interwell connectivity can be inferred only from the injection and production fluctuation data. However, quantitative connectivity index is not provided in the proposed Cross-Entropy method. For other approaches, professional petroleum knowledge is essential, and strict assumptions need to be met.

With more than twenty years of application in O&G field, ANN has been considered and utilized as an effective approach for reservoir characterization, management and optimization, such as optimization of well location [35], [36], optimization of oil recovery [37], reservoir monitoring and management [38], [39], and history matching [38], [40], [41].

## III. METHODOLOGY

In this study, a LSTM neural network based EFAST (LSTM-EFAST) method is proposed to evaluate interwell connectivity in a synthetic reservoir model. LSTM neural network is developed to build the complex non-linear reservoir model, and EFAST method is utilized to estimate global sensitivity index for interwell connectivity based on the generated LSTM neural network reservoir model. The development process is addressed in this section.

### A. LONG SHORT-TERM MEMORY

As an important and widely used deep learning method, recurrent neural network (RNN) is an important algorithm for processing sequential data because of the internal memory [42]. However, there are two major obstacles in standard RNN. They are vanishing gradients and exploding gradients, respectively. Therefore, LSTM neural network is proposed to solve the issues faced by standard RNN [43].

LSTM is an extension of classic RNN. A normal LSTM unit is composed of one cell and three gates: memory cell, input gate, output gate and forget gate. The memory cell is used to remember values over arbitrary time intervals, and the gates are used to manage and determine whether the information flow needs to go into and out of the cell or not.

Fig. 3 shows the architecture of LSTM. In this figure, the parameters $x_t$ and $o_t$ are the input and output at time step $t$, $c_t$ and $c_{t-1}$ are the cell states at time $t$ and $t$-1, and $h_t$ and $h_{t-1}$ are the hidden states at time step $t$ and previous time step,. The parameters $i_t$ and $f_t$ are the output of input gate and forget gate, respectively. The parameter $g_t$ is the mapping result after $x_t$ and $h_{t-1}$, and it is squashed between -1 and 1 using a tanh activation function. The functions $\sigma$ and tanh are sigmoid and hyperbolic tangent activation functions.

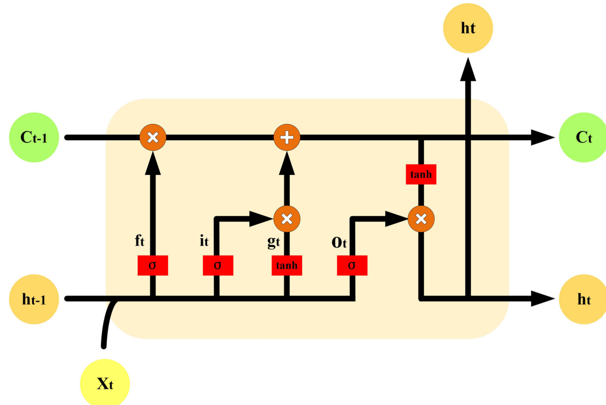


**FIGURE 3.** Long short-term memory architecture.

The relations between these parameters and functions can be summarized as follows.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3)$$
$$\overline{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (4)$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \overline{C_t} \quad (5)$$
$$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

where $W_f$, $W_i$, $W_o$ and $W_c$ denote the weights associated with forget gate, input gate, output gate, and cell state, respectively. The parameters $b_f$, $b_i$, $b_o$ and $b_c$ are bias weights connecting the corresponding gates and cell state.

### B. GLOBAL SENSITIVITY ANALYSIS

Sensitivity analysis is an efficient method to determine the importance and apportion the uncertainty of input factors to output factors of a model [44]. In general, there exists two main sensitivity analysis methods based on saliency measurement [45]: Local Sensitivity Analysis (LSA) and GSA. In LSA, the saliency measurement is given by the local sensitivity of the function. However, GSA is based on the Bayes' theory or Gram-Schmidt orthogonalization.

In this study, the EFAST [46] based GSA method is used to compute sensitivity index for interwell connectivity analysis. The EFAST method is a milestone for GSA of nonlinear systems [47]. It is an extension of classic Fourier amplitude sensitivity test (FAST) method. For FAST method, it mainly depends on the Fourier decomposition of the output variance in the frequency domain, and the key feature of FAST method is that each input factor is oscillated around their nominal value at a specific frequency [48], and multidimensional space of input factors is explored by a well-defined parametric equation [46]. Compared with FAST, EFAST method can not only compute the main effect or first-order sensitivity index, but also the total of each input factor to the output variance. Besides, EFAST is also a quantitative and model-form independent GSA method, which means it can be employed for any model. Therefore, a LSTM neural network model based LSTM method is proposed to estimate sensitivity index for injector-producer relationship identification in this paper.

