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3D Reservoir Geological Modeling Algorithm Based on a Deep Feedforward Neural Network: A Case Study of the Delta Reservoir of Upper Urho Formation in the X Area of Karamay, Xinjiang, China

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Abstract: Three-dimensional (3D) reservoir geological modeling is an advanced reservoir characterization method, which runs through the exploration and the development process of oil and gas fields. Reservoir geological modeling is playing an increasingly significant role in determining the distribution, internal configuration, and quality of a reservoir as well. Conventional variogram-based methods such as statistical interpolation and reservoir geological modeling have difficulty characterizing complex reservoir geometries and heterogeneous reservoir properties. Taking advantage of deep feedforward neural networks (DFNNs) in nonlinear fitting, this paper compares the reservoir geological modeling results of different methods on the basis of an existing lithofacies model and seismic data from the X area of Karamay, Xinjiang, China. Adopted reservoir geological modeling methods include conventional sequential Gaussian simulation and DFNN-based reservoir geological modeling method. The constrained data in the experiment mainly include logging data, seismic attribute data, and lithofacies model. Then, based on the facies-controlled well-seismic combined reservoir geological modeling method, this paper explores the application of multioutput DFNN and transfer learning in reservoir geological modeling. The results show that the DFNN-based reservoir geological modeling results are closer to the actual model. In DFNN-based reservoir geological modeling, the facies control effect is obvious, and the simulation results have a higher coincidence rate in a test well experiment. The feasibility of applying multioutput DFNN and transfer learning in reservoir geological modeling provides solutions for further optimization methods, such as solving small-sample problems and improving the modeling efficiency.

Keywords: deep feedforward neural network; multioutput feedforward neural network; transfer learning; reservoir geological modeling

1. Introduction

Geostatistics is an important tool for reservoir characterization and modeling. Fine and accurate 3D reservoir models are of great significance for the exploration and development of oil and gas [1]. Reservoir geological modeling technology has evolved well over the years, from the direct transformation of geological data to two-point geostatistics driven by variograms and then to multipoint geostatistics driven by training images and search templates. Currently, there are mainly two modeling approaches: deterministic modeling and stochastic modeling. The former includes methods such as the direct transformation of geological data, statistical interpolation, and kriging interpolation, while the latter includes techniques such as sequential Gaussian simulation, sequential indicator simulation, target-based random modeling, and multipoint random simulation [2–8].

Deep learning, an important class of methods that constitute the foundation for the emerging new generation of artificial intelligence, boasts powerful learning capabilities and has demonstrated powerful capabilities in data fusion, feature extraction, pattern recognition, and nonlinear fitting; as such, deep learning methods are able to provide a strong impetus for reservoir geological modeling. In particular, with the applications of deep learning to reservoir geological modeling, the distributions of reservoirs in 3D space can be more finely characterized. Artificial intelligence technology has experienced various stages of development from a knowledge base to machine learning, representation learning, and ultimately deep learning. In the initial stage, it is necessary to manually design a formal language for feature mapping. At present, it is now possible to employ simple or complex self-learning representations for feature mapping purposes. Moreover, with rapid improvements in storage and computing capabilities, people have gained the ability to train deep neural networks that were impossible to train before.

Some scholars have attempted to apply neural networks to model the physical properties of reservoirs. Previous research results show that the DFNN has a better effect on petrophysical parameter model established with logging curves as input [9,10]. However, the number of wells in the region is limited, and there is no logging curve between wells that can be used as input data. For instance, a previous study applied a method based on a high-order neural network and backpropagation (BP) neural network. X and y coordinates were adopted (and sedimentary facies codes) as the input data. Porosity is the output data. A reservoir attribute model was established in the entire area [11,12]. Based on a BP neural network, the time and coordinates (or the original porosity and saturation) can be taken as input, and reservoir attributes such as porosity and saturation can be output, thereby establishing a 4D attribute model of a reservoir [13–15]. At the same time, previous studies have also shown that the use of coordinates as the input data of the neural network can also be used to model petrophysical parameters of the reservoir, but limited by the types of available parameters, the modeling effect still needs to be improved. This paper draws on the research ideas of predecessors and uses a variety of data related to the physical parameters of the reservoir as the input of the neural network. The seismic attributes and lithofacies model are used as constraints to reduce the uncertainty in reservoir geological modeling. On the basis of the above research, in order to improve the efficiency of modeling and solve the problem of small samples, the multi-output neural network and transfer learning are applied to the DFNN-based reservoir geological modeling.

As the only cross-well constraint information with a certain lateral resolution, seismic data can reduce the uncertainty in the reservoir simulation process. However, spatial changes in reservoir physical properties are controlled by the spatial differences in sedimentary and diagenetic processes, and the physical properties and characteristics of reservoirs within different sedimentary facies vary. Therefore, facies-controlled reservoir geological modeling can further reduce the uncertainty in the reservoir simulation. On the basis of previous studies, this paper uses well data, seismic data, and sedimentary facies as multiple constraints to carry out reservoir attribute modeling based on a deep feedforward neural network (DFNN).

To improve the accuracy and efficiency of DFNN-based reservoir geological modeling adequately, this paper utilizes multioutput DFNN in conjunction with transfer learning. Compared with the conventional DFNN algorithm, multioutput DFNN predicts multiple parameters and trains only one model, which has a higher training efficiency and considers the correlation among the output parameters comprehensively; as a result, the spatial distributions of related attributes are relevant in the same implementation. Transfer learning is a novel learning method that focuses on storing models. Transfer learning can solve existing tasks and use them in other different (but related) tasks.

This paper takes the delta reservoir of the Upper Urho Formation in the X area of Karamay, Xinjiang, China as an example to carry out research on the proposed DFNN-based 3D reservoir geological modeling method. Comparative experiments are conducted using various simulation methods under different data conditions, and the application of multioutput DFNN and transfer learning in reservoir geological modeling is explored.

