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A Well Production Prediction Method of Tight Reservoirs Based on a Hybrid Neural Network

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Abstract: Tight reservoirs have poor physical properties: low permeability and strong heterogeneity, which makes it difficult to predict productivity. Accurate prediction of oil well production plays a very important role in the exploration and development of oil and gas reservoirs, and improving the accuracy of production prediction has always been a key issue in reservoir characterization. With the development of artificial intelligence, high-performance algorithms make reliable production prediction possible from the perspective of data. Due to the high cost and large error of traditional seepage theory formulas in predicting oil well production, this paper establishes a horizontal well productivity prediction model based on a hybrid neural network method (CNN-LSTM), which solves the limitations of traditional methods and produces accurate predictions of horizontal wells' daily oil production. In order to prove the effectiveness of the model, compared with the prediction results of BPNN, RBF, RNN and LSTM, it is concluded that the error results of the CNN-LSTM prediction model are 67%, 60%, 51.3% and 28% less than those of the four models, respectively, and the determination coefficient exceeds 0.95. The results show that the prediction model based on a hybrid neural network can accurately reflect the dynamic change law of production, which marks this study as a preliminary attempt of the application of this neural network method in petroleum engineering, and also provides a new method for the application of artificial intelligence in oil and gas field development.

Keywords: tight oil reservoir; CNN-LSTM neural network; production prediction; fracturing horizontal wells

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1. Introduction

As an unconventional oil and gas resource, tight oil and gas reservoirs constitute new territory in oil exploitation. At present, oil and gas in non-shale materials, such as tight sandstone, carbonate rock and clastic rock, whose reservoir permeability is less than 0.1 mD, are generally defined as tight oil and gas reservoirs internationally [1]. Tight oil and gas reservoirs are the most important resources in unconventional oil and gas reservoirs. In order to ensure the energy security of China, an increasing number of tight oil and gas reservoirs have been put into development. Tight oil, which is rich in reserves, is expected to alleviate the current situation wherein China's crude oil inventory is highly dependent on foreign countries, and it is also expected to become an important pillar to ensure national energy security. The geological resources in tight oil are about 200×10^8 t, and the technically recoverable resources are 20–25 $\times 10^8$ t, accounting for 40% of the recoverable petroleum resources in China [2–4]. Generally speaking, tight oil shows four obvious characteristics: (1) The pore throat diameter of tight oil is less than 1 μm, which makes it a micro-nano pore throat; (2) the porosity is generally less than 10%, the matrix permeability is less than 0.1 mD and the seepage channel is narrow, which shows obvious micro-scale effects [5,6]; (3) the drainage radius is small, there is no natural productivity and the flow resistance in the formation greatly hinders the fluid from flowing from the matrix to the fracture, which makes development difficult; and (4) the formation is affected by multi-stage tectonic action, the natural fractures develop completely and the brittle mineral content of tight oil layers is more than 35%, which is conducive to the use of horizontal well multi-stage fracturing technology and the increase in single well production [7].

Oil production prediction is one of the most critical problems in the area of oilfield development [8]. At present, reservoir development is mainly carried out by means of long-section horizontal wells and large-scale volume fracturing, and thus it is very important to accurately predict the production of fractured horizontal wells. Productivity prediction methods are mainly divided into two types: traditional model analysis and numerical simulation. The traditional mathematical model is not suitable for analyzing complex and high-dimensional prediction scenarios and the numerical simulation technology needs to be established. Therefore, in order to better describe the parameters and seepage mechanisms of horizontal wells, machine learning, especially using neural networks, has become a better choice.

1.1. Traditional Theoretical Prediction Models

After volume fracturing of horizontal wells, there will be media with different scales such as matrix micro-nano pores, artificial main fractures, natural fractures or secondary fractures in tight reservoirs [9]. The fluid seepage mechanism is very complex, and the seepage laws in different scale media are different, so it is difficult to predict production. Therefore, based on the understanding of seepage laws at different scales, domestic and foreign scholars have proposed a variety of productivity prediction models for horizontal wells and fractured horizontal wells. Due to the small pores of porous media in tight reservoirs and the coupling effect of fluid flow, the effective stress on the rock wall changes with tight oil flowing in the pores, which affects the fluid flow and pressure distribution in the reservoir space. Therefore, when analyzing the reservoir productivity performance based on the traditional percolation theory, it is necessary to fully understand the basic factors affecting the productivity [10,11]. Wei [12] believed that the single well productivity of tight oil is highly dependent on natural fractures, and there are different effects on productivity with different fracture scales and development degrees. Huang [13] connected the pressure drops of formations, fractures and wellbores, and considered the stress sensitivity and permeability of artificial fractures, which greatly improved the accuracy of the established productivity prediction model. Lei [14] comprehensively considered the interference of formation seepage and fractures and analyzed the pressure loss of horizontal wellbores. Due to the interference of fractures, pressure drop has a certain influence on output. These will have a certain impact on the actual mining processes of horizontal wells. The following details determine the specific factors affecting productivity through the exploration of the analytical model of fractured horizontal wells in tight reservoirs.

Giger [15] proposed that horizontal wells are the basis of unconventional oil wells. Considering the anisotropy of reservoirs caused by sedimentary processes and fractures, the one-way flow problem of an anisotropic reservoir is simplified into an 'equivalent anisotropy' one-way flow problem, and the simple productivity formula of horizontal wells is given, which is obtained with engineering units:

$$q = 8.37 \times 10^{-4} \frac{K \Delta p}{\mu} \cdot \frac{h^2}{L}, \tag{1}$$

where K is the matrix permeability, mD; h is the reservoir thickness, m; μ is the crude oil viscosity, mPa·s; Δp is the pressure difference, MPa and L is the length of horizontal well, m.

Joshi (1986) [16] established a mathematical equation to calculate the steady-state oil production of horizontal wells. The equation needs to consider the influence of reservoir anisotropy, thickness and well location outside the reservoir center on the horizontal well production. It can be used to explain the eccentricity of wells in the reservoir and can also theoretically predict the effective wellbore radius and skin factor of horizontal wells. The equation is as follows:

$$q = \frac{2\pi K \Delta p}{\mu B} \frac{1}{\ln\left(\frac{a+\sqrt{a^2-(L/2)^2}}{L/2}\right)}, \quad (2)$$

where B is the volume coefficient of crude oil and a is the semi-major axis of the ellipse, m.

Fan (1996) [17] deduced the steady-state productivity formula of horizontal wells based on the productivity formula of vertical fractured wells. In the process of derivation, the influence of heterogeneity of the fractured reservoirs and matrix anisotropy on the productivity of horizontal wells is considered. The productivity formula is expressed as follows:

$$q = \frac{2\pi K h \Delta p}{\mu B} \mathrm{arcch}^{-1}\left\{ \mathrm{ch}\left(\frac{\pi a}{2b}\right) \cdot \left[\sin\left(\frac{\pi L}{2b}\right) + \frac{h}{L} \ln\left(\frac{h}{2\pi r_{\mathrm{w}}}\right) \right]^{-1} \right\}, \quad (3)$$

where B is the short half-length of the ellipse; r_{w} is the wellbore radius and w_1 and w_2 are the weighting coefficients.

Song (1999) [18] obtained the steady-state production formula of horizontal wells in reservoirs using the average mass conservation method based on the theory of ellipsoidal flow pattern of horizontal wells and considering the starting pressure gradient. The research found that the impact on production increases with the increase in starting pressure, and the engineering unit is expressed as:

$$q = 86.4 \frac{2\pi K h (\Delta p - G \cdot r_{\mathrm{e}})}{\mu B \left[\left(\ln \frac{2r_{\mathrm{e}}}{L/2} \right) + \frac{h}{L} \left(\ln \frac{h}{2\pi r_{\mathrm{w}}} \right) \right]}, \quad (4)$$

where G is the starting pressure gradient, MPa/m and r_{e} is the radius of supply boundary, m.