Without loss of generality, a model $f(\bullet)$ such that $Y = f(X_1, X_2, \ldots, X_n)$ is considered, where the parameters $X_1, X_2, \ldots, X_n$ are input factors. GSA evaluates the effects of the input factors on the model output $Y$. In EFAST, each input factor $X_k$ is in connection with a specific frequency $\omega_k$. Therefore, multidimensional input space can be transformed into an one-dimensional variable $s$ by a set of well-defined parametric equations

$$X_k(s) = G_k(\sin(\omega_k s)) \quad \forall k = 1, 2, \ldots, n \tag{7}$$

where $s$ is a scalar parameter changing in the range $-\infty < s < +\infty$. These equations allows all the input factors to vary simultaneously when the variable $s$ varies. A classic parametric equation is

$$X_k(s) = \frac{1}{2} + \frac{1}{\pi}\arcsin(\sin(\omega_k s)) \tag{8}$$

This representation is widely used because of the uniform sampling of the input space. However, if the value range of a certain input factor $X_k$ is $[a_k, b_k]$, each factor oscillates in the range $[a_k, b_k]$, then the equivalent expression should be represented as

$$X_k(s) = \frac{b_k + a_k}{2} + \frac{b_k - a_k}{\pi}\arcsin(\sin(\omega_k s + \varphi_k)) \tag{9}$$

where $\varphi_k$ is a set of random phase-shift chosen uniformly in $[0, 2\pi)$. Whatever the model $f(\bullet)$ is, the output of the model is a combination function of a series of different frequencies $\omega_k = 1, 2, \ldots, n$, then the model becomes a $2\pi$ periodic function:

$$f(s) = f(X_1(s), X_2(S), \ldots, X_k(s), \ldots, X_n(s)) \tag{10}$$

Therefore, the function $f(s)$ can be expanded in the form of Fourier series:

$$f(s) = \sum_{j=-\infty}^{+\infty} (A_j \cos(\omega_j s) + B_j \sin(\omega_j s)) \tag{11}$$

where the parameters $A_j$ and $B_j$ are Fourier coefficients, and defined as

$$A_j = \frac{1}{2\pi}\int_{-\pi}^{\pi} f(s)\cos(\omega_j s)ds \tag{12}$$

$$B_j = \frac{1}{2\pi}\int_{-\pi}^{\pi} f(s)\sin(\omega_j s)ds \tag{13}$$

over the domain of integer frequencies with $j \in \mathbb{Z}$ and $s \in [-\pi, \pi]$.

The variance of output $D_y$ can be derived from equations (12) and (13) based on Parseval's theorem

$$D_y = Var(Y) = 2\sum_{k=1}^{+\infty}(A_k^2 + B_k^2) \tag{14}$$

and the expected variance $D_k$ for input factor $X_k$ is

$$D_k = Var_{X_k}[E(Y|X_k)] = 2\sum_{k=1}^{+\infty}(A_{k\omega_k}^2 + B_{k\omega_k}^2) \tag{15}$$

where the parameters $A_{k\omega_k}$ and $B_{k\omega_k}$ are the Fourier coefficients for the base frequency $\omega_k$ and all of its higher harmonics $k\omega_k$.

For FAST method, the first-order sensitivity index or main effect of the $k$-th factor $X_k$ is given by

$$S_k = \frac{D_k}{D_y} = \frac{Var_{X_k}[E(Y|X_k|)]}{Var(Y)} = \frac{2\sum_{k=1}^{+\infty}(A_{k\omega_k}^2 + B_{k\omega_k}^2)}{Var(Y)} \tag{16}$$

The set of frequencies is free of interferences of $M$-th order. Therefore, the first-order sensitivity index can be approximated as follows when the first ($M$-1) harmonics are considered:

$$S_k = \frac{D_k}{D_y} = \frac{Var_{X_k}[E(Y|X_k|)]}{Var(Y)} \simeq \frac{2\sum_{k=1}^{M}(A_{k\omega_k}^2 + B_{k\omega_k}^2)}{Var(Y)} \tag{17}$$

where the parameter $M$ is called the interference factor (usually 4 or 6 in GSA community). Besides, the number of simulation $N$ needs to satisfy the Nyquist-Shannon sampling theorem, that is $N = 2M\omega_{max} + 1$, where $\omega_{max} = \max(\omega_k)$, $k \in [1, n]$. That means $N$ system evaluations are required to compute the main effect or first-order sensitivity index. However, it is difficult to properly choose a set of frequencies to not only avoid the interferences up to order $M$, but also coordinate the correlation between the number of input factors and model evaluations [48].