2. Mathematical Background

2.1. Basic Principles of DFNN

DFNN is one of the most basic types of deep learning network structures. Compared with the conventional two-layer fully connected network, DFNN has a significantly improved learning ability and achieves better performance through the constant iterative update of the variables automatically learned from the data set, that is, the weight parameter w and the bias b. According to the universal approximation theorem, a sufficiently complex DFNN model with a nonlinear activation function can approximate a continuous function in real space with arbitrary precision. One potential application scenario of DFNN in reservoir geological modeling employs the spatial positions of wells as the input to learn the spatial relationship among variables to carry out cross-well attribute modeling. Alternatively, in the case of seismic interpretation data, the seismic data are used as the input to model the reservoir through well-seismic fusion.

2.2. DFNN-Based 3D Reservoir Geological Modeling Method

On the basis of a 3D reservoir structure model and sedimentary facies model, the physical properties derived from well log interpretation (such as porosity and oil saturation) are upscaled to a grid model, and seismic attributes are resampled onto the grid model. This grid model contains the following two types of points: (1) conditional data points, which contain upscaled physical properties, facies data, and seismic attributes, and (2) points to be simulated, including facies attributes and seismic attributes without physical properties. As shown in Figure 1, the conditional data point set is used as the training set, and DFNN is used to learn the relationship among the reservoir physical properties, that is, the sedimentary facies and seismic properties (spatial locations); throughout this process, the neural network is continuously optimized.

In the training process of the model, an indicator to judge whether the model has been trained is whether it is overfitting. We expect the model to be able to meet our needs. But sometimes there will be overfitting. Overfitting means that the model performs well on the training set but does not perform well on the cross-validation data and test data. In other words, the prediction performance (generalization ability) of the model for unknown samples is poor. The performance of the model in training data and validation data can be used to judge whether it is overfitting. There are many ways to prevent overfitting. In the case of limited data conditions, methods such as early stopping and regularization are usually used to prevent overfitting. Finally, the network training parameter file of the task can be obtained.

In the prediction process (Figure 2), the parameter file is reloaded with the spatial positions, facies data, and seismic attributes of the points to be simulated as the input of DFNN. Therefore, the physical properties of the reservoir are predicted at all points to be simulated.

The output layer of the multioutput DFNN model is multiple neurons. Considering the correlation among the output parameters, DFNN can establish multiple attribute models at the same time to enhance the modeling efficiency. The multioutput DFNN data set is similar to the aforementioned DFNN data set, but multiple instances of labeled data may be present. The spatial distribution characteristics of multiple attributes are learned simultaneously with the relationship among the wells, after which the parameters of the multioutput DFNN model are adjusted according to the learning results, and then a multioutput deep learning network is obtained that can be used for regional prediction. On this basis, multiple physical properties are modeled simultaneously.

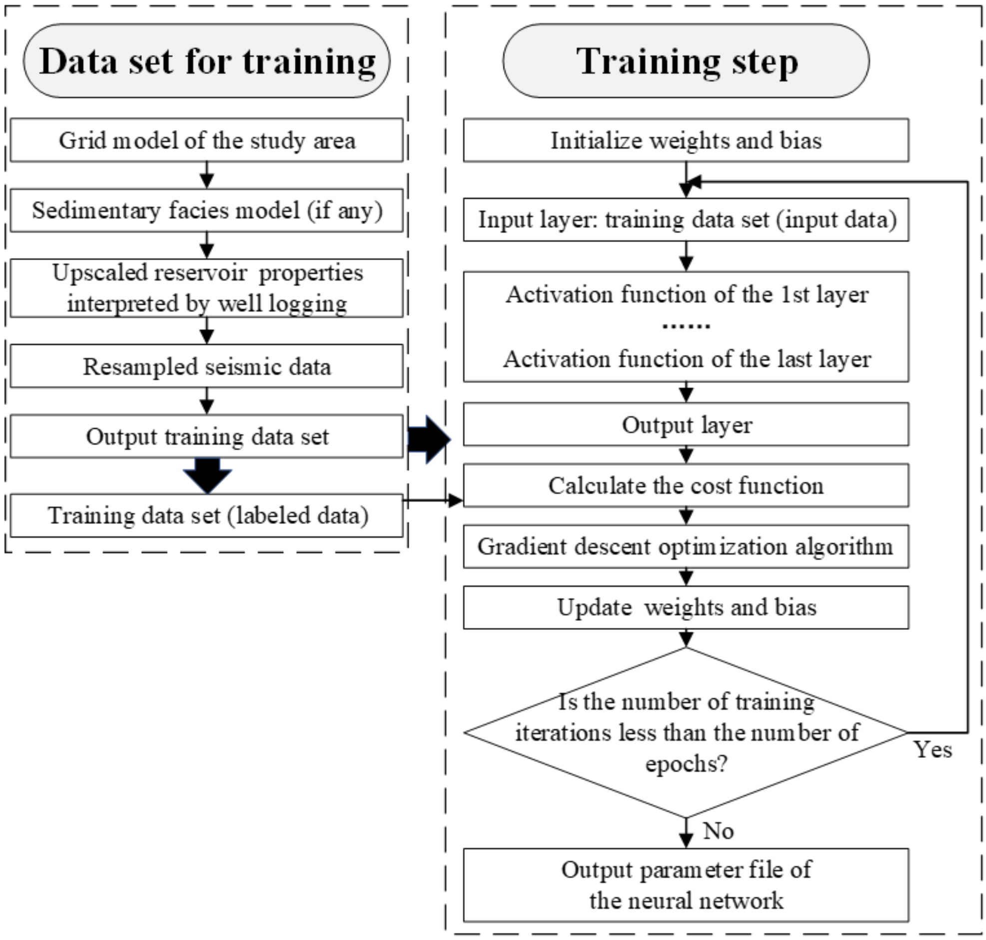


Figure 1. Flow chart of the deep feedforward neural network (DFNN) training process for 3D reservoir geological modeling.