Wu (2017) [19] derived the pressure drop equation of horizontal flows considering the starting pressure gradient. Combining the equation with the pressure drop equation of vertical flows, the single-phase flow production formula of horizontal wells is obtained by using the perturbation elliptic flow theory:

$$q = \frac{2\pi K h \Delta p}{\mu B \left(\mathrm{arch}(2r_{\mathrm{e}}/L) + \frac{h}{L} \ln \frac{h}{2\pi r_{\mathrm{w}}} \right)} \left[1 - \frac{G}{\Delta p} \left(\frac{L}{\pi} \sinh(\mathrm{arch}(2r_{\mathrm{e}}/L)) + \frac{h}{2\pi} - r_{\mathrm{w}} \right) \right]. \quad (5)$$

Horizontal wells are of great significance in the process of oilfield development. Over the years, the productivity prediction model of horizontal wells has been constantly improved, forming a relatively complete technical series from the study of a single horizontal well productivity prediction model in the last century to the wide application of multi-stage fracturing technology today, as shown in Figure 1. In tight reservoirs, based on the theory of seepage mechanics and the principle of superposition, considering the influence of formation and engineering factors on wells and the interference of flow between fractures, a mathematical model of productivity of fractured horizontal wells is established. The flow rate of fluid from reservoir to horizontal wellbore is divided into four parts: from reservoir to fracturing zone, linear flow in fracturing zone, fracture tip to horizontal wellbore and flow in horizontal wellbore [20] (2020). The formula is as follows:

$$q = C_{\mathrm{t}} \pi h \phi \frac{\mathrm{d}}{\mathrm{d}t} \left[\left(r^2(t) - x_{\mathrm{f}}^2 \right) \right] \Delta \overline{p}, \quad (6)$$

where,

$$\Delta\overline{p} = \frac{1}{4}\left\{\left\{-Gx_\mathrm{f} - \frac{1}{\alpha_\mathrm{k}}\ln\left[e^{-\alpha_\mathrm{k}Gr(t)} + \frac{q\mu\alpha_\mathrm{k}}{172.8\pi k_\mathrm{i}h}\left(\ln\frac{x_\mathrm{f}}{r_\mathrm{e}} + \alpha_\mathrm{k}G(r(t) - x_\mathrm{f})\right)\right]\right\} + \frac{q\mu L_\mathrm{d}}{x_\mathrm{f}hk_3} + \frac{q\mu}{172.8\pi k_4 w_\mathrm{f}}\ln\frac{h}{2r_\mathrm{w}} + \frac{q\mu(x_\mathrm{f} - 0.5h)}{172.8k_4 w_\mathrm{f} h}\right\},$$

$$r(t) = \frac{(r_\mathrm{m} + r_\mathrm{mf})L}{2},$$

where r_m is the radius of matrix circle, r_mf is the radius of micro-crack circle and L_d is the average linear flow distance.

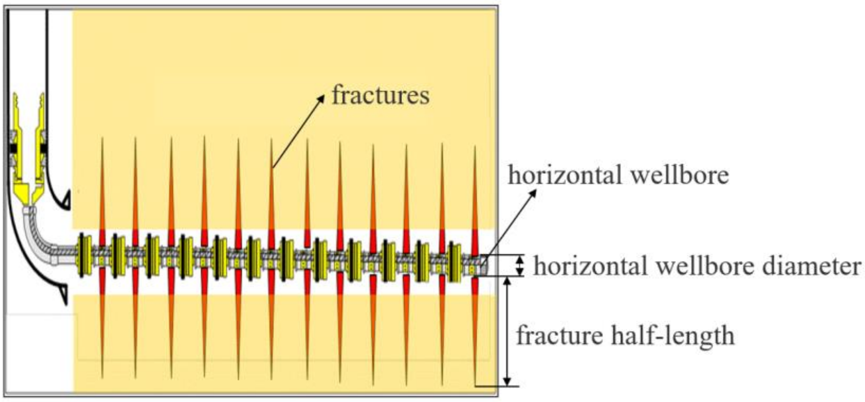


Figure 1. Physical model of multi-stage fracturing horizontal well.

The traditional seepage formula needs to master the parameter information of oil wells in different blocks. Due to the nonlinear change in oil production in time series and the complexity of field conditions, a series of boundary conditions need to be introduced to simplify the problem, so as to establish an idealized mathematical model. However, the application scope of the model is narrow, and the complex seepage law and the change in reservoir performance in the actual flow process cannot be represented by traditional models. In addition, the analysis method relies on time-consuming and expensive physical experiments while the neural network method does not need to analyze the seepage mechanism of a tight reservoir in detail. The dynamic data and geological parameters that are used as the main factors affecting productivity and the correlation between horizontal well productivity and various factors is known, so that the productivity prediction model can be established to achieve the goal of rapid and effective prediction of time series oilfield production. At the same time, considering the difference of main control factors of different types of reservoirs, the established method is further applied to the production prediction of other types of reservoirs.

1.2. Neural Network Prediction Models

At present, most oil and gas production prediction requires a comprehensive description of the geological factors and formation fluid characteristics of oil and gas fields [21]. Due to the difficulty of data acquisition and rock and fluid property characterization, it takes significant time and energy to analyze the main factors affecting productivity. In recent years, with the rise of machine learning, the main factors of sustained high production of fractured horizontal wells in tight reservoirs have been analyzed qualitatively and quantitatively and various intelligent algorithms such as neural networks and decision trees have been used to predict the production. Based on the fracturing dynamic data of historical wells, a more accurate prediction model is established here, which provides a broad application prospect for the subsequent use of horizontal well volume fracturing to enable efficient development of tight oil [22,23].

A complete neural network structure is divided into three types of neurons: input neurons that receive external input values, output neurons that output predicted values and hidden neurons that neither directly accept external signals nor send signals to the outside world [24]. Generally speaking, the hidden layer's purpose is to divide the characteristics of the input data. When the external data is transmitted from the input layer to the hidden layer, it is transmitted and fitted by the activation function, and the error is reduced according to the gradient descent method to better fit. Finally, it is transmitted to the output layer for the final output. The empirical formula of the number of hidden layer neurons in the three-layer neural network is shown in (7) [25]. The neural network method has many advantages, such as function approximation, self-learning, fast optimization calculation, strong robustness and fault tolerance of highly parallel distributed information storage, and it has been widely used in data prediction. It is simple and practical to use machine learning algorithms to establish the production prediction model. Many scholars use random forest [26], support vector machine (SVM) [27] and multiple linear regressions [28] to realize the dynamic prediction of oil well production. The application results show that, due to the anisotropy and heterogeneity of the reservoir, in addition to using very complex mathematical models to analyze and evaluate the oil production capacity of the reservoir, the neural network method can also be used to establish a prediction model; divide data sets for training, verification and testing and continuously reduce the error and approximate the actual value. Figure 2 shows the prediction of the oil production of oil wells using an artificial neural network model. The relationship between various influencing factors and production characteristics of the reservoir is analyzed through characterization. Based on the feature extraction technology of fluid physics, the reservoir parameters, fluid parameters, horizontal well parameters and fracturing parameters are randomly combined as new input and output eigenvalues of the model and the prediction error is minimized by adjusting the connection weights between neurons. This kind of oilfield production prediction method based on data mining has good application value.

$$K < \sum_{i=0}^{n} c \begin{pmatrix} n_1 \\ i \end{pmatrix} \tag{7}$$

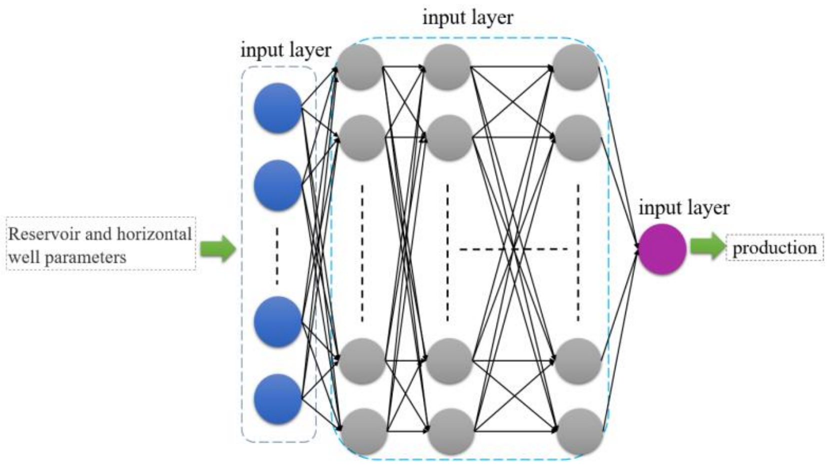


Figure 2. Structure of artificial neural network model.

Artificial neural networks are a kind of feedforward network, which is a kind of static network. The information transmission is one-way. The output of the network only depends on the current input, and it has no memory ability. The input and output items follow point-to-point mapping, and the data before and after are not related. When there are important interactions or complex nonlinear structures in the data set, the prediction results will often deviate greatly. For the complex reservoir characteristics of tight reservoirs and many productivity factors of horizontal wells, the ANN method is not applicable.

In the paper, a hybrid neural network model type of Convolution Neural Network based on the Adam optimization algorithm and Long Short-Term Memory neural network is established, and each sub-model is used to overcome its own shortcomings, so as to accurately predict the production of fractured horizontal wells in tight reservoirs. At the same time, the existing studies have found that no deep learning algorithm is always superior to other models in the application of real problems. By integrating multiple prediction models, combining different algorithms and making use of the different advantages of each algorithm, it has become a new direction in the field of time series prediction. In view of the characteristics of long-term time series correlation and large differences in parameters, it is necessary to select several neural network methods with good adaptability to establish a hybrid neural network productivity prediction model, which is helpful for improving the accuracy of production prediction under different oil well characteristics.