Therefore, EFAST, as an extension of the FAST approach, is proposed by Saltelli [46], which improve FAST method in the following two ways:

1) It estimates not only the first-order sensitivity index but also total index.
2) It can choose the set of frequencies more easily to deal with the problem of interferences.

In the EFAST approach, the total effect of the $k$-th factor $X_k$ will be found in the higher part of the spectrum, and all the others effects will be found in the lower part. Therefore, the expected variance $D_k$ for factor $X_k$ can be defined as the complementary variance of all the other variables, that is

$$DT_k = D_y - D_{\sim k} \tag{18}$$

where $\sim k$ stands for all but $k$. Then, the total sensitivity index is given by

$$ST_k = \frac{DT_k}{D_y} \tag{19}$$

and can be estimated by

$$ST_k \simeq 1 - \left( \sum_{\omega=1}^{M\max(\omega_{\sim k})} (A_\omega^2 + B_\omega^2) \right) / \left( \sum_{\omega=1}^{M\omega_k} (A_\omega^2 + B_\omega^2) \right) \tag{20}$$

with $\omega_k = 2M\max(\omega_{\sim k})$ and $N = 2M\omega_k + 1$, where the frequency $\omega_k$ is the highest frequency allocated to the $k$-th input factor, and $\max(\omega_{\sim k})$ is the maximum frequency allocated to all the remaining input factors except the factor $X_k$.

Once the total sensitivity indexes for all the input factors are derived, it is necessary to normalize each $ST_k$ by the sum of all the indexes

$$\overline{ST_k} = ST_k / \sum_{i=1}^{n} ST_i \tag{21}$$

### C. LONG SHORT-TERM MEMORY BASED EXTENDED FOURIER AMPLITUDE SENSITIVITY TEST METHOD

In O&G field, the process of oil production and water injection is a complicated, strongly coupled and nonlinear process with multiple objectives and constraints. Production and injection wells distribute spatially across the whole field, and the production and injection data is collected across all the O& field and spans more than tens of years of the field history. It's difficult to model the reservoir system and evaluate the interwell connectivity using the massive historical production and injection data.

LSTM, as an extension of classic RNN network, is an important algorithm for processing sequential data. It is designed to learn the long-term dependency between model inputs and outputs, and a long period of valuable information is able to be remembered via the input, output and forget gates. For this reason, LSTM neural network is chosen to solve this problem. EFAST is a model form independent method to determine the importance and apportion the uncertainty of input factors to output factors of a model, which computes both the main effect and the total sensitivity index. Therefore, a LSTM-EFAST is proposed to model the reservoir in this study. Fig. 4 shows the organization and workflow between the important steps, and the detail of this method is given in Algorithm 1.

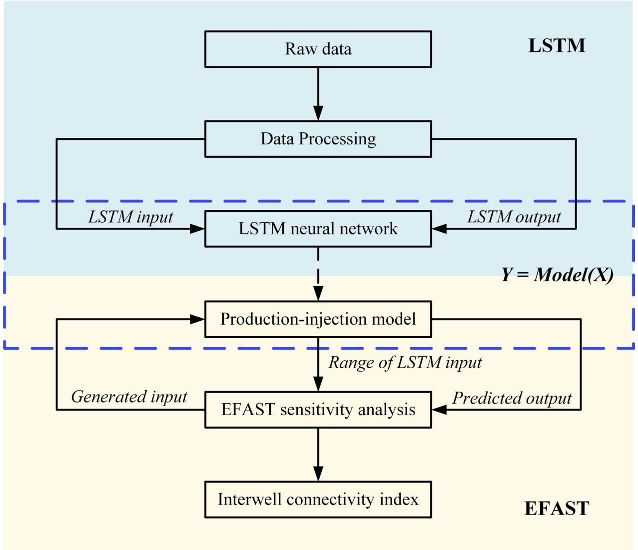


**FIGURE 4.** Workflow of the proposed LSTM-EFAST Algorithm.

LSTM-EFAST method applied to GSA for interwell connectivity evaluation is shown in Fig. 5. All the input factors oscillate with a specific frequency $\omega_k$ based on the parametric equation defined by (9), and $N$ simulation e valuations are executed by varying each input factor, which enables the calculation of the percentage importance of each input factor to output factor.

## IV. EXPERIMENT

In this section, Sobol's G function [49], [50] is used as a benchmark test to validate the performance of the proposed LSTM-EFAST method, and then the proposed hybrid algorithm is applied to evaluate interwell connectivity using injection and production fluctuation data of a synthetic reservoir system.