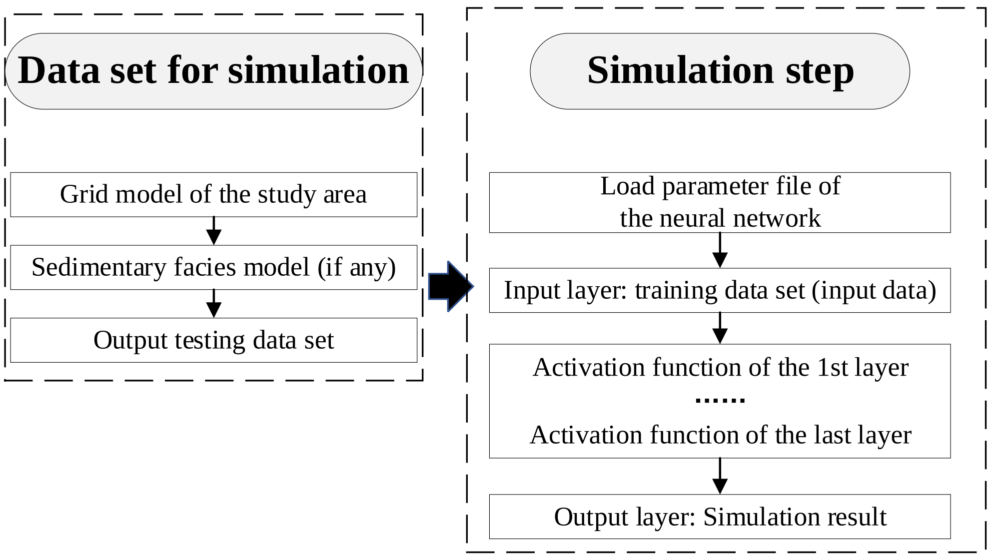


Figure 2. Flow chart of the DFNN simulation process for 3D reservoir geological modeling.

A current ubiquitous difficulty is the need to design specific neural networks for specific tasks. Obviously, the design of this specific neural network has limitations for the scalability of the results and the trained neural network, because we cannot directly apply the trained neural network to another new task. Transfer learning, developed in recent years, seems to be able to make a certain contribution to improving the scalability of the results and the trained neural network. Transfer learning is an important research direction in machine learning. The goal of transfer learning is to apply the knowledge or patterns learned in a certain field or task to different but related fields or problems [16]. In addition to improving the scalability of the results and the trained neural network, it can also solve the problems of small samples and improve modeling efficiency. We used the advantages of migration learning to apply to reservoir geological modeling. The purpose is to explore the application of transfer learning in improving the scalability of the results and the trained neural network.

Transfer learning realizes reservoir geological modeling through the memory of past modeling experience and the relearning of new modeling tasks. As illustrated in Figure 3, a historically trained network that has been used for other related tasks is used as the starting point for the current model training; accordingly, the network already has reservoir geological modeling experience when it starts to train. The network is further adjusted by inputting data from the current work area; through appropriate adjustments, the network can obtain the distribution characteristics of the reservoir properties in the current work area and, on this basis, predict the reservoir physical properties of a new work area. Neural networks trained on other (but related) modeling tasks can perform the basic capabilities of reservoir geological modeling, and by continuously learning on new tasks, the neural network can be used in new work areas more quickly. The learning experience gained by the neural network in new work areas can be input into the model and then continue to improve the modeling process.

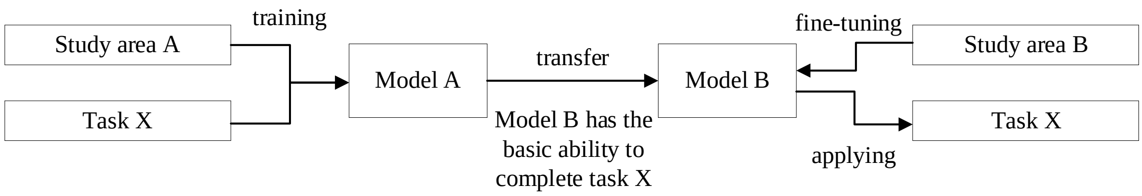


Figure 3. Schematic diagram of transfer learning for 3D reservoir geological modeling.

We would like to explore the feasibility of transfer learning in reservoir geological modeling. If we have specific task requirements in future research work, we can also modify/reserve the weight and bias terms of neural units of certain layers, because weight and bias of neural units of certain layers already have a certain degree of feature extraction ability for the study area A data set. Subsequently, we used a similar but different study area B data set to fine-tune the weight and bias. The purpose is to reuse similar models in the case to reduce the number of samples to speed up the training process.

3. Case Studies

To verify the validity and practicability of the DFNN-based reservoir geological modeling algorithm, this paper takes the delta reservoir of the Upper Urho Formation in the X area of Karamay, Xinjiang, China as an example for test analysis. First, a comparative test is conducted based on both DFNN-based reservoir physical property modeling methods and the conventional sequential Gaussian simulation property modeling method. Then, based on the facies-controlled well-seismic modeling method, this study explores the application of multioutput DFNN and transfer learning to reservoir geological modeling. The abovementioned experiment employs test wells to validate the modeling effect, and the test wells do not participate in the training process. The parameter settings of the network are shown in Table 1. The code and program used in this article are written based on Python 3.6.11 and TensorFlow 1.10.0.

Table 1. Neural network parameter settings.

Number of layers	8
Number of input nodes	Determined by the number of characteristic data types, detailed in the following sections
Number of output nodes	Determined by the number of label data types, detailed in the following sections
Number of nodes in hidden layers	(30,25,20,15,10,5)
Activation function	leaky-relu (α: 0.01)
Optimization algorithm	Adam (learning_rate: 0.001; β_1: 0.9; β_2: 0.999; $\varepsilon: 1 \times 10^{-8}$)
Initialization strategy	glorot_uniform
Data split	Training data (70%), validation data (20%), and test data (10%)

The setting of neural network is relatively complicated, involving the choice of multiple formulas and hyperparameters. It mainly includes the number of layers of the neural network, the number of neurons, the activation function, the cost function, the optimization algorithm, and the initialization method. There are some theoretical foundations or empirical methods for the selection of the above formulas or hyperparameters. If there is no hidden layer in the neural network, it can only represent linearly separable functions or decisions. Theoretically, the deeper the layer of the neural network, the greater the ability of the neural network to fit functions, and the effect may be better. But in fact, a deeper number of layers may cause overfitting problems, and at the same time it will increase the difficulty of training and make it difficult for the model to converge. Neural network settings for a specific task may need to be obtained through constant trials. At the same time, the influence of other optimization algorithms must be integrated. At present, activation functions such as sigmod and tanh are prone to gradient disappearance. Relu may cause the death of some neurons. Leak-relu is currently a more commonly used activation function. The gradient descent algorithm mainly includes SGD, BGD, and MBGD. Choosing an appropriate learning rate for this type of method may be difficult. A learning rate that is too small will result in a slow convergence rate. On the contrary, it will hinder convergence and cause the loss function to fluctuate near the minimum or even deviate from the minimum. The gradient descent optimization algorithm developed later may be able to solve the above problems. Adam method combines the advantages of Momentum and RMSprop and is an algorithm for adaptive learning rate.