The structure of this manuscript is as follows: The second part proposes and analyzes the applicability and limitations of various neural network prediction methods for horizontal well productivity. The third part compares the results of various neural network production predictions through a specific example of the oil field block and proves the applicability of the proposed method in such scenarios. The fourth part provides the conclusion.

2. Materials and Methods

2.1. Recurrent Neural Network (RNN) Method

The traditional artificial neural network, such as the multi-layer perceptron model established by Orbach [29] and Rumelhart [30], propagates the information flow in a single direction from the input layer to the output layer. This kind of neural network model cannot accurately predict the dynamic parameters related to the time series in the oil field, while the RNN neural network is good at processing sequence data [17]. As shown in Figure 3, the cycle layer is expanded into a complete network, x is the input, h is the hidden state that gives the network memory ability and the subscripts $t-1$, t and $t+1$ represent different time steps. W, U and V are hyperparameters of different layers, where W is the weight matrix of the last value of the hidden layer as the input of this time, U is the weight matrix from the input layer to the hidden layer and V is the weight matrix from the hidden layer to the output layer, and W, U and V are shared by weights. Taking the prediction of the production of fractured horizontal wells in tight reservoirs as an example, the whole prediction process needs to collect a large amount of relevant factor data that affect the production of oil wells and classify them as input elements. However, RNN is limited to recalling the latest information and cannot retrieve any information from the past [31]. The memory capacity of its storage features is limited, and it is easy to encounter problems such as gradient disappearance and gradient explosion, which introduces large errors into the long-term prediction of oil well production results. Therefore, it is necessary to try to improve the method to solve these defects.

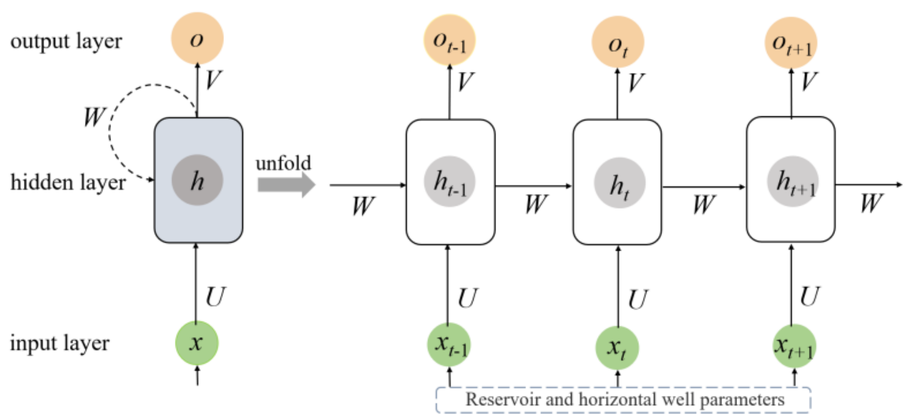


Figure 3. Structure of RNN hidden layer deployment.

2.2. Convolutional Neural Network (CNN) Method

The main feature of the convolutional neural network is that it can process multi-channel parallel time series data, which is composed of five parts: input layer, convolution layer, pooling layer, fully connected layer and output layer [32]. The input layer is used to input data, and the convolution operation is performed in the convolution layer to fully extract the potential important features of the data, and then the pooling operation is performed to extract local features to reduce the number of parameters. After this, the fully connected layer is used to integrate the previously extracted features to reduce the loss of feature information and finally output the prediction results.

Wu [33] mainly used the CNN model for fault detection, extracted character features from complex images and used synthetic seismic records to extract training data sets to simulate faults with different dip angles and different distances. In addition, CNN is also applied in ore identification and classification, logging curve prediction, lithology identification and other fields. CNN technology has advantages in time series processing. It can classify different types of input data and then quickly extract effective feature data. Especially in the prediction of oil well production, due to the many types of factors affecting oil well production and the large amount of data, the method can be used to summarize different types of data in a data set, extract local features through the convolution kernel in the convolution layer, and then add a pooling layer to reduce the number of extracted features and reduce the dimensions of the model data. It reduces the burden in the training process and greatly improves the data processing ability. The network structure principle is shown in Figure 4. However, CNN needs to use the back propagation algorithm in the process of actual data processing [34], and the existence of the pooling layer leads to the loss of much valuable information. At the same time, the correlation between the production and the factors affecting the production are ignored, which leads to the inability to accurately judge the current production status of the oil well, so that the prediction results include large errors.

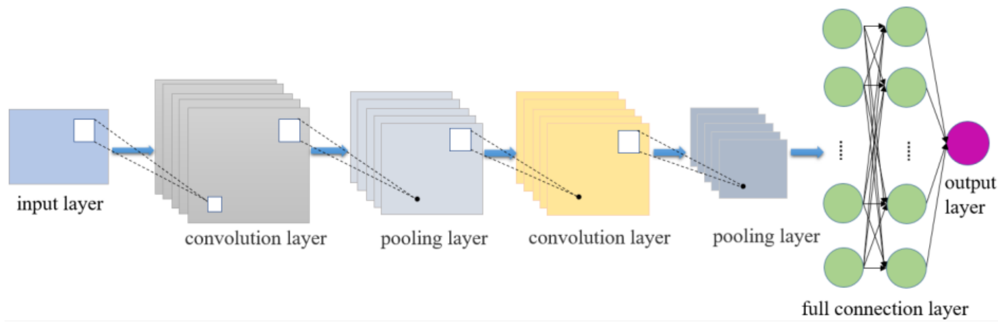


Figure 4. Structure of convolutional neural network diagram.

2.3. Long Short-Term Memory Neural Network (LSTM) Method

Compared to RNN, the network architecture of the LSTM neural network has been further improved by introducing a memory unit to replace the hidden layer unit of RNN. The memory unit of an LSTM neural network has three gates, namely the input gate, forget gate and output gate [35]. The input gate can control the addition or filtering of new information, the forget gate can forget the information that needs to be lost and retain the useful information before and the output gate enables the memory unit to output only information related to the current time step. The three gate structures perform matrix multiplication and nonlinear summation operations in the memory unit, so that the memory does not decay during iteration, as shown in Figure 5.

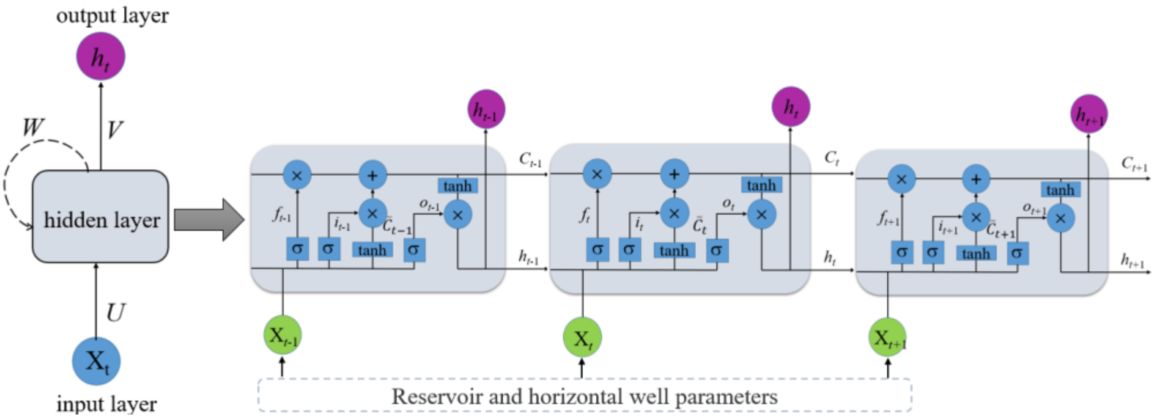


Figure 5. Structure of LSTM neural network.

The LSTM neural network extracts the correlation information from the time series data through the gate controller and the new memory unit, so that the long-term memory is stored on the original short-term memory, thereby overcoming the problem of the disappearance of the RNN gradient and retaining the correlation information from the previous longer steps. Horizontal well production data are typical time series data. The LSTM network is used to process the time series data, and the change trend and correlation of production dynamic data are fully considered, so as to realize the accurate prediction of production [36]. However, LSTM needs to consider the long-term dependence in the input time series data when dealing with a large number of data sets, but the predictive ability for the nonlinear long-term dependence between data is limited. When the input time is too long, the derivative of the LSTM activation function is a number less than 1, and the multiplication of multiple derivatives less than 1 will eventually lead to the disappearance of the gradient. When the input time is too short, the periodic information cannot be captured, meaning that the effective information and potential relationship between discontinuous data cannot be fully grasped.

The advantages, disadvantages and applicable scenarios of the four mainstream neural networks are summarized in Table 1.

Table 1. Mainstream neural network model structure comparison.