### A. BENCHMARK TEST

The effectiveness and performance of the proposed LSTM-EFAST method is first validated by the widely used Sobol's G function, which is defined as:

$$G = G(X_1, X_2, \ldots, X_I, a_1, a_2, \ldots, a_I) = \prod_{i=1}^{I} g_i$$
$$g_i = \frac{|4X_i - 2| + a_i}{1 + a_i} \tag{22}$$

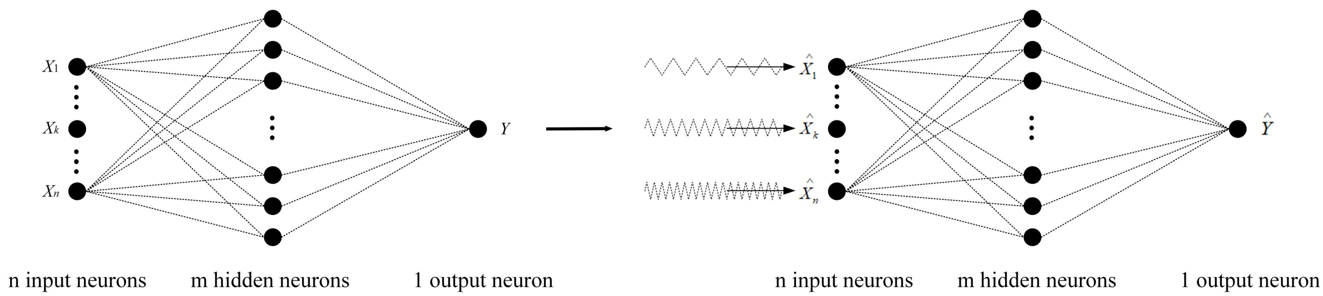


**FIGURE 5.** LSTM-EFAST method applied to global sensitivity analysis for interwell connectivity evaluation.

**Algorithm 1** LSTM based EFAST Algorithm

Input: $X, Y, M, N$
Output: $\overline{ST_k}$

1: Choose the input $X$, output $Y$, and record the number of input factors $K$ and the number of samples $Z$.
2: Normalize the input $X$ and output $Y$ in the range [-1,1] using $x_k^* = 2(x_k - a_k)/(b_k - a_k) - 1$ with $a_k = \min(x_k)$ and $b_k = \max(x_k)$, $i \in [1, Z]$, $k \in [1, K]$.
3: Select the number of hidden neurons and the LSTM training parameters.
4: Train the LSTM neural network.
5: Set the interference factor to $M = 4$, and select the number of simulation runs $N$ when training is done.
6: Compute the maximum frequency $\omega_k = (N-1)/2M$.
7: Set the frequency $\omega_{\sim k}$ for remaining input factors.
**for** $i = 1 \rightarrow K$ **do**
  $\omega_{\sim k}[i] = \omega_k/(2M * i)$
**end**
8: Calculate scalar variable $s$.
**for** $j = 1 \rightarrow N$ **do**
  $s[j] = 2\pi/(N * j)$
**end**
9: Set the sample frequency $\omega^*$ and sample point.
**for** $i = 1 \rightarrow K$ **do**
  $\omega^*[i] = \omega_k$
  $o \leftarrow 1, \ldots, N \text{except} i$
  $\omega^*[o] \leftarrow \omega_{\sim k}$
  **for** $j = 1 \rightarrow N$ **do**
    $g_i = (b_i + a_i)/2 +$
      $(b_i - a_i)/2 * \arcsin(\sin(\omega^*[j] * s + \varphi_i))$
    $X[i, j] = g_i$
  **end**
**end**
10: Evaluate $Y = Model(X)$, the model used is the well-trained LSTM neural network in step 4.
11: Compute total sensitivity indexes for all the input factors using equation (20).
12: Standardize each total sensitivity index $ST_k$ by the sum of all the indexes using equation (21), and denoted by $\overline{ST_k}$.

where $X_i \in [0, 1]$, $a_i \geq 0$, $\forall i = 1, \ldots, I$, and $I$ is the number of the input factors for G function. Fig. 6 shows an example with $a_i = 0, 1, 10$, respectively. The G function is affected by the values of the parameter $a_i$ and the dimensionality $I$. Small values of parameter $a_i$, such as $a_i = 0$, imply an important effect [50].

