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Interwell Connectivity Analysis Method Based on Injection–Production Data Time and Space Scale Coupling

Hong Ye [1], Jibin Deng [1], Jianjie Ma [1], Kai Zhang [2], Yujia Li [2], Huaqing Zhang [3,*] and Kang Zhong [4]

[1] Petroleum Engineering Technology Research Institute, Jiangsu Oilfield Branch, Sinopec, Yangzhou 225012, China; yehong.jsyt@sinopec.com (H.Y.); dengjb.jsyt@sinopec.com (J.D.); majianjie.jsyt@sinopec.com (J.M.)
[2] School of Petroleum Engineering, China University of Petroleum (East China), Qingdao 266580, China; zhangkai@qut.edu.cn (K.Z.); 19825353566@163.com (Y.L.)
[3] College of Science, China University of Petroleum (East China), Qingdao 266580, China
[4] Oil Production Plant 1, Jiangsu Oilfield Branch of Sinopec, Yangzhou 225265, China; zhongk.jsyt@sinopec.com
* Correspondence: zhhq@upc.edu.cn

Abstract: In this paper, aiming at the challenges of injection–production optimization, especially the contradiction between injection and production in water flooding development of oil and gas fields in China, an interwell connectivity analysis method (TAGNN) based on the time–space scale coupling of injection–production data is proposed. This method uses the existing injection–production well data, combined with the reservoir system seepage mechanics law, to quantitatively characterize and evaluate the interwell connectivity, which overcomes the limitations of traditional methods. The TAGNN method introduces asymmetric time alignment and advanced feature extraction technology to solve the problem of asymmetric injection–production data in time dimension, and considers the spatio-temporal scale coupling characteristics of injection–production data, which can capture the temporal variation and spatial distribution characteristics of data at the same time. The experimental results showed that this method more accurately reflected the interwell connectivity status and improved the fitting and prediction accuracy, compared with the existing GNN method. This method can promote the effective injection of water from the injection well to the production well and optimize the injection production structure and development plan, thereby improving the recovery rate.

Keywords: interwell connectivity; space–time scale coupling; machine learning; multi-scale time series

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1. Introduction

At present, the dominant method for oil and gas field exploitation in China is water drive development, and the core challenge of enhancing oil recovery is to solve the contradiction between injection and production [1–4]. In the process of oilfield development, the high permeability channel will promote the water flooding front to reach the production well quickly, which makes it difficult for the energy injected by the water injection well to reach the low permeability area and effectively displace the residual oil, which not only hinders the improvement of oilfield recovery, but also causes a lot of resource loss. The connectivity analysis between injection–production wells can trace the connectivity status of water injection wells and production wells. The data-driven model based on injection–production dynamic signals can predict the future production of oil wells through the learned injection–production correlation, thus providing a basis for the implementation of hydrodynamic adjustment, chemical plugging, and other measures in the oilfield and

guiding the subsequent injection-development optimization [5–8]. Therefore, research on the connectivity analysis between injection–production wells in waterflooding reservoir is the key work of dynamic analysis of reservoir development, which has practical application value for comprehensive adjustment of oilfield, description of remaining oil distribution and improvement of waterflooding development effect.

In recent years, the rapid development of the petroleum industry and the in-depth application of artificial intelligence science in the field of petroleum engineering have significantly accelerated the pace of intellectualization in the petroleum industry. With the continuous growth of global energy demand, the development of oil and gas fields is facing unprecedented challenges [9,10]. The inversion of the underground model is very difficult because the traditional pure physical model oversimplifies the physical process [11]. Therefore, oil and gas enterprises urgently need to adopt new information technology and intelligent management processes to improve management efficiency and optimize development effects. In this context, combining reservoir development with big data analysis, machine learning, and artificial intelligence to help reservoir engineers design better development strategies and improve work efficiency has become an inevitable trend of industry development [12].

In oilfield development, the injection–production well data is relatively easy to obtain and has strong continuity, which can reflect the dynamic changes in the reservoir in real time [13]. However, due to the limitations of production environments, economic conditions, and geological data, how to effectively use these data to analyze the connectivity between wells has become a challenge. The method proposed in this paper is to solve this problem by coupling the time scale and spatial scale to fully tap the potential information in the injection–production data and provide a scientific basis for the sustainable development of the oilfield.