Name	Advantage	Disadvantage	Applicable Scene
ANN	The model has simple structure and strong parallel distributed processing ability.	The model has poor convergence ability and is prone to overfitting.	Suitable for scenes with simple features
RNN	Sequence content can be modeled	Too many parameters are prone to gradient disappearance and gradient explosion.	Apply and process data related to time series
CNN	Strong generalization ability of model	Gradient dissipation is prone to occur.	Excellent performance in large image processing applications
LSTM	The long-term dependence problem of RNN is improved.	There are disadvantages in parallel processing, and the calculation is time-consuming.	Prediction production, mechanical fault diagnosis, speech recognition

2.4. Hybrid Neural Network (CNN-LSTM) Method

In order to improve the prediction accuracy of daily oil production of horizontal wells and make up for the shortcomings of the LSTM network, a new time series prediction model is proposed here, which is a hybrid model prediction method based on a convolutional neural network and long short-term memory neural network [37]. The method combines the respective characteristics of CNN and LSTM networks and uses the dynamic parameters that affect the daily oil production of horizontal wells as input. The convolution kernel in CNN is used to extract the potential relationship between continuous data and discontinuous data in the graph to form a feature vector. Then, the feature vector is constructed in time series and used as input data. Following this, the LSTM network is used to predict the productivity [38]. The structure diagram is shown in Figure 6. This method solves the limitations of characterizing reservoir characteristics and establishing complex mathematical models by considering many influencing factors in the past. It can not only capture the changing trend of data and extract the effective characteristics of data, but also characterize the dependence of time series data, retain longer effective memory information as much as possible and solve the problem of gradient dispersion. Therefore, it shows high prediction accuracy when predicting complex nonlinear problems such as oilfield production changes.

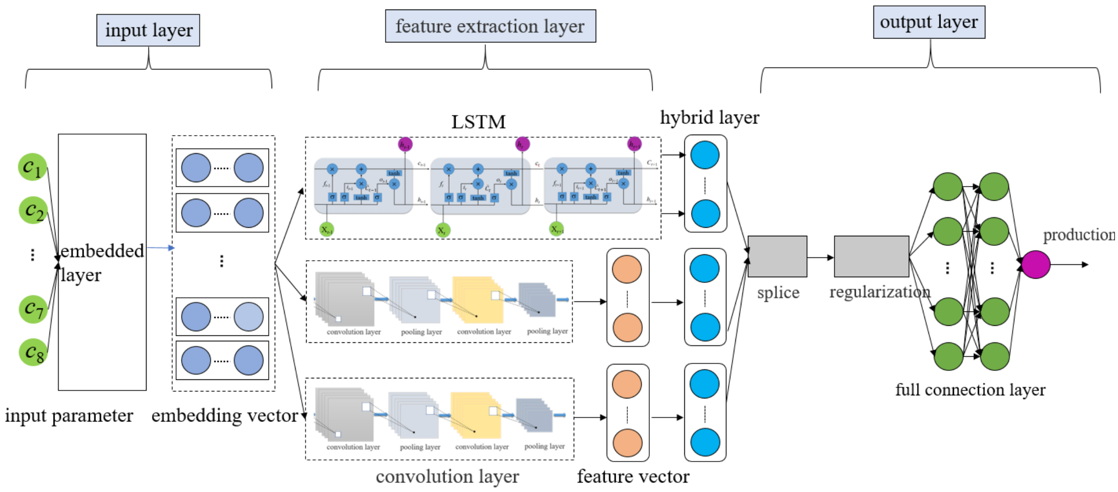


Figure 6. Structure of the CNN-LSTM neural network diagram.

The CNN-LSTM prediction model mainly includes two points: (1) The current research mainly focuses on univariate prediction. Starting from the three factors of geology, development and engineering, the factors that are easy to obtain are selected as input variables to predict oil production. (2) The CNN-LSTM prediction method has strong robustness, mainly using the ReLU activation function. It aims to mine the effective information contained in the production data by predicting the law of capacity change, adjusting the development plan in time, understanding the production changes in advance and finally obtaining the maximum economic benefits.

In this paper, the data of fractured horizontal wells in tight reservoirs is used as the input for the prediction model and the production value is used as the output. The whole CNN-LSTM network training prediction model is shown in the Figure 6, and the CNN-LSTM network model is mainly composed of two parts. Firstly, the input data passes through the CNN network and the data features are extracted and reduced by the convolution and pooling operations. Next, the data processed by the CNN network is input into the LSTM network, and the forget gate, input gate and output gate in the LSTM network adjust their own parameters through continuous iterative training of a large amount of data, so that the network can learn the time fitting relationship between data from the data information extracted by the CNN network, thus effectively modeling the input and output data of prediction time series. Finally, the trained data is fitted by the CNN-LSTM network and the predicted value is output through the fully connected neural network. The whole prediction process needs to be trained with data to determine the network model parameters.

3. Model Analysis

A tight reservoir in the Daqing Oilfield was selected as the research object. The reservoir is distributed with natural fractures, which leads to the permeability of the tight reservoir being greater than 0.1 mD. It is characterized by poor physical properties, low viscosity of crude oil and strong heterogeneity. In this paper, 100 fractured horizontal wells with long production times, no major measurement adjustments and stable production were selected from the oil field blocks. The BP neural network model, RBF model, RNN model, LSTM model and CNN-LSTM model were trained, respectively, and the daily oil production of one horizontal well from January 2016 to October 2018 was predicted, and these predictions were compared with actual data to analyze the prediction effects. Firstly, according to the productivity formula of the classical percolation theory, the main factors affecting oil well production are geological factors (porosity, permeability and reservoir pressure), development factors (horizontal well length, dynamic liquid level, initial water cut, water production, wellhead pressure, fracturing sand volume and sand strength) and engineering factors (stroke, stroke frequency, pump efficiency and pump depth). These characteristic parameters were used as initial input variables, and the changes in single well production with time were used as output variables. Table 2 lists the parameters of typical fractured horizontal wells.

Table 2. Parameter statistics of partially fractured horizontal wells in a block of the Daqing Oilfield.

Well Number	Geological Factors		Development Factor					Engineering Factors	
	Permeability/mD	Reservoir Pressure/MPa	Length of Horizontal Well/m	Dynamic Liquid Level/m	Moisture Content/%	Water Production/m^3	Fracturing Sand Amount /m^3	Pump Efficiency/%	Pump Depth/m
Well no.1	1.8	0.4	1046	1382	28	0.8	30	12.8	98
Well no.2	2.8	0.4	1211	1409	14	0.6	37	17.4	71
Well no.3	1.2	0.5	821	873	85	3.8	18	17.6	588
Well no.4	0.8	0.4	730	1272	89.6	4.5	45	15.5	188
Well no.5	3.5	0.5	1096	600	14	1.3	25	26.6	799
Well no.6	1.4	0.6	1234	1331	59.9	5.0	29	25	149

3.1. Factor Analysis

In order to accurately predict the change law of oil well production after fracturing, it is necessary to screen the main factors affecting the production of fractured horizontal wells in tight reservoirs. If all the factors are used as input parameters, it is necessary to ensure that all the data are of high quality. The factors with low correlation will interfere with the accuracy of the model, and the time complexity of the model will become very high. When some data vary greatly, the prediction results become inaccurate. Therefore, in order to reduce the time complexity of the algorithm, increase the flexibility and improve the prediction accuracy of the output, 14 typical factors affecting the post-fracturing production of the oilfield were selected from geology, development and engineering, and the one-way correlation between each factor and the initial production was judged. The greater the correlation coefficient, the greater the impact on production.

The linear transformation equation is shown in Formula (8) [39], and the factors that have a great influence on the oil well production are screened out:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}. \tag{8}$$

The ordinate shows the input characteristic parameters and the abscissa shows the correlation degree of the input parameters to the single well production (shown in Figure 7). The importance of each characteristic parameter to production was judged by comparison. The overall order is as follows: water production > permeability > water cut > dynamic liquid level > pump depth > pump efficiency > wellhead pressure > fracturing sand addition > horizontal well length > porosity > fracturing sand addition strength > reservoir pressure > stroke > stroke. Finally, three factors were comprehensively considered.

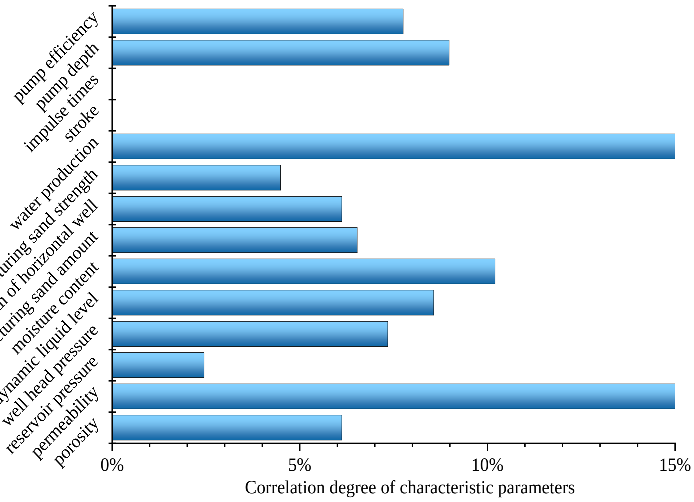


Figure 7. Histogram of correlation coefficient importance.