3.1. Overview of the Study Area

Strata are extensively and thoroughly developed in the X area in Karamay, Xinjiang, China, where the Upper Urho Formation of Permian age can be divided into three members. The first and second members of the Upper Urho Formation are the main oil-producing members, which are composed of gray-green interbedded groups of thick glutenite and thin mudstone; these members represent the main objective of this study. The total thickness of the formation is 120–170 m, which has a stable lateral distribution.

The area of the workspace is 376 km^2, and it can be divided into seven layers from top to bottom: A_1 ~ A_4 belong to the second member of the Urho Formation, while A_5~A_7 belong to the first member of the Urho Formation. In this study, layer A_1 is utilized to verify the modeling effect. Grid model parameters of the study area are shown in Table 2.

There are 70 wells in the workspace, and the physical property interpreted by well log curves include porosity, oil saturation logging curves, and lithofacies logging profile. The porosity ranges from 0 to 0.17, and the oil saturation is within the range of 0 ~ 94.4%. In addition, there are six types of discrete lithofacies in the logging profile, namely, shale, gravity-current glutenite, medium-fine sand, pebbled coarse sand, first-class tractive-current glutenite, and second-class tractive-current glutenite (labeled 1 ~ 6 in succession). This area is generally considered a tight glutenite oil deposit.

Table 2. Grid model parameters of the study area.

Number of layers	7
Layers	A_1–A_7
Grid cells (ni × nj × nk)	240 × 165 × 7
Total number of grid cells	277, 200
Number of properties	7
Properties	(1) Upscaled well data (porosity and oil saturation) (2) Resampled seismic data (relative wave impedance, root mean square amplitude, fluid factors, and hydrocarbon indicators) (3) Lithofacies

A total of 4 prestack and poststack seismic attribute data volumes are collected for the study area (as shown in Figure 4): the relative wave impedance (seismic attribute reflecting changes in the lithology and porosity), root mean square amplitude (used to predict common seismic attributes for sand bodies and oil-bearing reservoir), fluid factor, and hydrocarbon indicator. After applying time-depth conversion to the seismic data, each seismic attribute is resampled along each layer to a 3D grid model.

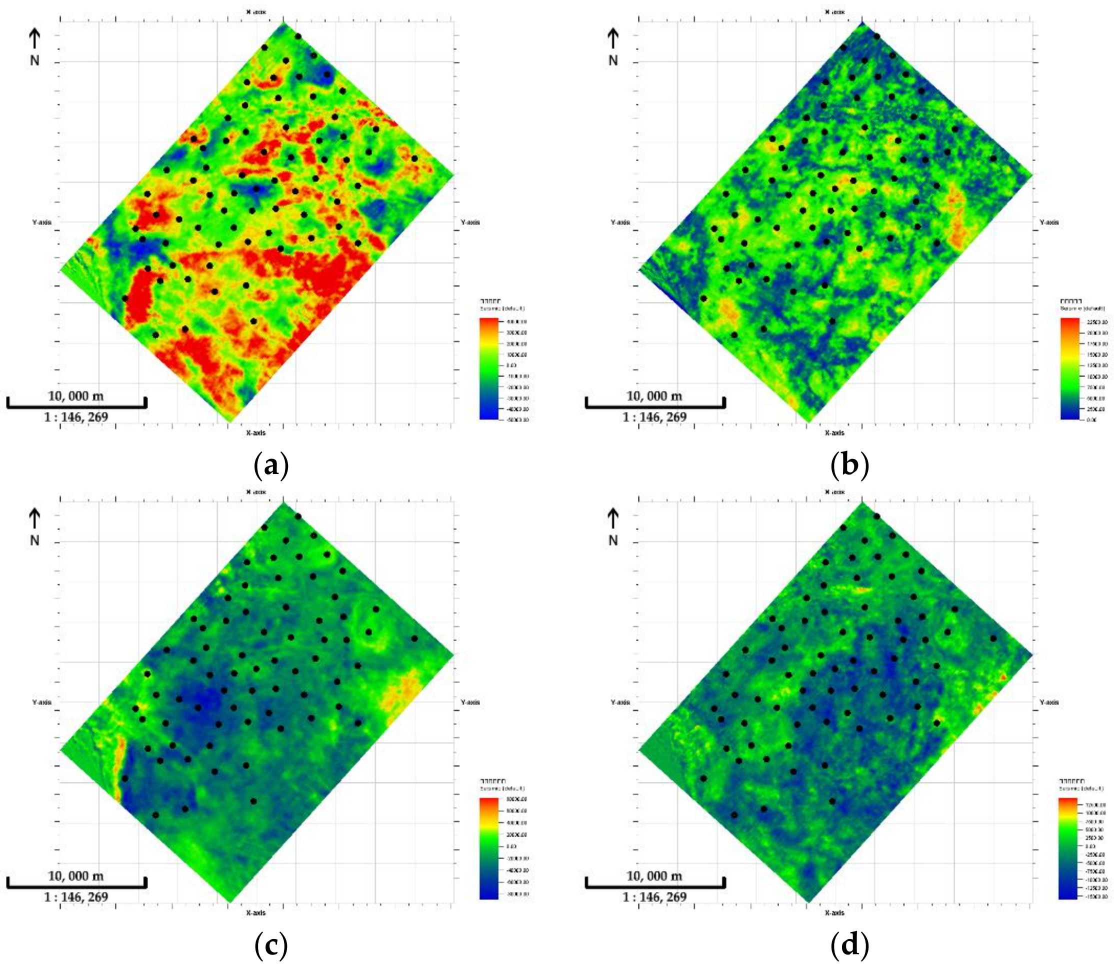


Figure 4. Seismic attribute data of the study area: (**a**) relative wave impedance; (**b**) root mean square amplitude; (**c**) hydrocarbon indicator; and (**d**) fluid factor.