In order to solve the problems of limited data use and poor reliability of machine learning models in analyzing the connectivity between wells in water-drive reservoirs, this paper proposes a method for analyzing the connectivity between wells based on the coupling of time and space scales of injection–production data (TAGNN). The method makes full use of the existing injection–production well data and combines with the seepage mechanics law of the reservoir system to quantitatively characterize and evaluate the connectivity between wells. This method not only avoids the complexity of obtaining multiple relevant parameters, but also dynamically adjusts the weights of static and dynamic parameters according to different stages of oilfield development so as to achieve more accurate analysis results. This innovative method overcomes the limitations of traditional methods and provides a new solution for the connectivity analysis of waterflooding reservoirs, which has important theoretical and application significance.

2. Related Work

2.1. Connectivity Analysis Based on Machine Learning

Interwell connectivity analysis plays an important role in oilfield development, which is directly related to oilfield production, recovery, and economic benefits. Although the traditional methods, such as static method and dynamic method, can evaluate the connectivity between wells to some extent, they often have the problems of insufficient accuracy, difficult implementation, and high cost [14]. In recent years, with the rapid development of machine learning technology, its application in the analysis of interwell connectivity has become increasingly widespread.

Interwell connectivity analysis based on machine learning mainly uses machine learning algorithms to process and analyze the dynamic production data in the oilfield to predict and evaluate interwell connectivity. Scholars at home and abroad have been trying

to use neural networks to solve the problem of injection–production well connectivity analysis, and have achieved some research results, which is usually called a data-driven injection–production well connectivity analysis model.

A neural network-based proxy model with L1-norm minimization is presented for the identification of interwell connectivity and the prediction of well production performance by promoting sparsity in the estimated model weights [15]. An interpretable graph neural network is presented to imitate the interacting process of the real interwell flow regularity based on a self-defined recurrent structure [16]. This method makes use of both rate information and bottomhole pressure to describe the hidden state of wells and the energy information exchanged among them. A bilateral sensitivity analysis method is proposed based on deep neural networks to analyze the injection–production relationship [17], taking water injection rate and oil production rate as the input. After the network training, the sensitivity between input and output is obtained through input disturbance, which is used as a measure of the degree of connectivity between injection wells and production wells. A new deep-learning-based surrogate model [18] is developed based on the graph neural networks and long short-term memory techniques to characterize the interwell connectivity, where the long short-term memory is utilized to simulate the evolution of the constructed models over time. A data-driven interwell simulation model is devised to deduce variations in well-connectivity and forecast the bottom-hole pressure of wells [19]. In this approach, an algorithm for tracking flow paths to determine the dynamic properties between wells. Although these machine learning methods and data-driven methods are able to infer interwell connectivity through their powerful nonlinear mapping capabilities, they are often considered to limit their application in reservoir sites due to the weakness of the physical interpretability of such methods [20].

2.2. Time Series Analysis and Modeling Based on Deep Learning

Time series analysis is an important branch of statistics and machine learning, which focuses on the modeling and prediction of time series data. In recent years, with the rapid development of deep learning technology, its powerful feature extraction and representation learning capabilities provide new solutions and methods for time series analysis.

The main models include recurrent neural networks (RNNs), long short-term memory networks (LSTMs), gated recurrent units (GRUs), convolutional neural networks (CNNs), and transformer models [21]. Among them, the RNN is one of the earliest deep learning models applied to time series analysis, and it is a neural network used especially to process sequence data. Series data can be time series or other types of series such as text, but they all reflect the state or degree of change in an element or phenomenon over time. Different from the basic neural network, the RNN establishes weight connections between neurons between layers, so that it can better capture the correlation between the data before and after the sequence data. As shown in the following figure, this connection makes RNNs more suitable for processing data with temporal relationships and can better capture the long-range dependence in the sequence.

LSTM is an improved version of recurrent neural networks. Due to the problem of gradient vanishing, the traditional RNN can only maintain short-term memory. The LSTM network uses a gating mechanism to add the previous features, which mitigates the gradient loss due to feature loss. It is worth noting that although LSTM solves this problem to some extent, it may still encounter the situation of gradient disappearance when dealing with too long sequences, so LSTM is called a little longer short-term memory.

LSTM was originally proposed by Hochreiter et al. [22] and recently improved and generalized by Alex et al. [23]. In many problems, LSTM has achieved remarkable success and has been widely used. LSTM avoids the long-term dependency problem through a

well-designed mechanism. In practice, LSTM retains long-term information in a default manner without substantial cost, which makes it an effective tool for handling sequential tasks with long-term dependencies. All recurrent neural networks are composed of a series of repeated neural network modules. Modules that are repeated in a standard RNN usually contain only one simple Tanh layer. LSTM also has repeated modules, but these modules have different structures, which can more effectively capture the long-term dependence in sequential data. GRU is a simplified version of LSTM, which reduces the complexity of the model by reducing the number of gating mechanisms. GRU has a faster training speed and a smaller number of parameters while maintaining the performance of LSTM (Table 1).