3.2. Model Trainings and Predictions

3.2.1. Training of Four Neural Network Models

According to the previous preprocessing of the input parameters, the eight characteristic parameters affecting the change in oil well production were taken as input nodes and the production value was taken as an output node. In order to improve the generalization ability of the model, the input parameters were randomly initialized and the input parameters and actual daily oil production in the same time range were collected. The data source was the daily oil production data of typical horizontal wells from 2016 to 2018, which was divided into a training set, verification set and test set. The data from the first 600 days were taken as the training set, the data from the next 200 days were taken as the verification set, and the data from the next 200 days were taken as the test set. The model was trained by the training set, and the neural network hyperparameters were adjusted by the verification set. Finally, the predicted value and the actual value obtained after the model test were compared.

(1) BPNN model

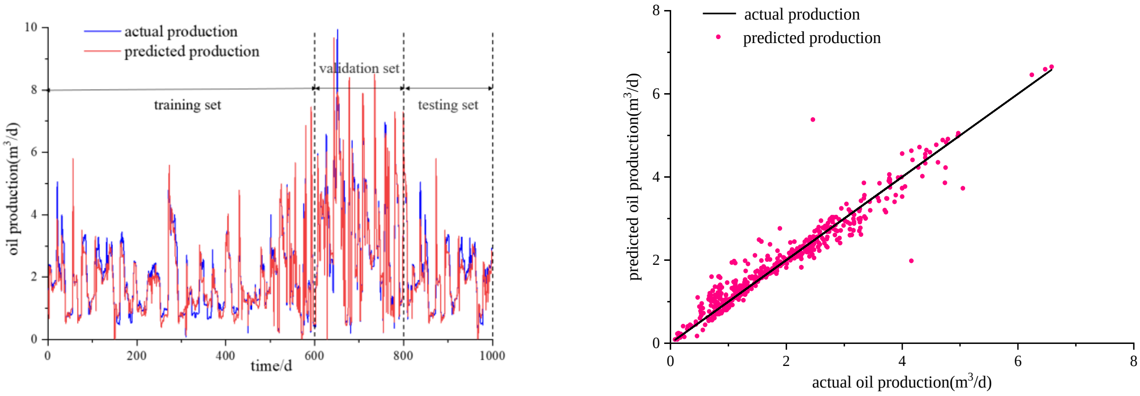
The BPNN model was divided into four layers, and the number of nodes in each hidden layer was set to eight [40]. After BP neural network model training and learning, it can be seen from Figure 8a that the average relative error of the test results was 18.26%, which indicates that the productivity prediction model established by this neural network method could not accurately describe the trend of productivity change and could not meet the accuracy requirements of on-site productivity prediction.

(2) RBF model

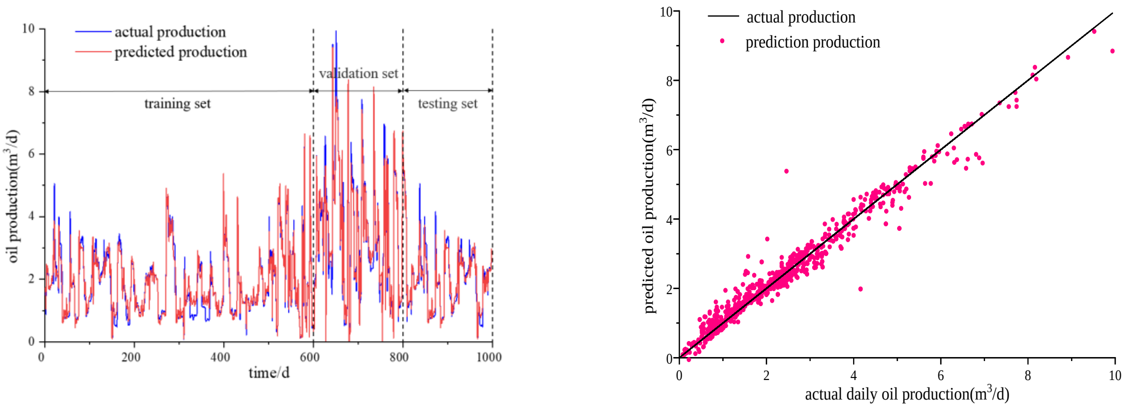
An RBF neural network is a three-layer feedforward neural network with good performance and a single hidden layer. The transformation of the model from the input layer to the hidden layer is nonlinear and the transformation from the hidden layer to the output layer is linear [41]. The hidden layer activation function is a radial basis function, as shown in Formula (9):

$$h_t = \exp\left(-\frac{\|x - c_i\|^2}{2{\sigma_i}^2}\right), \tag{9}$$

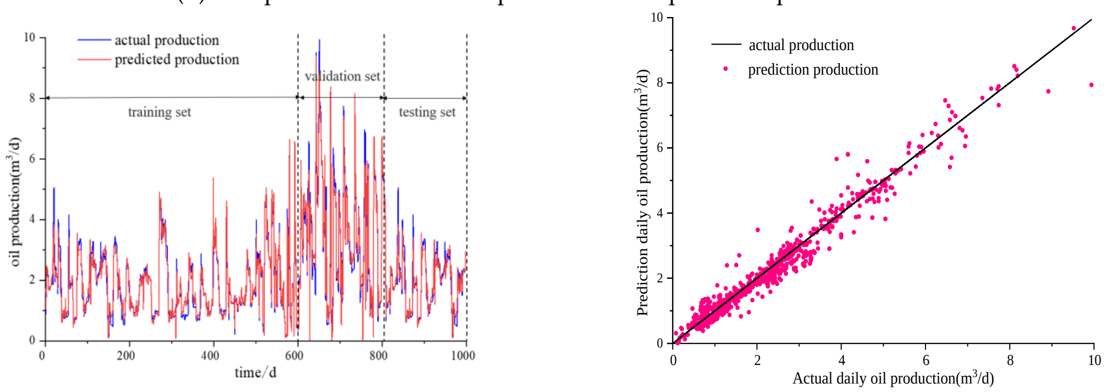
where x is the input factor, c_i is the center of the basis function, σ_i is the smoothing parameter, m is the number of sensing units and $\|\cdot\|$ is the norm. The output formula is expressed as: $y = \sum_{i=1}^{m} w_i h_t(x)$.



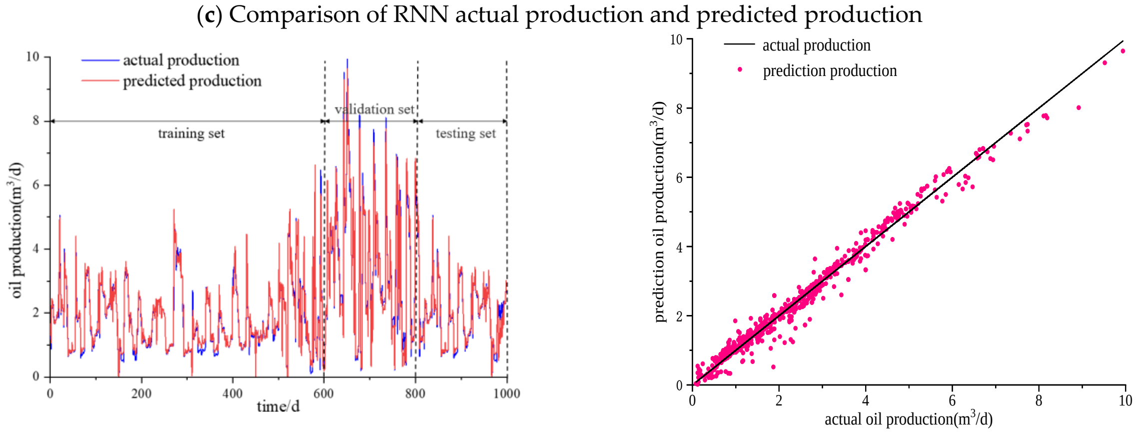
(**a**) Comparison of BPNN actual production and predicted production



(**b**) Comparison of RBF actual production and predicted production



(**c**) Comparison of RNN actual production and predicted production



(**d**) Comparison of LSTM actual production and predicted production

Figure 8. Prediction results of four neural network models.