Lateral variations in the reservoir physical properties are controlled by the lateral differences in sedimentary and diagenetic processes. In particular, the distribution characteristics of the reservoir physical properties vary with the sedimentary microfacies, and the facies-controlled reservoir physical properties can further reduce the uncertainty in the reservoir simulation. Reservoir physical properties such as porosity and oil saturation are obviously controlled by sedimentary facies. A sedimentary facies map of the second member of the upper Urho Formation in the study area is presented in Figure 5a, indicating that the reservoir is a delta with a northwestern provenance direction. The lithofacies model of the study area is displayed in Figure 5b–d, which are established by the DFNN method. Compared with the theoretical sedimentary facies of the study area presented in Figure 5a, with the dark blue mudstone as the background, the edges of the glutenite facies in Figure 5b resemble a leaf-like shape, similar to that in Figure 5a. After the test well experiment, the lithofacies model conforms to a high degree. Therefore, in facies-controlled reservoir property modeling, this model is used as facies-controlled data.

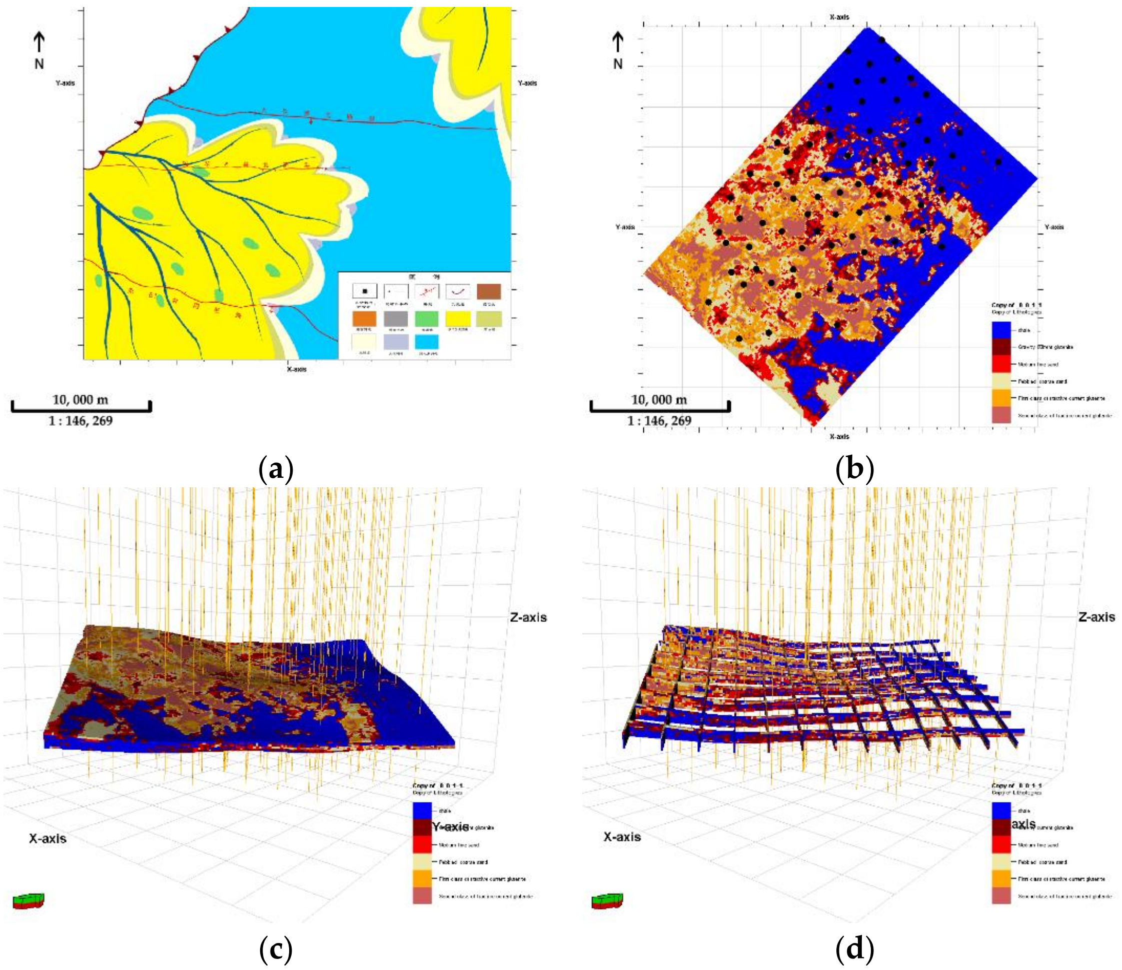


Figure 5. Lithofacies model of the X area of Karamay, Xinjiang, China: (**a**) sedimentary facies map of the second member of the Urho Formation; (**b**) lithofacies model of A_1; (**c**) 3D lithofacies model of the X area in Karamay, Xinjiang, China; and (**d**) 3D perspective lithofacies model of the X area in Karamay, Xinjiang, China.

3.2. DFNN-Based Modeling of Reservoir Physical Properties

3.2.1. Comparative Experiment with Conventional Reservoir Attribute Modeling Methods

To verify the effectiveness of the proposed DFNN-based reservoir geological modeling method, a comparative analysis was conducted in the study area between the conventional sequential Gaussian simulation method and the DFNN-based reservoir geological modeling method.

Porosity is considered as an example to compare the effects of different reservoir physical property modeling methods. Figure 6a,b set out the sequential Gaussian simulation results (non-facies-controlled and facies-controlled), where the porosity generally appears in a significant increase from northeast to southwest. The experimental results of the 7 test wells in Table 3 show an average error of two method are 31.73% and 26.89%.