Table 1. Symbol table.

Symbol	Name
$X = (x_1,x_2,x_3,...,x_T)$	Time series data
T	Duration length of time series
M	Number of record type categories
x_i	Point in time with M record types
X_{1d}	Original one-dimensional time series data
K	Convolution kernel of GCN
k	Output dimension of GCN
X^*_{1d}	Preliminary time series characterization after feature transformation
P	Cycle
S	Number of cycles included in the time length
X_{2d}	Two-dimensional injection–production timing matrix
L	Low frequency component
H	High frequency component
$iFFT$	Inverse Fourier transform
X'_{2D}	Two-dimensional data after information fusion
X^*_{2D}	Reshaped two-dimensional data
X'_{1d}	New one-dimensional injection–production time series data

3. Interwell Connectivity Analysis Based on Injection–Production Data Time–Space Scale Coupling

3.1. Problem Definition

This paper focuses on how to effectively use injection–production data (including injection volume, injection pressure, and injection rate of the injection wells, as well as production rate, water cut, and bottom-hole pressure of the production wells), combined with the coupling effect of time scale and spatial scale, to accurately analyze and predict the connectivity between wells.

In the process of reservoir exploration and development, in order to accurately evaluate the connectivity between wells, it is necessary to analyze a large number of real-time data recorded by various equipment and sensors in the process of injection–production, which reflects the dynamic changes in the reservoir. They all change with time, so they can form a series of time series. These time series data are not only digital piles, but also contain abundant information. Therefore, the time series of injection–production dynamic data should be fully considered and applied in the work of connectivity analysis.

When forming time series, injection–production data often show complex multi-time patterns, which lead to the asymmetry of data in the time dimension. Specifically, different types of injection–production data may have different acquisition frequency and regularity. For example, fluid production data are usually collected on a daily basis, because the frequency of daily collection is enough to meet the needs of daily reservoir management. However, the water injection data are different, because the water injection operation

requires more elaborate control and monitoring, so the data collection frequency is often higher, sometimes even once every half an hour. When trying to apply these time series data to connectivity analysis, this asymmetry can directly affect the accuracy and reliability of the analysis and processing. In addition, the data of multiple time patterns may also lead to the complexity of the analysis model and reduce the efficiency and real-time of the analysis.

3.2. Multi-Scale Temporal Knowledge Feature Learning

In order to deal with these asymmetric injection–production data in the time dimension, this paper introduces an asymmetric time-aligned interwell connectivity analysis method, which will use the method based on graph convolution, multi-scale time window reconstruction and Fourier transform to extract the characteristics of interwell connectivity from the injection–production data, and finally obtain the characterization of interwell connectivity (Figure 1).

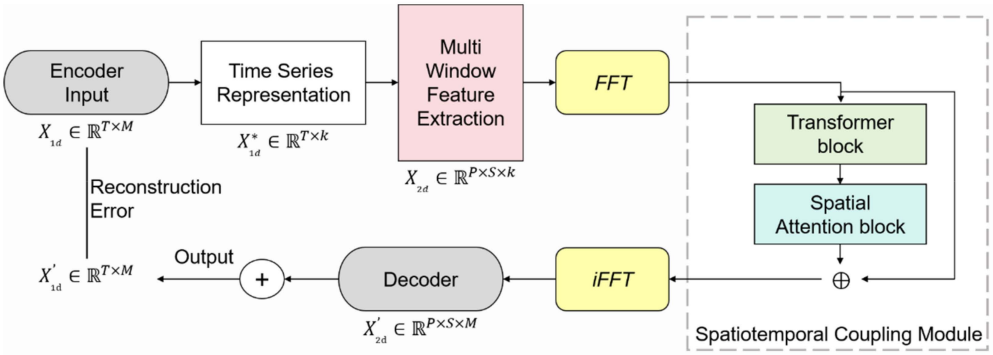


Figure 1. Overall architecture of the TAGNN method.

3.2.1. Initial Timing Characterization

Firstly, based on the graph convolution, the preliminary characterization of the original one-dimensional injection–production time series is constructed, and the graph structure framework of the interwell connectivity analysis model is built. The injection–production dynamic data of the block to be studied can be obtained from the monitoring system of the reservoir block. Because the injection and production sampling time intervals are different, the original one-dimensional injection–production time series data with asymmetry in time dimension are formed.