The structure layer of the RBF neural network model was set to three layers, the number of neurons in the middle-hidden layer was seven, and the running time was about 121 s. Through repeated training, the parameters of the optimized model were finally obtained. The measured value of daily oil production and the predicted value of the model are shown in Figure 8b. The average relative error was calculated to be 17.34%. The RBF neural network used the best approximation of the continuous function. Compared to the BPNN model, it solved the problem of local convergence. However, since the production was a dynamic parameter that changes with time, the deviation between the predicted value and the actual value of some production was still large in the prediction process. Therefore, it was necessary to introduce a neural network about time series.

(3) RNN model

The RNN neural network prediction model has a total of 4 layers with 2 hidden layers in the middle, 10 nodes in the first layer, 3 nodes in the second layer and the output was daily oil production. The input parameters were randomly initialized, the model was trained by the training set and the neural network hyperparameters were adjusted by the verification set. Finally, the model effect was evaluated by the test set, and the total running time was 103 s. Figure 8c shows the comparison between the measured and predicted values of the three data sets. The average relative error of the calculated production prediction was 10.44%, which is 4.82% higher than that of the RBF neural network. However, with the increasing number of days, the gradient of the RNN will disappear in the process of back propagation, which affects the production prediction results. Therefore, an improved recurrent neural network that can overcome the disappearance of gradient is needed to ensure the long-term correlation of dynamic parameters in the learning process.

(4) LSTM model

The LSTM neural network has a long-term dependence on historical data and can accurately predict the variation of yield value with time. According to the training set composed of the determined main control input parameters and the daily oil production of horizontal wells, the LSTM neural network was trained to optimize each weight system of the neural network. After continuous debugging and searching, batch size was set to 100, time step was set at 12, iteration was set to 10, the hidden layer had 56 neurons, the sigmoid activation function was adopted, the loss function adopted the root mean square error function and the optimizer adopted the Adam optimization algorithm. The comparison between the predicted value and the actual value is shown in Figure 8d, and the average relative error was 8.21%, which indicates that the prediction effect of LSTM model is better than the BPNN, RBF and RNN.

3.2.2. Specific Analysis of the CNN-LSTM Model

(1) Model establishment

The CNN-LSTM hybrid neural network prediction model proposed in this paper is an extension of the LSTM model. Because of its characteristics of capturing local important features and using nonlinear activation functions in each layer, it can accurately describe the nonlinear trend in data and remember historical information for a long time. Therefore, the CNN-LSTM has been successfully applied to many time series problems. When establishing the prediction model, different parameter combinations are listed through grid search and random search to determine the structure with the best performance. The model is mainly composed of two parts. The CNN part is mainly responsible for feature extraction and the LSTM network is mainly responsible for capacity prediction. CNN has two convolution layers and the number of convolution kernels is set to 16 and 32, respectively. CNN can set the kernel size smaller or larger. Many effective features are extracted from the input time series data according to the size of the kernel. Considering that the actual oil production comprised a set of data every day, in order to make full use of the existing data, the convolution kernel size was set to 3×3, and the pool size in the pool layer was 2. In the LSTM network part, it was found through experiments that increasing the LSTM neural network unit to increase the depth of the model helped to improve the prediction ability of the model, and so the number of neurons was 56. At the same time, the random inactivation method was adopted between each layer of the LSTM network layer to prevent the model from over fitting. Finally, the vector of the specified format was produced through the fully connected layer, namely the daily oil production of a horizontal well in a block of a tight oil reservoir.

Secondly, due to the complex structure of the CNN-LSTM model, it is very important to set the hyper-parameters in the model. Through trial and experiment, the number of iterations was set to 200, 400, 600, 800, 1000, 2000 and 5000; other hyper-parameters were used in the training process. The batch size was set to 100, the optimization function was Adam, the time step was set to 12, the initial learning rate was 0.01 and the learning rate of the final model after training was 0.0001. The optimal structure of the model is shown in Table 3.

Table 3. Information about the optimal structure of model.

Name	Value/Content	Name	Value/Content
number of inputs	8	output variable	daily oil production
optimization algorithm	Adam	activate the functions	tanh, sigmoid
learning rate	0.0001	traversal times	10,000
time step	12	batch size	100

(2) Loss function improvement

The problem of oil field dynamic production prediction is different from typical problems for which machine deep learning is trained at ordinarily. The difference in our study was that the data given by the typical feedforward neural network during training was real and effective and the production dynamic data fed back by the oil field had some missing values of production, some of which led to no production on some days, and some data may have been lost or omitted. Therefore, when this part of the data was used as characteristic parameters for learning, the network training was biased, thus affecting prediction accuracy. Based on this characteristic of the data, the original commonly used fitting loss function RMSE loss was improved, so that the improved RMSE could automatically ignore the default value, as shown in Formula (10). The new root mean square error function was multiplied by a coefficient after each biased term. When the training data is 0, the error of the data point is 0, and when it is not 0, the error value of the function remains basically unchanged, thus making up for the problem of missing training or test data and improving the prediction accuracy of the model, as shown here:

$$RMSE_{new} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[(y_i - \hat{y}_i)^2\left(\frac{y_i}{y_i + a}\right)\right]}, \tag{10}$$

where, y_i and $\hat{y}_i$ represent the real value of oil well production and the predicted value of the model, respectively, and a is a small constant.

(3) Training and prediction effects

Firstly, the training data was input and passed through the convolution layer and pool layer in turn. Then, the CNN identified and extracted the features of the input data and generated an output value for the input for the LSTM. In the CNN layer, the process of feature extraction was mainly based on the input time series data, and in the LSTM layer, the prediction process was mainly based on the observed time series values, in which the output value from LSTM layer became the input of the full connection layer. Following this, the final prediction value was generated by the full connection layer, and the prediction training process was completed in this stage. We calculated the average relative error of the prediction results, as shown in Figure 9.

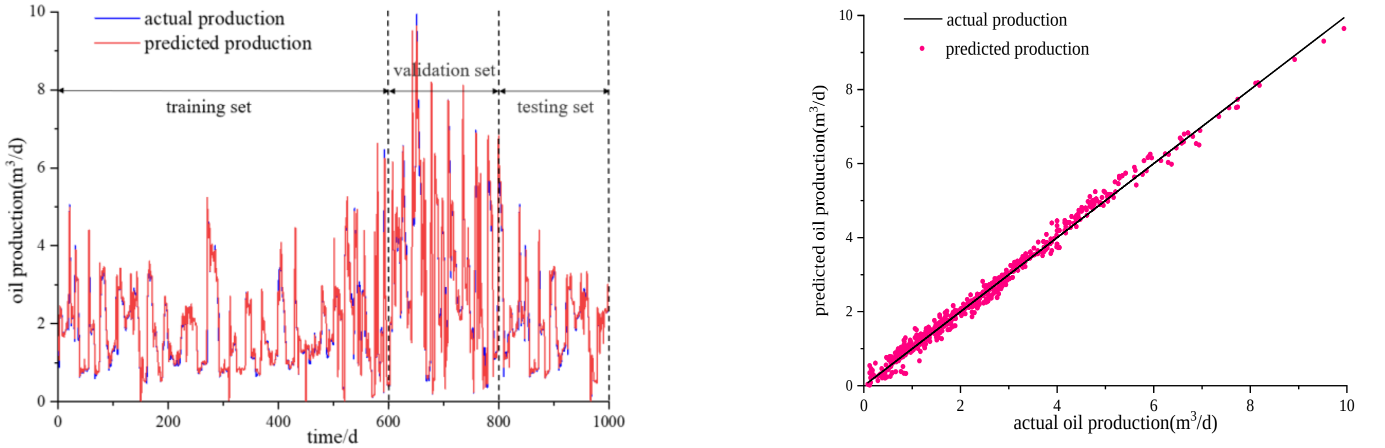


Figure 9. Comparison between actual production and predicted production by the CNN-LSTM neural network.

(4) Prediction error comparison

From Figure 8a,b, it can be seen that many points of the BPNN and RBF deviate from the actual value too much and many of the predicted values exceed 20%, with some even close to 80%. After the RNN and LSTM models were introduced into the time series, the prediction effect was better than the first two models, but there were still some data errors, with individual data close to 60%,as shown in Figure 8c,d. However, almost all the data obtained from the CNN-LSTM were concentrated within 20%. The results show that the model can not only give global trend prediction, but it also has accurate single-point prediction. Table 4 shows the average relative error values of the five models. It can be seen that the error value of the CNN-LSTM model is significantly smaller than other four models, and it meets the engineering accuracy requirements. Therefore, it can be used as a model method to predict the production of horizontal wells.

Table 4. The average relative error of five neural network models.

Model	BPNN	RBF	RNN	LSTM	CNN-LSTM
Average relative error	18.26%	17.34%	10.44%	8.21%	5.00%

4. Results and Discussion

4.1. Comparison of Prediction Models

From the experimental results, it can be seen that the CNN-LSTM network hybrid model takes into account the characteristics of both the CNN model and LSTM model. To some extent, the global and local characteristics are integrated, and there is almost no production value that deviates greatly. It can be seen from Table 5 that the predicted value of the CNN-LSTM prediction model is closest to the actual output value, and the relative error is less than 5%, taking the 200th, 400th, 600th, 800th and 1000th days as examples. It can be seen from Figure 9 that the CNN-LSTM model considering the time series of daily oil production is superior to the four other models, namely the BPNN, RBF, RNN and LSTM models.