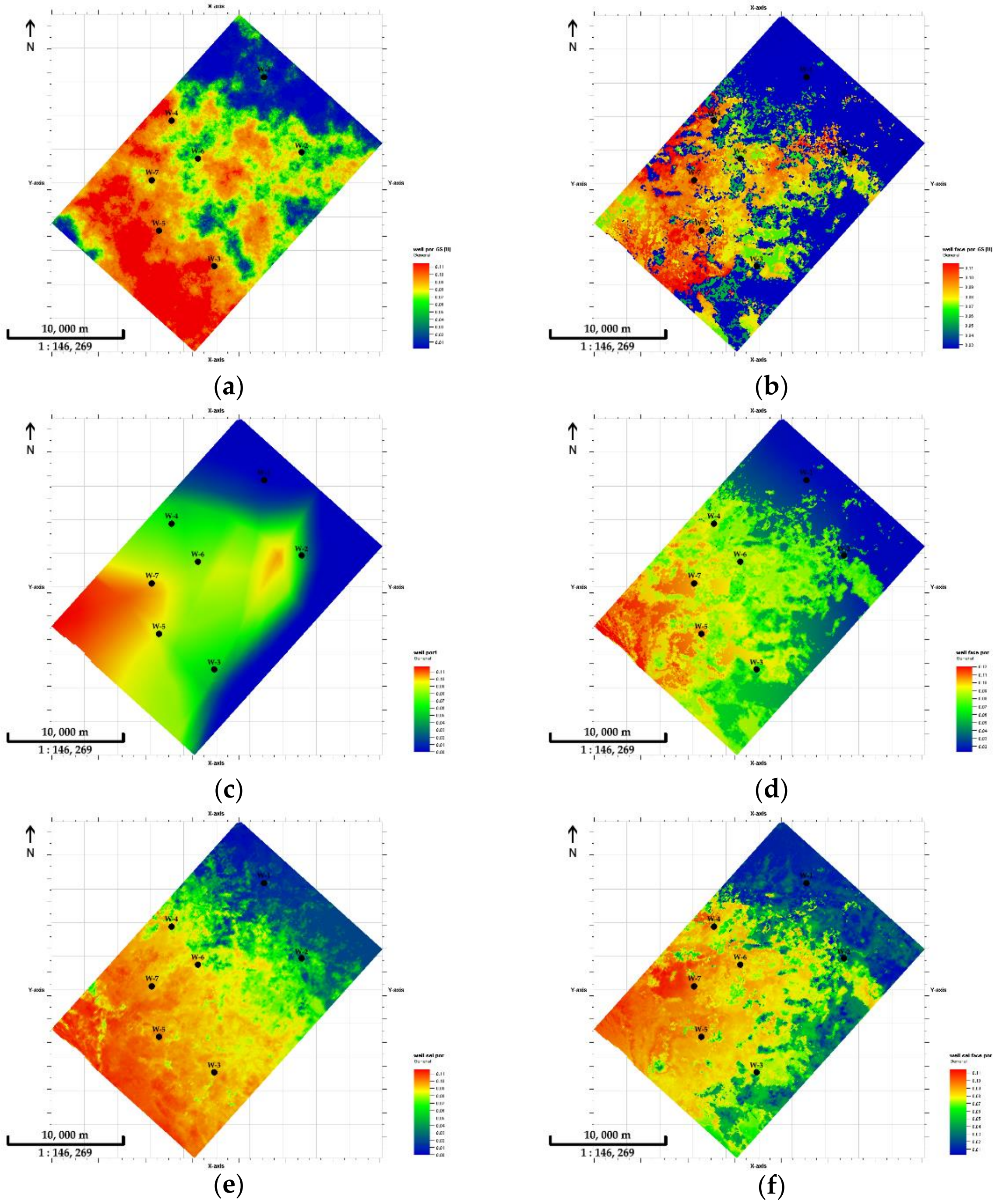
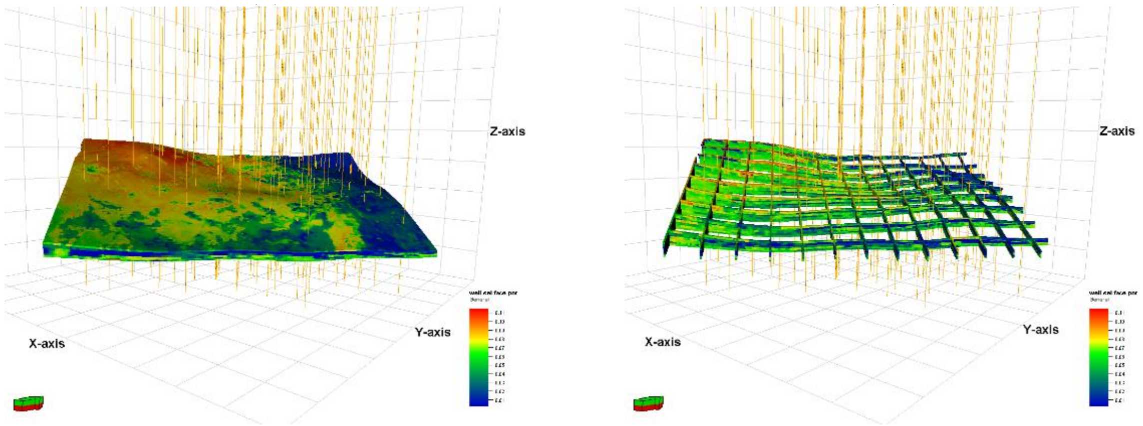


Figure 6. *Cont.*



(**g**) (**h**)

Figure 6. Porosity model of the X area in Karamay, Xinjiang, China: (**a**) porosity model simulated by the conventional sequential Gaussian simulation method; (**b**) porosity model simulated by the facies-controlled conventional sequential Gaussian simulation method; (**c**) porosity model simulated by the DFNN-based reservoir geological modeling method; (**d**) porosity model simulated by the DFNN-based facies-controlled reservoir geological modeling method; (**e**) porosity model simulated by the DFNN-based non-facies-controlled well-seismic combined reservoir geological modeling method; (**f**) porosity model simulated by the DFNN-based facies-controlled well-seismic combined reservoir geological modeling method; (**g**) 3D porosity model of the X area in Karamay, Xinjiang, China; and (**h**) 3D perspective porosity model of the X area in Karamay, Xinjiang, China.