Denote $X = (x_1, x_2, x_3, ..., x_T)$ as time series data, T denotes the duration length of the time series, and each Xi is a time point with M record types, so the original one-dimensional time series data is denoted as $X_{1d} \in \mathbb{R}^{T\times M}$. When using graph convolutional networks (GCNs) to analyze the connectivity between wells, feature embedding is performed on the original one-dimensional time series data. Through the joint action of image convolution mapping and position coding, the original asymmetric one-dimensional injection–production time series in time dimension is input into the embedding module for processing and feature conversion, so as to obtain the preliminary characterization of injection–production data time series. Here, we assume that the convolution kernel of GCNs is K and the output dimension is K. At the same time, in order to deal with the asymmetry in the time dimension, position coding is introduced. Through the joint action of GCNs and position coding, the original one-dimensional time series data are input into the embedding module, and the feature conversion is carried out to obtain the preliminary time series representation $X^{*}_{1d} \in \mathbb{R}^{T\times k}$.

3.2.2. Multi-Window Feature Extraction

According to different time window settings in the spatial domain, the one-dimensional injection–production time sequence structure is reshaped into a two-dimensional injection–production time sequence structure to extract the characteristics of interwell connectivity. Specifically, according to the acquisition frequency characteristics of the produced fluid and water injection data of the block to be studied, a plurality of different time windows are selected as the period P of the two-dimensional injection–production timing structure to be reshaped. For example, 1 h, 6 h, 12 h, or the like may be selected as the period P.

For each selected period P, the original one-dimensional injection–production time-series data are segmented by P as the time length and reshaped into a $P \times S$ two-dimensional matrix $X_{2d} \in \mathbb{R}^{P \times S \times k}$. Where S represents the number of cycles included in the time length. In this way, the feature extraction of interwell connectivity in the spatial domain is carried out.

This structure is designed to simultaneously show the changing trends of data in a single cycle, as well as changes and relationships between data across S cycles. This conversion method not only retains the time sequence characteristics of time series data, but also makes the injection–production data with different periodic attributes blend and interact with each other in two-dimensional space through spatial display, and further excavates and reveals the deep-seated information of injection–production time series data.

3.2.3. Fourier Transform in Frequency Domain

The characterization of the interwell correlation degree of 2D injection–production time series data is carried out in frequency domain by Fourier transform. The 2D injection–production timing structure is decomposed by Fourier transform in the frequency domain to obtain a series of 2D injection–production timing representations with different frequency characteristics. In view of the two-dimensional injection–production time series structure, the Fourier transform technology is applied to realize the Fourier decomposition of the signal, so as to obtain a series of different Fourier components. These components contain the detailed characteristics of the original sequence and the overall trend characteristics, which can accurately capture the local changes in the signal in both time and frequency dimensions.

The specific working principle of the Fourier transform (as shown in Figure 2) consists of two stages. First, a one-dimensional fast Fourier transform operation is performed on each row of two-dimensional data, thereby obtaining a low-frequency component L and a high-frequency component H of each row in the horizontal direction. Then, a one-dimensional fast Fourier transform operation is performed again on each column of the data after the row transform, thereby obtaining four different frequency component combinations.

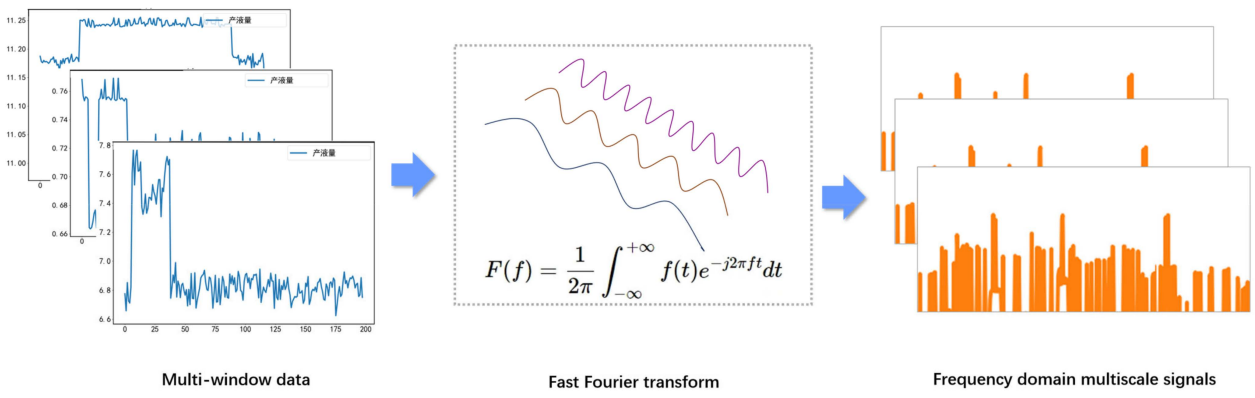


Figure 2. Multi-window feature extraction and Fourier transform components.