Table 5. Comparison of predicted values and real values of typical single wells.

Day	Actual Value	Predicted Value				
		BPNN	RBF	RNN	LSTM	CNN-LSTM
200	1.57	1.87	1.94	1.46	1.98	1.64
400	3.02	2.51	2.96	3.12	2.96	3.05
600	0.38	0.21	0.34	0.48	0.34	0.35
800	6.71	5.74	6.73	6.98	6.73	6.75
1000	2.93	3.01	2.96	2.85	2.96	3.02

The deviation between actual oil production and predicted oil production is small, and the predicted trend is highly consistent with the change trend of actual oil production. Therefore, the method is suitable for horizontal well production prediction.

Because the loss function of the neural network model changes with the learning process, the training effect of the model is usually evaluated using the loss function curve. By monitoring the convergence trend of the loss function curve, it can be determined whether the model has reached the best state [42]. When the convergence speed of the loss function of the model is slow and tends to be stable, it cannot be predicted. This model can only be used for prediction when the loss function reaches stability.

In order to fully compare the generalization ability of several models, 600 training samples were selected. As can be seen from Figure 10, the BPNN and RBF models are types of feedforward neural networks, which are prone to over fitting, thus reducing the generalization ability of the models. Therefore, the loss functions of these two models converge slowly. Although there is no such problem in the RNN or LSTM network, when the training samples increase, there may be some problems such as gradient explosion, gradient disappearance and topological structure expansion, which will lead to the decrease in prediction accuracy of these two models. The loss function curve of the CNN-LSTM model has the best convergence effect, and the convergence rate is still very fast when there are not many training samples, as shown in Figure 10a. The curve gradually begins to converge after training 100–300 samples, and the trend is relatively stable after training to the 400th sample. It can be seen that the loss function of the model gradually decreases and quickly tends to be stable with the increase in training times, and the prediction model has not been over-fitted or under-fitted. Figure 10b shows the error range of random samples. It can be seen that the error fluctuation range of CNN-LSTM model is the smallest, and almost all sample test points are accurately attached to the sample curve, which indicates that the model can be used to predict the daily oil production of fractured horizontal wells in the tight reservoir.

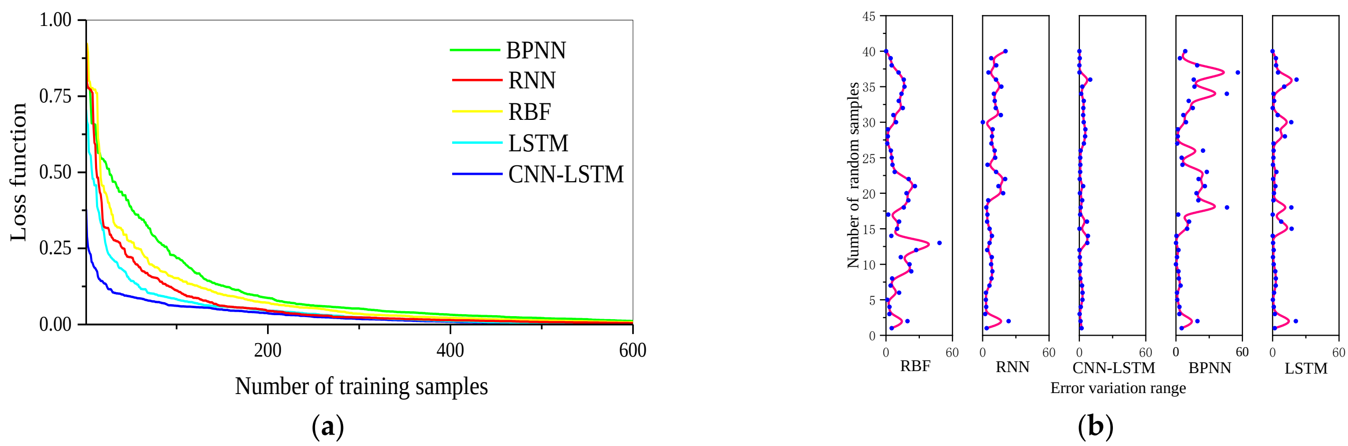


Figure 10. Error Change in Loss Function.

The test set is the most critical data set to judge the prediction performance. Therefore, when the model training is completed, the results of test set need to be further analyzed [43]. The relative errors of the five methods were calculated respectively, and the distribution characteristics of the relative errors are plotted in Figure 11.

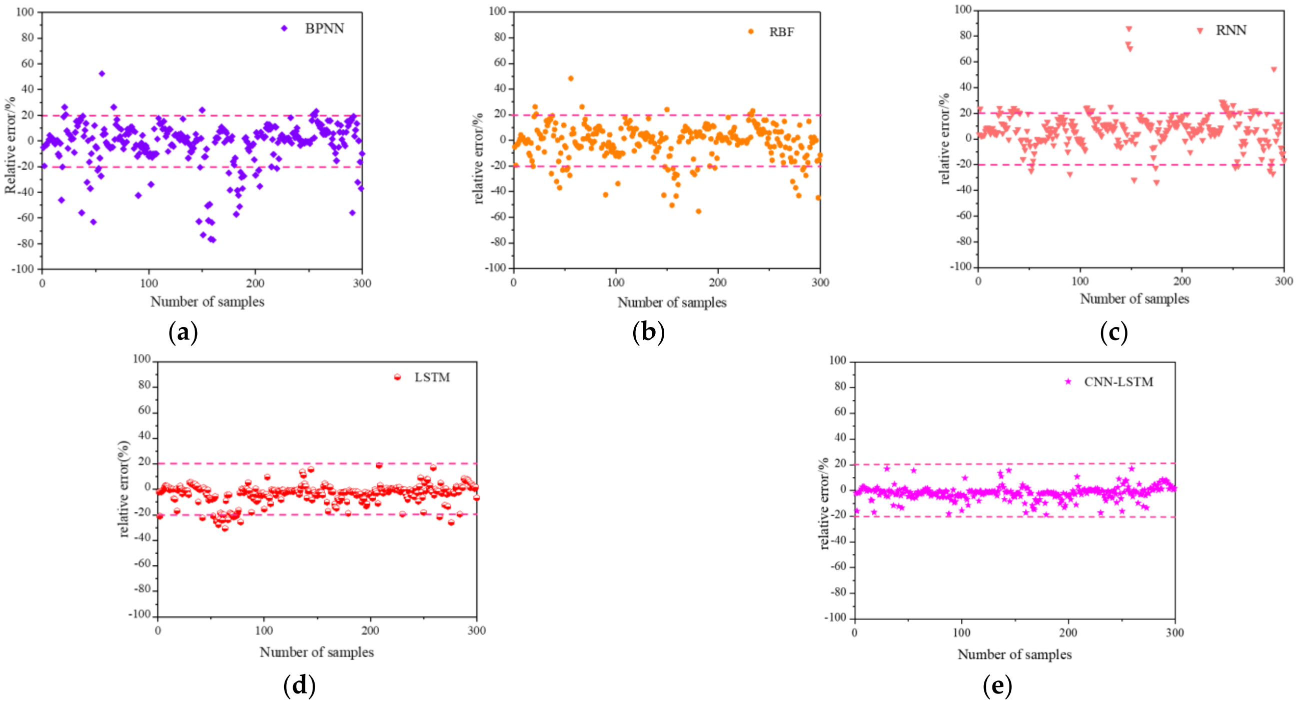


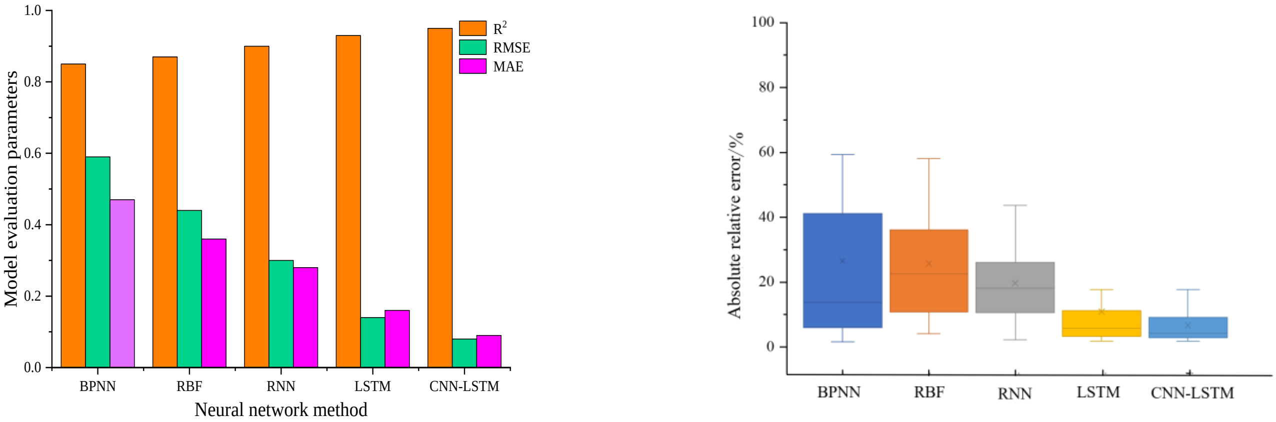
Figure 11. Relative error of five models.