Table 3. Test well experiment for porosity modeling based on different methods.

Test Wells in Figure 6 [1]	Actual Porosity	Figure 6a	Figure 6b	Figure 6c	Figure 6d	Figure 6e	Figure 6f
W-1	0.0012	0.0023	0.0017	0.0011	0.0009	0.0017	0.0015
W-2	0.0566	0.0612	0.0236	0.0348	0.0398	0.0479	0.0558
W-3	0.0603	0.0895	0.0512	0.0851	0.0642	0.0689	0.0719
W-4	0.0636	0.0883	0.0911	0.0814	0.0767	0.0772	0.0598
W-5	0.0786	0.0973	0.0891	0.1057	0.0925	0.0917	0.0796
W-6	0.0835	0.0823	0.0791	0.0822	0.0859	0.0823	0.0893
W-7	0.1011	0.0912	0.1125	0.1017	0.1029	0.1043	0.0953
Average error/%	None	31.73	26.89	21.80	14.87	16.28	9.37

[1] The test wells are randomly selected from X area.

In the DFNN-based modeling method, there are 3 or 4 input layer nodes in the neural network (the point coordinates i, j and k and lithofacies (if any)), and there is only 1 output layer node (porosity). Figure 6c, d show the simulation results of this method. The porosity is relatively low in the northeast and east. The porosity distribution is generally close to the trend of the sedimentary facies model for this layer (Figure 6d). The experimental results of the 7 test wells in Table 3 show an average error of 21.80% and 14.87%.

The conventional geostatistical modeling approach like sequential Gaussian simulation mainly uses variogram to characterize the correlation between two points in space. In the experiment, we added the above comparison experiment (Figure 6a–d) between the DFNN-based method and the sequential Gaussian simulation method under the condition of well data (without seismic attributes). It further proved that the method in this study is better than the geostatistical method.

In the DFNN-based non-facies-controlled well-seismic combined modeling method, there are seven input layer nodes in the neural network (the point coordinates i, j and k, relative wave impedance, root mean square amplitude, fluid factor and hydrocarbon indicator), and there is only one output layer node (porosity). Figure 6e shows the simulation results of this method. The porosity is relatively low in the northeast and east, and the porosity distribution is generally close to the trend of the sedimentary facies model for this layer (but in the southwest, the facies model is influenced by seismic data and shows low porosity). The experimental results of the 7 test wells in Table 3 show an average error of 16.28%.

In the DFNN-based facies-controlled well-seismic combined modeling method, there are eight input layer nodes of the neural network (the point coordinates i, j and k, lithofacies, relative wave impedance, root mean square amplitude, fluid factor, and hydrocarbon indicator), and there is only one output layer node (porosity). Figure 6f shows the modeling results of this method, and the lithofacies model in Figure 5b is utilized to the simulation. As demonstrating in Figure 6, the facies control effect is obvious. In addition, the porosity at the boundary between the mudstone and sandstone presents a transitional trend. The southwestern part of the model presents a high porosity, which is basically consistent with the tendency of the lithofacies model. The experimental results of the 7 test wells in Table 3 show an average error of 9.37%.

3.2.2. Reservoir Physical Property Modeling Experiment Based on Multioutput DFNN and Transfer Learning

To further solve the small-sample problem and improve the modeling efficiency, this paper explores the application of multioutput DFNN and transfer learning in the modeling of reservoir physical properties. The abovementioned DFNN-based facies-controlled well-seismic combined reservoir geological modeling method is taken as an idea for experimental testing.

To model the reservoir physical properties with multioutput DFNN, the porosity and oil saturation are taken as examples to test the modeling effect. There are eight input layer nodes of the neural network (the point coordinates i, j and k, lithofacies, relative wave impedance, root mean square amplitude, fluid factor, and hydrocarbon indicator), and there are two output nodes. The porosity and oil saturation are used as labeled data at the same time, and multiple attributes are output simultaneously during the simulation. The simulation results are shown in Figure 7b,c. The trends of the porosity and oil saturation models are similar to those in the sedimentary facies map of the study area (Figure 7a), and the multioutput porosity model is almost consistent with the conventional single-output porosity model. As shown in Table 4, the test results of the test are in good agreement.

In the transfer learning-based reservoir geological modeling method, the study area is divided into area A (northwest side of Figure 7d) and area B (southeast side of Figure 7d). The neural network model used for transfer learning in this study is similar to the DFNN method: there are eight input layer nodes of the neural network (the point coordinates i, j and k, lithofacies, relative wave impedance, root mean square amplitude, fluid factor and hydrocarbon indicator), but there is only one output layer node (porosity). Area A is taken as the pretraining task area with a total of 49 wells, and area B is the area to be simulated. According to Figure 3, first, the neural network model uses the data set in area A for pretraining. At this time, the neural network has the ability to initially express the relationship between the input data and the output data. Subsequently, the data set from area B is utilized to fine-tune the model and complete the adjustment of the neural network. Finally, the adjusted and optimized neural network model is used to simulate area B. Figure 7 shows that the facies control effect in zone B is still obvious, and the overall morphology is similar to the plan view of sedimentary facies in this zone. The test results of the test wells exhibit a high degree of conformity (Table 5).

In the future, research on if it is necessary to establish a reservoir geological model similar but different from the X Area of Karamay, Xinjiang, China (equivalent to study area A in Figure 3) will be considered. At the same time, there may be few well log data in this area, which cannot meet the needs of modeling. We can consider transferring the neural network model in X area to this task (equivalent to study area B in Figure 3). In this process, we can modify/reserve the weight and bias terms of neural units of certain layers. Then, we can reuse the existing model in the case to reduce the number of samples to speed up the training process.