The correlation degree of the one-dimensional structural Fourier components under each independent frequency component is characterized, and the multi-scale information is integrated through a fusion strategy. This helps us to more fully understand the inter-well connectivity-related properties contained in the injection–production data. Perform inverse Fourier transform on the data after information fusion to restore the data to a two-dimensional structure. The formula is as follows:

$$X_{2D}^{*} = iFFT\left(X_{2D}^{'}\right) \in \mathbb{R}^{P \times S \times c} \quad (1)$$

In the formula, X_{2D}^{*} is the two-dimensional original data of a certain remodeling, $iFFT$ is represented by the inverse Fourier transform process, and $X_{2D}^{'}$ is the data after information fusion.

According to a plurality of reconstructed two-dimensional data $X_{2d}^{'} \in \mathbb{R}^{P \times S \times M}$ sets, the two-dimensional injection–production data structures based on different time modes are restored to the original one-dimensional state one by one, and the two-dimensional injection–production data structures are integrated into a complete and more meaningful new one-dimensional injection–production time sequence data $X_{1d}^{'} \in \mathbb{R}^{T \times M}$ through a fusion reconstruction technology. At this time, the injection–production data conform to the symmetrical relationship in space.

By finally obtaining the reconstruction error between the new one-dimensional injection–production time series data and the original injection–production data, the learning criterion for model training is constructed, and the parameters in the model are updated gradually through gradient-based methods. Finally, the characterization result of the inter-well connectivity guided by the reconstruction error after data alignment is obtained, and the production dynamic data of the liquid production of each production well is output (Figure 2).

3.3. Interwell Connectivity Model Based on Spatio-Temporal Scale Coupling

Considering that the reservoir is a complex geological system, and the oilfield development is a dynamic process, the injection–production unit data have a certain similarity in space and a certain hysteresis and dependence in time. According to the temporal and spatial characteristics of injection–production data, the spatio-temporal scale coupling architecture of injection–production unit is proposed, which includes a time scale module and a spatial scale module.

3.3.1. Spatiotemporal Coupling Module

Time scale module. The injection–production performance data are a complex nonlinear time series with time lag, and the injected water in the porous media needs several days or even weeks to reach the bottom of the production well. Therefore, production signals such as liquid production rate and water cut have strong dependence on water injection signals in time scale. By using these historical data as input, the transformer model can automatically learn and identify time trends, periodic changes, and response patterns of emergencies in the data, and then predict the connectivity between wells and assess how these historical dynamics affect the current injection–production efficiency.

Spatial scale module. Through the combination of the transformer and spatial attention mechanism, it can help the model to understand the interaction of production activities between different geographical locations, and further enhance the ability of the model to deal with spatio-temporal data, while the multi-level decomposition of time is helpful to capture the dynamic characteristics of different time scales, so that it can more accurately simulate and predict the changes in injection–production relationship. On the spatial scale of waterflooding reservoirs, the production behavior of each production well depends

not only on its production regime, but also on the signals of surrounding injection and production wells. Therefore, the mutual interference between injection–production well groups should be taken into account when simulating the injection–production performance of water drive reservoirs. Therefore, the self-attention mechanism is introduced, so that the model can focus on the important characteristics of injection–production signals in the process of injection–production simulation, and effectively consider the impact of mutual interference between injection–production units on connectivity analysis at the spatial scale.

3.3.2. Connectivity Characterization

Through the spatio-temporal coupling module, the reconstruction error between the new one-dimensional injection–production time series data and the original injection–production data are finally obtained, the learning criterion for model training is constructed, and the parameters in the model are gradient updated. Finally, the characterization result of the interwell connectivity guided by the reconstruction error after data alignment is obtained, and the production dynamic data of the liquid production of each production well is output.