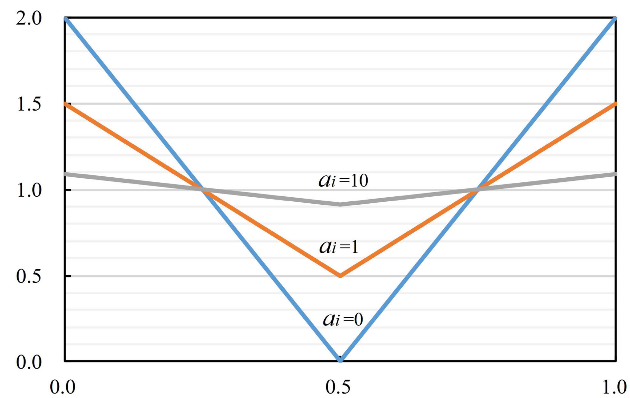


**FIGURE 6.** G function for $a_i$ =0, 1,10.

In this test, the value of $I$ is set to 2, and $a_1$ and $a_2$ are set to 0 and 10, respectively. First, the sample set are set large enough to train a high-precision LSTM model. And then the performance of the proposed LSTM-EFAST method would be compared with the analytic solution. The results are shown in Table 1.

**TABLE 1.** Comparison of sensitivity index between LSTM-EFAST method and analytic solution.

| Input | Parameter $a_i$ | Analytic solution | LSTM-EFAST |
|---|---|---|---|
| 1 | 0 | 0.992 | 0.974 |
| 2 | 10 | 0.011 | 0.026 |

The analytic solution shows that the input with $a_i = 0$ has the most important effect on the G function, and the sensitivity index is 0.992. For LSTM-EFAST method, the index is 0.974, which shows LSTM-EFAST can compute the total sensitivity index with high precision, and identify the most and the least significant input factors for model output.

### B. CASE STUDY: A SYNTHETIC RESERVOIR MODEL

In this case, a synthetic reservoir model is built using CMG reservoir simulation software [51], which is based on the

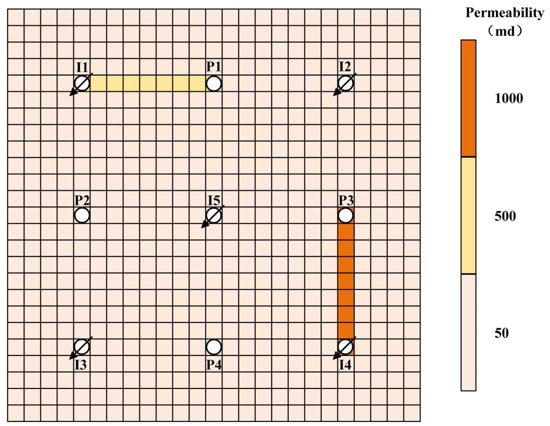


**FIGURE 7.** **Well locations and permeability distribution in the synthetic reservoir model.**

geological and petrophysical information of an oilfield in the north of China. Four production wells and five injection wells are constructed in this reservoir model. Fig. 7 shows the locations of the wells and the distribution of permeability in the model, where "P" denotes producers, and "I" identifies the surrounding injectors.

The base permeability of this reservoir model is 50md, and two high-permeability streaks are added manually:

1) Streak 1: 500 md between wells I1 and P1.

2) Streak 2: 1000 md between wells I4 and P3.

A constant porosity of 0.25 is assigned globally in the synthetic reservoir model. Total mobility of oil and water ($\lambda_0 + \lambda_w$) is 0.45 and is independent of saturation. The oil, water and rock compressibility are $3 \times 10^{-5}\text{psi}^{-1}$, $3 \times 10^{-6}\text{psi}^{-1}$ and $3 \times 10^{-6}\text{psi}^{-1}$, respectively. This reservoir model is built with 1 layer and 25 grid blocks in both x and y directions with grid sizes of 100 ft by 100 ft. The thickness of the synthetic reservoir is fixed at 50 ft.

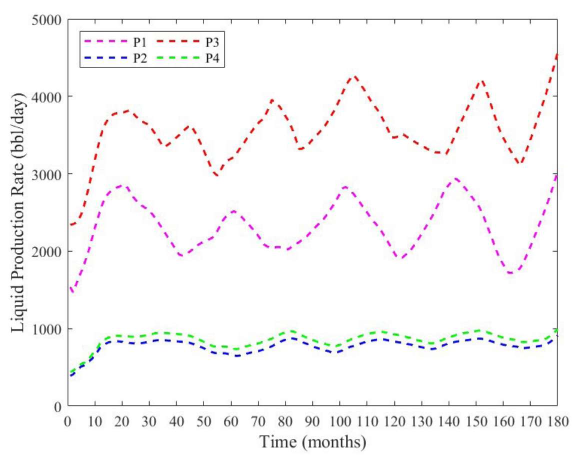


**FIGURE 8.** **Monthly liquid production rates of the synthetic reservoir model.**

Fig. 8 displays the monthly liquid production rates for all the producers for 180 months (5478 days in total), which is the result of reservoir simulation with given water injection rates. and the BHP for these producers is constant at 250 psi. The water injection rates for these injectors are dynamically changed and manually adjusted with a limited and maximum BHP of 5000 psi, and the monthly water injection rates for these five injection wells are shown in Fig. 9.