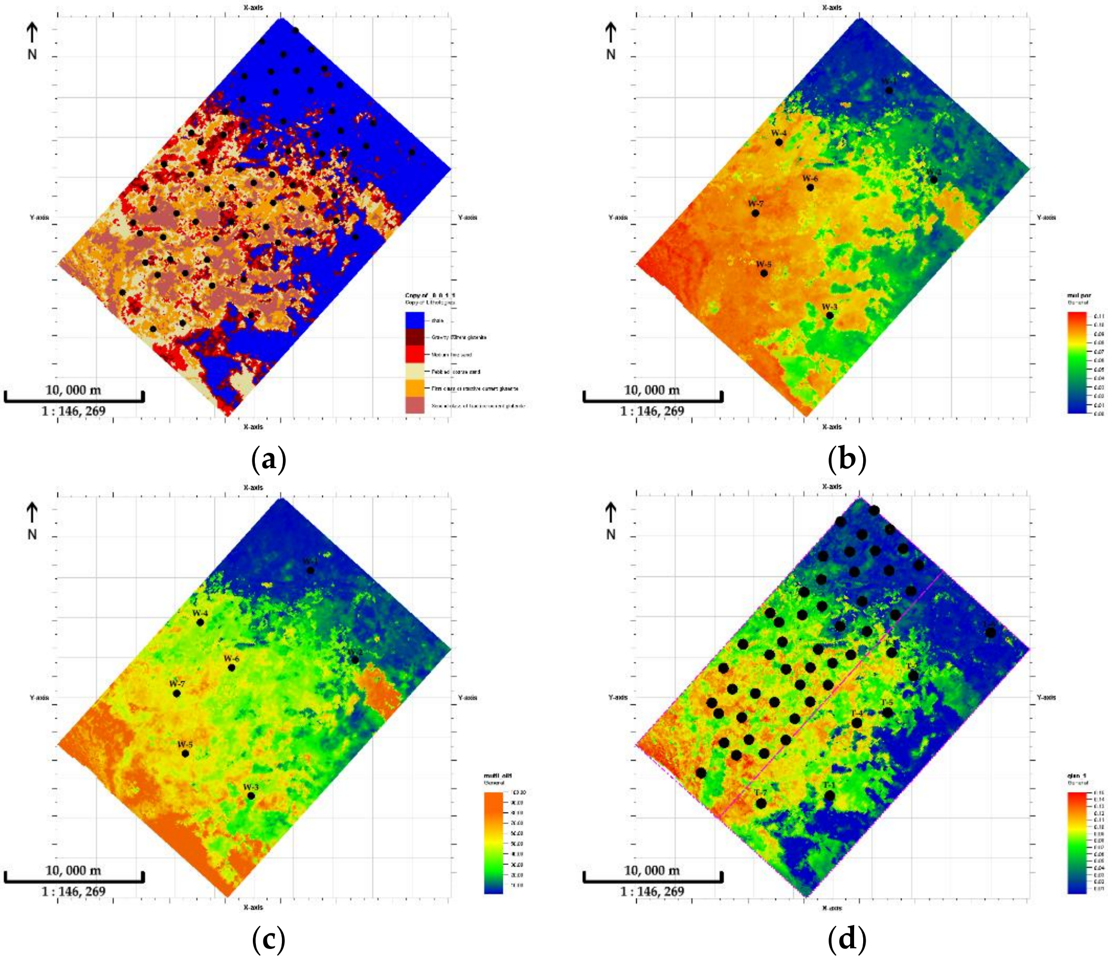


Figure 7. Reservoir physical properties model simulated by multioutput DFNN and transfer learning: (**a**) lithofacies model of the study area; (**b**) porosity model simulated by multioutput DFNN; (**c**) oil saturation model simulated by multioutput DFNN; and (**d**) porosity model simulated by transfer learning.

Table 4. Test well experiment for the porosity and oil saturation modeling based on multioutput DFNN.

Test Wells [1]	Actual Porosity	Porosity Simulated by Multioutput DFNN	Actual Oil Saturation/%	Oil Saturation Simulated by Multioutput DFNN/%
W-1	0.0012	0.0013	11.2201	12.0202
W-2	0.0566	0.0409	22.7448	17.2667
W-3	0.0603	0.0538	28.4563	25.1571
W-4	0.0636	0.0723	27.2473	33.3585
W-5	0.0786	0.0781	43.7985	49.0736
W-6	0.0835	0.0881	47.2937	60.0671
W-7	0.1011	0.0874	53.7845	54.8524
Average relative error/%	None	11.42	None	15.18

[1] The test wells are randomly selected from X area.

Table 5. Test well experiment for porosity modeling based on transfer learning.

Test Wells in Area B [1]	Actual Porosity	Porosity Simulated by Transfer Learning	Relative Error/%	Average Relative Error/%
T-1	0.0602	0.0570	5.32	
T-2	0.0787	0.0720	8.51	
T-3	0.0994	0.1082	8.85	
T-4	0.0749	0.0912	21.76	13.46
T-5	0.0161	0.0145	9.94	
T-6	0.0264	0.0210	20.45	
T-7	0.1301	0.1049	19.37	

[1] The test wells are randomly selected from area B.

4. Conclusions

In this paper, taking the delta reservoir of the upper Urho Formation in the X area of Karamay, Xinjiang, China as an example, with the combination of wells and well-seismic data, DFNN-based 3D reservoir physical property modeling is carried out. The application of multioutput DFNN and transfer learning in 3D reservoir physical property modeling is explored. The main conclusions are summarized as follows:

- Experimental results show that, compared with conventional geostatistical methods, the reservoir physical property modeling results based on DFNN are closer to the actual model. In the process of DFNN-based reservoir physical property modeling, the constraints of seismic data and facies controls are obvious, and the facies-controlled simulation results have a higher test well coincidence rate.
- The feasibility of applying multioutput DFNN and transfer learning to reservoir geological modeling is preliminarily verified, and solutions are provided to further solve small-sample problems and improve the modeling efficiency and other optimization methods. In the future, convolutional neural networks or other more complex neural network models can be used for partial transfer learning, and new network models can be constructed according to the simulation needs.
- In the future, it will be necessary to explore the use of deep learning methods to establish more refined and highly accurate reservoir models. A reservoir geological modeling process based on deep learning will be gradually established that completes both the exploration and the development of oil and gas fields.

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