4. Experiment and Result Analysis

TZ Formation reservoir in CB Oilfield is a layered reservoir with multiple oil–water systems, and TZ Formation reservoir is a layered structural reservoir with a unified oil–water contact. According to the drilling results of the drilled wells in C2-01 inclined fault block, the sand layer correlation, structure and oil-bearing regularity of each well, it is considered that C2-01 inclined fault block conforms to the reservoir regularity of CB oilfield, and X reservoir is also a typical layered reservoir with multiple oil–water systems, the oil–water relationship is more complex, the oil-bearing belt width of each oil sand body in the sand group is not consistent, and there is no unified oil–water contact.

The depositional stage of TZ Formation in CB Oilfield is a sedimentary process in which the sedimentary range is gradually expanded and the sedimentary water body is gradually deepened. From bottom to top, the lithology changes from coarse to fine, the content of mudstone increases from less, and the color changes from dark purple and grayish green to gray and dark gray. The single sand body of reservoir in X formation in this area is 1–6 m thick, mainly composed of thin sand layers. Due to the broken structure and developed faults, some reservoirs are lost in X of many wells, but the main oil sand body is distributed stably on the plane and has good connectivity.

The reservoirs in CB Oilfield are all porous sandstone reservoirs. According to the analysis of casting thin section and scanning electron microscope, the reservoir pores in this area are mainly intergranular solution pores, accounting for 75~80% of the total pores, with a small amount of primary intergranular pores and occasional intragranular solution pores and moldic pores. The structural map of the top surface of the well group in the test block is shown in Figure 3.

The connectivity inversion results of TAGNN and common graph neural network GNNs in reservoir cases are shown in Table 2. From the table, it can be seen that both methods can to some extent characterize the connectivity between wells, but the results of the TAGNN method are more in line with the actual situation of the oilfield. For example, P2 has a weaker connectivity with I1 and a stronger connectivity with I2. The results of TAGNN precisely reflect this situation, with values of 0.1490 and 0.3082, respectively. But in the results of GNN, the two are comparable, and even the connectivity between P2 and I2 is slightly lower than that with I1, at 0.3625 and 0.3302, respectively.

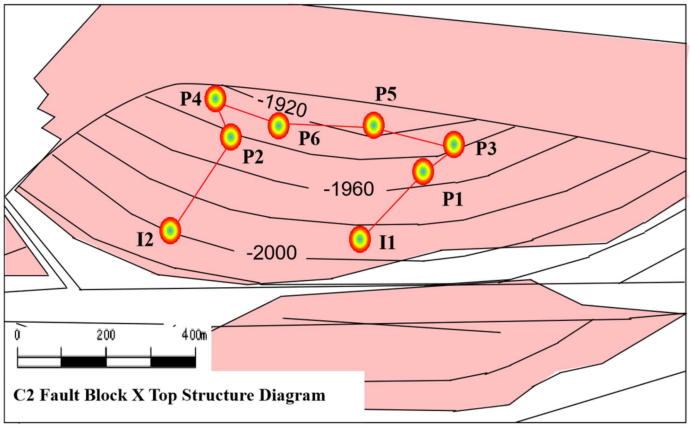


Figure 3. Top surface structure of well cluster in block CB oilfield. Well Is are injection well and Well Ps are production well.

Table 2. The connectivity inversion results of common GNN and TAGNN.

Method	Wells	P1	P2	P3	P4	P5	P6
GNN	I1	0.5222	0.3625	0	0.4469	0.5359	0
	I2	0	0.3302	0	0.5768	0.3447	0
TAGNN	I1	0.3306	0.1490	0	0.1702	0.3465	0
	I2	0	0.3082	0	0.4096	0.0282	0

The historical matching results of TAGNN and common graph neural network in the reservoir case are shown in Figure 4. We show the first two production wells for comparative analysis. It can be seen from the figure that the matching effect of TAGNN on production wells is significantly better than that of a common GNN. Specifically, for the production well P1 with little change in liquid production rate, as shown in Figure 4a, the ordinary GNN can fit the basic trend of the liquid production rate signal. However, when the fluid production rate of production wells fluctuates greatly, it is difficult for ordinary GNNs to accurately approximate and predict the fluid production signal containing drastic changes, and it is difficult to depict the pulse characteristics of fluid production rate, and its history matching results obviously deviate from the actual observed value. In addition, as shown in Figure 4a, the fitting results of ordinary GNNs in P1 and P2 are more gentle than the real observed values, which cannot reflect the detailed characteristics of the real liquid production rate curve. As shown in Figure 4b, TAGNN can more accurately fit the liquid production rate on its production wells, except for the deviation of the liquid production rate fitting results during the subsequent shut-in period of P2 (due to human intervention, the last period of data was not successfully fitted).