It can be seen from Figure 11 that many points of the BP neural network and RBF neural network exceed 20%, and the relative error of some data even reaches 80%, which indicates that these two models are not suitable for predicting these kinds of problems when the production of the day cannot be predicted in the case of oilfield shut in or failure, as shown in Figure 11a,b. Although the RNN model contains time series, and the prediction results are better than those of the first two models, some data are over 60%, and the LSTM model reduces the relative error to about 20% due to the introduction of time series, as shown in Figure 11c,d. However, the data errors obtained from the CNN-LSTM model are almost all within 20%, and most of them are within 10%, as shown in Figure 11e. The results show that the model can not only meet the prediction of the whole trend of daily oil production with time, but also accurately predict the daily single point.

4.2. Model Evaluation

The generalization ability of the prediction model is evaluated in the training set and test set, that is, the output prediction effect of the model [44]. The LSTM and RNN models have certain accuracy, and the CNN-LSTM model has the best prediction effect.

After the model training, the test data were used to evaluate the performance of the models. The error analysis of the measured and predicted five models is represented in the model evaluation chart, and it can be intuitively determined that the CNN-LSTM model has the highest prediction accuracy, as shown in Figure 12. The adopted prediction effect evaluation indexes include: determination coefficient R^2, average relative error MRE and root mean square error RMSE, as shown in Figure 12a and Table 6. Three evaluation criteria of five model test sets are listed. It can be seen that the evaluation parameters of the CNN-LSTM prediction model adopted in this paper are the global optimal values of all prediction models, and its performance on R^2, RMSE and MAE evaluation indexes is better than the other four models, with the correlation coefficient reaching 0.95. The relative error and root mean square error are all less than 10%, which meets the engineering accuracy requirements. The MRE error of the predicted values is less than BPNN (67%), RBF (60%), RNN (51.3%) and LSTM (28%). In addition, Figure 12b shows the absolute relative errors of the five models, and the accuracy of the CNN-LSTM prediction model is further verified, which shows that the CNN-LSTM neural network method used in this paper can better extract the correlation of time series data.



(**a**) (**b**)

Figure 12. Evaluation of prediction effect of several models.

Table 6. Effect evaluation of five models.

Model	R^2	RMSE	MRE
BPNN	0.85	0.59	0.47
RBF	0.87	0.44	0.36
RNN	0.90	0.30	0.28
LSTM	0.93	0.14	0.16
CNN-LSTM	0.95	0.08	0.09

4.3. Analysis of Predicted Production Factors

Eight of the 14 related factors were selected for specific analysis. The trained CNN-LSTM neural network model was used to keep other parameters unchanged. By changing one parameter, the impact on the production of fractured horizontal wells in tight reservoirs was analyzed, and the main factors of productivity change in a certain block were verified in reverse. Take the analysis of permeability and fracturing sand addition as examples:

The porosity was 0.09, the water cut was 0.5, the dynamic liquid was 1200 m, the pump depth was 200 m, the pump efficiency was 20%, the fracturing sand amount was 1.5, the horizontal well length was 1250 m, the reservoir pressure was 0.4 MPa and the permeability was 0.246, 0.818, 1.154, 1.88, 2.053, 2.20, 2.25 and 2.702 mD, respectively. The output of the oil well was calculated using the trained CNN-LSTM neural network. It can be seen from Figure 13 that the relationship between permeability and daily oil production is non-linear when other parameters are constant. With the increase in permeability, the production keeps increasing, which shows that permeability is the main factor affecting the productivity.

On the other hand, due to the complexity of oil well production performance curves and the complexity of the field situation, the traditional productivity prediction formula needs to make many assumptions and introduce a series of boundary conditions to simplify the problem, and then use the regression idea to accurately fit the curve. With the gradual change in the seepage law, the application scope of the model is narrowed, and it is inevitable that there will be a slight error in the initial stage of prediction, which will be accumulated continuously in the latest stage of recursive prediction, resulting in poor final prediction effect. It can be seen from Figure 13 that the output predicted by the traditional model is not much different from that predicted by the neural network model at the beginning, and then the error gradually increases, which further shows that the neural network method effectively solves the problem of over fitting of historical production dynamics.

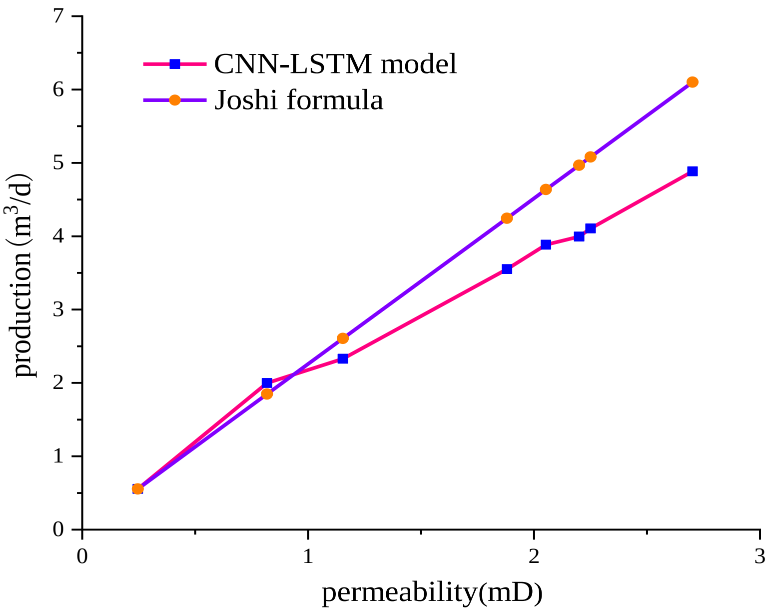


Figure 13. Effect of permeability on production.

To summarize, the LSTM prediction model based on time series has certain defects. Theoretically, the longer the step length is, the more information will be mined. However, when the step length exceeds a certain length, there will still be problems such as long-distance memory loss and gradient disappearance. Therefore, on the basis of the LSTM neural network, the CNN-LSTM neural network method is adopted, and one static factor and seven dynamic factors are comprehensively considered, establishing a neural network model for productivity prediction, thus realizing the prediction of oil production of a horizontal single well. The application of this model to other blocks in tight reservoirs can quickly determine the main factors that affect the seepage mechanism and physical parameters of this block, which has important guiding significance for the subsequent adjustment and optimization of development plans in the tight oil reservoir.

5. Conclusions

Based on the analysis of mainstream neural network models, this paper establishes a CNN-LSTM neural network model based on the Adam optimization algorithm to predict the daily oil production of fractured horizontal wells in tight reservoirs. The model fully considers the heterogeneity of tight reservoirs, effectively establishes the relationship between reservoir parameters and oil production, and accurately obtains the dynamic change law of oil well production to guide oil field production. The main conclusions are as follows:

(1) The CNN-LSTM neural network model provides an effective method for prediction based on time series data, which can be applied to the prediction of other time-varying dynamic parameters of tight reservoirs;

(2) The prediction effect of the CNN-LSTM neural network model is better than that of the BPNN, RBF, RNN and LSTM models, and the average relative error is less than 5%. Therefore, it can more accurately capture the variation law of production capacity under various complex factors, which shows that no learning algorithm is always superior to other

models. By integrating multiple prediction models and using the different advantages of various algorithms, it presents a new research direction in the field of time series prediction;

(3) The model has no fitting parameters in the training process and its generalization ability is high. The accuracy of the model can be improved by improving the loss function and selecting the main control factors affecting the production.

In the future, we will study the use of the CNN-LSTM model to process production prediction in different scenarios of tight reservoirs. The model here is a preliminary attempt to use the neural network method in petroleum engineering. With the continuous construction of digital oilfields, it is expected to be more widely used in oil and gas field development.

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Data Availability Statement: Part of the data used in the manuscript to support the results of this study has been included in the article and supplementary information files. At present, the original/processed data required for these studies cannot be shared and copied, because these data are also part of the ongoing research and are true and effective. In order to prevent the disclosure of data information, all data cannot be provided free of charge. It is hereby declared.

Conflicts of Interest: The authors declare no conflict of interest.

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