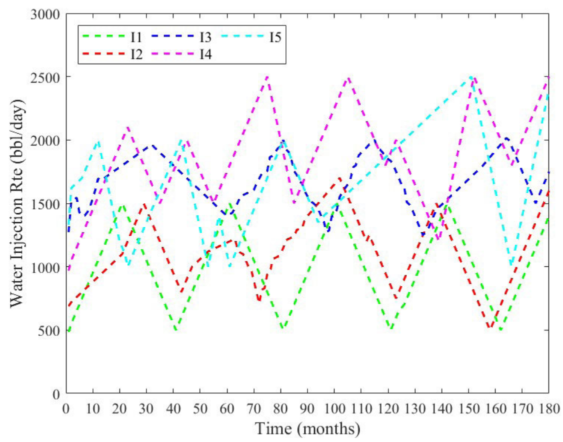


**FIGURE 9.** **Monthly water injection rates of the synthetic reservoir model.**

## C. ALGORITHM IMPLEMENTATION

In order to identify the relationship between producers and surrounding injectors based on the massive historical data, a three-layer feedforward LSTM neural network is built for each producer in the synthetic reservoir model, and the number of neurons in hidden layer is set to 20 units according to test results. Therefore, a 5-20-1 LSTM network is constructed for each producer. The LSTM neural network uses logistic sigmoid and hyperbolic tangent function as activation functions, and a linear activation function is utilized for fully connectivity layer with one neuron. In this experiment, dropout technique is used to prevent LSTM neural network from overfitting, and the retained possibility of the hidden layer is set to 0.5 [52].

The varying daily water injection data from these injectors is selected as the input of the LSTM network, and the corresponding daily liquid production data from the surrounding producers is selected as the output of the constructed artificial neural network. The input and output data of the network are normalized to the range [-1,1] to eliminate the mutual effects between some extremely large values and small values in the oilfield dataset. The normalization method can be described as:

$$x_k^* = \frac{2(x_k - \min(x_k))}{\max(x_k) - \min(x_k)} - 1 \tag{23}$$

where the parameters $x_k^*$, $x_k$, $\max(x_k)$, $\min(x_k)$ are normalized input, original input, maximum value, and minimum value for the $k$-th input factor, respectively.

In this experiment, 80% of the historical injection and production fluctuation data is used to train the proposed LSTM network, and 20% of the history data is used for testing.

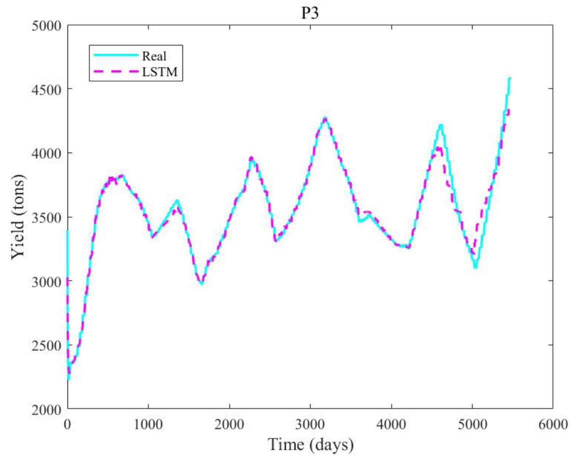


**FIGURE 10.** The history matching result of producer P3.

Root mean squared error (RMSE) is adopted to evaluate the performance of LSTM prediction. Based on the constructed synthetic reservoir model, Producer P3 has the largest liquid production rate and connectivity index with injector I4. Therefore, take P3 as an example, the prediction result is shown in Fig. 10. The RMSE is convergent to 0.02 after 200 times of iterations.

Once the LSTM neural network-based reservoir model is well trained, the EFAST analysis can be performed based on this model. Considering the EFAST application in a LSTM based reservoir model, the following difference expressions are used to compute Fourier coefficients $A_j$ and $B_j$, which can be represented as [53], [54]:

$$A_j = \begin{cases} 0, & \text{if } j \text{ is odd} \\ \dfrac{1}{N}(y_0 + \sum_{k=1}^{q}(y_k + y_{\sim k})\cos(\dfrac{j\pi k}{N})), & \text{if } j \text{ is even} \end{cases} \tag{24}$$

$$B_j = \begin{cases} 0, & \text{if } j \text{ is even} \\ \dfrac{1}{N}(\sum_{k=1}^{q}(y_k - y_{\sim k})\sin(\dfrac{j\pi k}{N})), & \text{if } j \text{ is odd} \end{cases} \tag{25}$$

where $q = (N-1)/2$, and $y_k$ is the predicted output of LSTM neural network for $k$-th input.