Table 3 shows the mean square error (MSE), mean absolute error (MAE), and R-square R^2) of liquid production rate history matching and prediction of ordinary GNNs and TAGNN for the first two production wells. The "lpr" in the legend represents the liquid production rate, while the "pre-lpr" represents the liquid production rate predicted by the model. The MSE of liquid production rate history matching of ordinary GNNs in this reservoir case is 0.0726, while the MSE of TAGNN is 0.0157, which is 78.37% lower than the former. Meanwhile, the MAE of GNN and TAGNN is 0.0852 and 0.0379, respectively. In addition, the predicted MSE of liquid the production rate of TAGNN is 0.0339, which is 82.73% lower than that of the ordinary GNN (0.1963). The experimental results show that under the guidance of asymmetric time alignment analysis, the TAGNN shows superior fitting and generalization performance by systematically analyzing the time-scale dynamic

correlation characteristics of injection–production signals through the spatio-temporal scale coupling module.

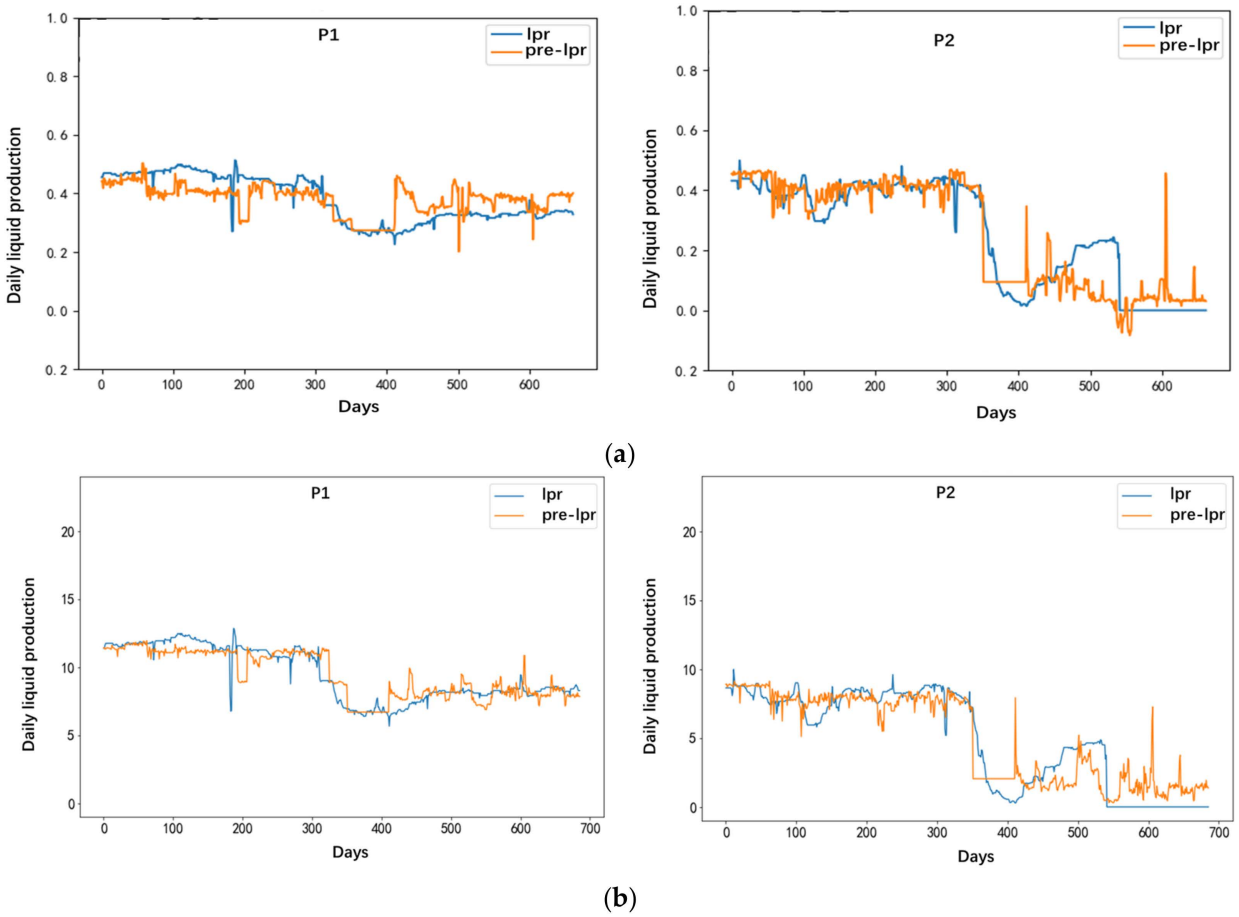


Figure 4. Fitting curve of liquid production rate of single well in well group of block CB oilfield area. (**a**) Fitting effect of liquid production rate for common GNN. (**b**) Fitting effect of liquid production rate for TAGNN.