**TABLE 2.** The interwell connectivity index evaluated by proposed LSTM-EFAST method.

| Index | I1 | I2 | I3 | I4 | I5 |
|---|---|---|---|---|---|
| P1 | 0.427 | 0.232 | 0.075 | 0.164 | 0.102 |
| P2 | 0.164 | 0.270 | 0.160 | 0.143 | 0.263 |
| P3 | 0.026 | 0.082 | 0.062 | 0.750 | 0.080 |
| P4 | 0.180 | 0.210 | 0.197 | 0.210 | 0.203 |

Table 2 is the standardized total sensitivity indexes derived from the proposed LSTM-EFAST sensitivity analysis method, which illustrates the estimation of the importance of the surrounding injectors to each related producer.

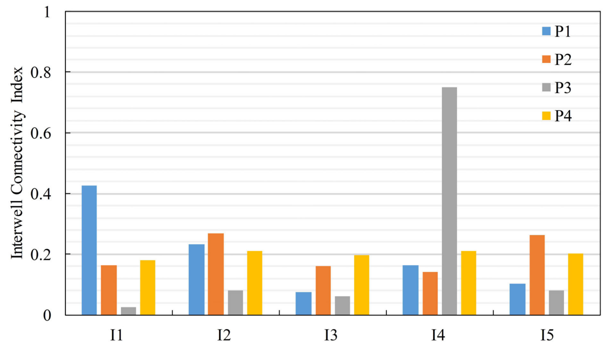


**FIGURE 11.** The distribution of interwell connectivity index.

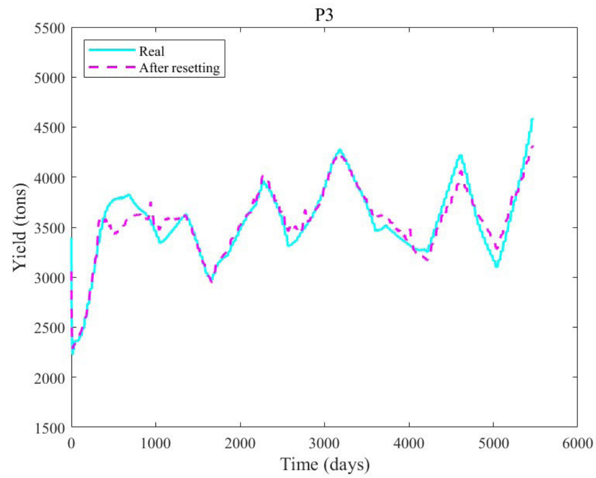


**FIGURE 12.** Liquid production rate estimation after reset for the least sensitive input factor I1.

Through comparing the obtained data in the table, some conclusions can be drawn:

1) Injector I1 is the most effective injector for producer P1, whereas the injector I4 has low relevance to the producer.
2) Injector I4 is the most sensitive injector for producer P3, whereas the injector I1 is the least effective injector for it.

From the perspective of permeability, the results are consistent with the constructed reservoir model. Therefore, small changes on injectors I1 and I4 can result in relatively large production variations of producers P1 and P3, respectively. Similarly, a relatively small changes can happen even if the least effective factors changes drastically.

Two additional experiments are performed to verify the effectiveness of this approach. In order to compare the importance of each injector to producers of the reservoir model distinctly, the distribution of interwell connectivity index is given in Fig. 11. From Fig. 11, the facts that P3 and I4 have maximum connectivity value, and P3 and I1 have minimum value can be derived directly. Therefore, producer P3 and its surrounding injectors are further considered in this paper.

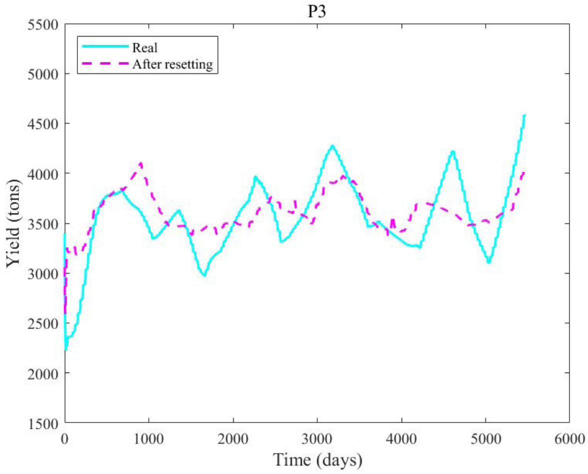


**FIGURE 13. Liquid production rate estimation after reset for the most sensitive input factor I4.**

In these tests, the well-trained LSTM neural network is used to predict the liquid production rates by setting the input factors I1 and I4 to zero, respectively, to imitate injector shut-in operation in oilfield. The effects on the output of the LSTM network can be observed, as shown in Fig. 12 and Fig. 13. As shown in Fig. 12, the predicted liquid production rates are very close to the real value when the least sensitive input factor is reset, which shows that the injector I1 has almost none effect on producer P3. Similarly, when the most sensitive factor I4 is reset to 0, the result can not follow the change of the real data. From these figures, the effectiveness and validity of the proposed LSTM-EFAST analysis method can be further verified by resetting the least and most sensitive injectors, respectively.

## V. CONCLUSION AND FUTURE WORK

Oil production is a highly complex, strongly coupled and nonlinear process with multiple objectives and constraints in O&G field, therefore it is difficult to evaluate interwell connectivity accurately. In this paper, a novel LSTM neural network-based GSA method is proposed to estimate interwell connectivity for a waterflooded reservoir. The proposed LSTM-EFAST approach is applied to a synthetic reservoir model to estimate connectivity index, and two additional experiments are performed to verify the effectiveness and validity of this method. The results show that the LSTM based EFAST global sensitivity analysis technique is an efficient method for evaluating interwell connectivity.

In the future, we plan to use the obtained information and knowledge about interwell connectivity to understand reservoir properties, determine water injection rate, and enhance oil recovery for O&G field. The proposed method will be applied to a real industry oil field to further verify the performance of the hybrid algorithm, and more complex changes in field operation, such as the switch of producers to injectors and the shut in of producers and injectors, will be considered when estimate interwell connectivity.

## NOMENCLATURE

| | |
|---|---|
| $a_k$ | Minimum of the $k$-th input factor of LSTM |
| $A_j$ | Fourier coefficient |
| $A_{k\omega_k}$ | Fourier coefficient for the base frequency |
| $b_c$ | Bias weight of cell state of LSTM |
| $b_f$ | Bias weight of forget gate of LSTM |
| $b_i$ | Bias weight of input gate of LSTM |
| $b_k$ | Maximum of the $k$-th input factor of LSTM |
| $b_o$ | Bias weight of output gate of LSTM |
| $B_j$ | Fourier coefficient |
| $B_{k\omega_k}$ | Fourier coefficient for the base frequency |
| $c_t$ | Cell state of LSTM at time stamp $t$ |
| $DT_k$ | Expected variance for $k$-th input for EFAST method |
| $D_k$ | Expected variance for $k$-th input for FAST method |
| $D_y$ | Variance of model output |
| $f$ | Considered model for sensitivity analysis |
| $f_t$ | Output of forget gate of LSTM |
| $G_k$ | Parametric equation |
| $h_t$ | Hidden state of LSTM at time stamp $t$ |
| $i_t$ | Output of input gate of LSTM |
| $I$ | Number of input factors of Sobol's G function |
| $K$ | Number of input factors of LSTM-EFAST method |
| $m$ | Number of hidden neurons |
| M | Interference factor |
| $n$ | Number of input factors |
| N | Number of simulation for EFAST method |
| $o_t$ | Output of LSTM neural network at time stamp $t$ |
| $s$ | One-dimensional scalar parameter |
| $ST_k$ | Total sensitivity index |
| $\overline{ST_k}$ | Normalized total sensitivity index |
| $S_k$ | First-order sensitivity index of the $k$-th factor |
| $t$ | Time stamp of LSTM |
| $W_c$ | Weight of cell state of LSTM |
| $W_f$ | Weight of forget gate of LSTM |
| $W_i$ | Weight of input gate of LSTM |
| $W_o$ | Weight of output gate of LSTM |
| $\lambda_0$ | Oil mobility |
| $\lambda_w$ | Water mobility |
| $\varphi_k$ | Random phase-shift |
| $\omega_k$ | Frequency for the $k$-th input factor |
| $x_i$ | Original input of LSTM-EFAST algorithm |
| $x_i^*$ | Normalized input of LSTM-EFAST algorithm |
| $x_t$ | Input of LSTM at time stamp t |
| $X_k$ | Input factor of model $f$ |
| $y_p$ | Predicted output of LSTM for $p$-th input |
| $Y$ | Output of model $f$ |
| $Z$ | Number of input samples of LSTM |

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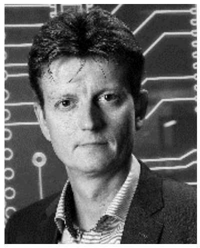

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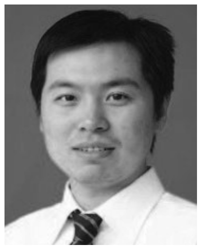

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