Table 3. Mean square error of liquid production rate history fitting and prediction of common GNNs and TAGNN.

Model		GNN	TAGNN
Fitting Error	MSE	0.0726	0.0157
	MAE	0.0852	0.0379
	R^2	75.34%	79.58%
Prediction Error	MSE	0.1963	0.0339
	MAE	0.2354	0.0412
	R^2	67.32%	83.33%

In addition, the history matching result of the overall liquid production rate of TAGNN in the reservoir block of the reservoir case is shown in the figure. It can be seen from the figure that TAGNN has a significant effect on the overall liquid production rate matching of all production wells in the block, and the matching coincidence rate reaches 85.85%, which can provide a reference for the field (Figure 5).

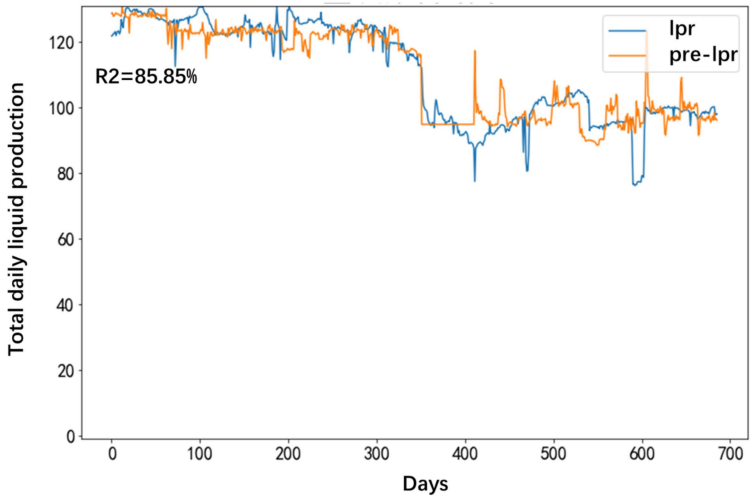


Figure 5. Fit curve of overall liquid production rate of CB oilfield block.

5. Conclusions

Based on the coupling characteristics of injection–production data in temporal and spatial scales, a connectivity analysis method (TAGNN) based on the coupling of injection–production data in temporal and spatial scales is constructed, and asymmetric time alignment and advanced feature extraction technology are introduced. The effectiveness of the method in solving the problems of production prediction and connectivity analysis between wells is proven by reservoir field experiments. The following conclusions can be drawn:

(1) TAGNN aiming at the problem that the traditional analysis method is difficult to effectively deal with the asymmetric injection–production data in time dimension, this paper creatively introduces an asymmetric time alignment analysis method to overcome the obstacle of data asymmetry and deeply mine the characteristics of interwell connectivity contained in injection–production data.

(2) In order to achieve a more comprehensive analysis, this paper also considers the spatio-temporal scale coupling characteristics of injection–production data. By designing a special spatio-temporal scale coupling module, this method can capture the temporal variation and spatial distribution of data at the same time, so as to reflect the actual situation of interwell connectivity more accurately.

(3) This method not only improves the analysis accuracy, but also effectively solves the data limitations and reliability problems faced by machine learning models in the analysis of interwell connectivity in water-drive reservoirs by extracting advanced interwell connectivity features from the injection–production data.

The TAGNN method can be easily integrated into real-time reservoir monitoring and control systems. Because once its model is trained, the time for prediction is very short. Thousands of data predictions can be made in less than a second, meeting real-time demand. In the future, we will consider how to extend this method to analyze reservoirs with more complex geological features, such as fractures and multiple layers.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: Authors Hong Ye, Jibin Deng and Jianjie Ma were employed by the company Petroleum Engineering Technology Research Institute. Author Kang Zhong was employed by the company Jiangsu Oilfield Branch of Sinopec. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

TAGNN	Interwell connectivity analysis method in this paper
GCN	Graph convolution neural network
MLP	Multilayer perceptron
RNN	Recurrent neural network
LSTM	Long short-term memory
GRU	Gated recurrent unit
CNN	Convolutional neural network
GNN	Graph neural network

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