

Article

Productivity Evaluation Method for Offshore Thick–Thin Interbedded Reservoirs Based on Graph Attention Multilayer Perceptron

Bin Jiang ^{1,2} , Shiqing Cheng ^{1,*} , Yinliang Shi ¹ and Ruikai Duan ²¹ State Key Laboratory of Petroleum Resources and Engineering, China University of Petroleum (Beijing), Beijing 102249, China; 2022211256@student.cup.edu.cn (Y.S.)² CNOOC Research Institute Co., Ltd., Beijing 100028, China

* Correspondence: chengsq973@163.com

Abstract: Offshore multilayer sandstone reservoirs are characterized by complex vertical alternating thick and thin layers, resulting in significant heterogeneity. Traditional productivity evaluation methods often fail to effectively represent the dynamic production patterns of individual wells. This study focuses on the S oilfield offshore (Bohai Bay, China) as a case study. By considering the structural characteristics of thin layers and sand bodies, the reservoir is classified into four types: strong continuous thick layers, weak continuous thick layers, alternating thick–thin layers, and weak continuous thin layers. Based on this classification, a multilayer perceptron classification model based on graph attention neural networks is developed. The model achieves a high classification accuracy of 96.6% by mining the interdependencies between 14 input parameters. Further, by fitting the relationship between interlayer interference coefficients and water cuts for typical wells, a dynamic variation diagnosis plot for interlayer interference coefficients under different reservoir combinations is established. Additionally, a calculation method for the oil productivity index based on reservoir combination patterns is proposed. The method's effectiveness was validated through field application, where the results significantly improved the correlation between the water-free oil productivity index and flow coefficient, with calculation errors of less than 10% compared to measured values.



Academic Editor: Qingbang Meng

Received: 30 December 2024

Revised: 10 February 2025

Accepted: 11 February 2025

Published: 13 February 2025

Citation: Jiang, B.; Cheng, S.; Shi, Y.; Duan, R. Productivity Evaluation Method for Offshore Thick–Thin Interbedded Reservoirs Based on Graph Attention Multilayer Perceptron. *Processes* **2025**, *13*, 525. <https://doi.org/10.3390/pr13020525>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: reservoir combination pattern; graph attention mechanism; interlayer interference; productivity evaluation; thick–thin interbedded reservoirs

1. Introduction

Multilayered combined waterflooding development is the main development method for offshore multilayer hydrocarbon reservoirs [1–3]. However, for thick–thin interbedded sandstone reservoirs, the total thickness of the oil layers is large, with a significant vertical span. Moreover, because the thick and thin reservoirs are vertically interbedded, the reservoir heterogeneity is strong, making it difficult to characterize the multilayer combination features [4–6]. As a result, the production characteristics of oil wells vary significantly, and the dynamic production patterns are unclear. Therefore, establishing a reservoir combination model for thick–thin interbedded sandstone reservoirs and studying the production patterns under different combination modes are of great importance for evaluating the development effect and potential of offshore multilayer combined production reservoirs.

In traditional reservoir classification methods [7–10], the effective thickness of layers and the microscopic pore structure of cores are usually used as the main basis for reservoir

classification. For example, using reservoir thickness as the classification criterion, offshore multi-layered sandstone reservoirs typically categorize reservoirs thicker than 5 m as Class I, those between 2 and 5 m as Class II, and those thinner than 2 m as Class III. These methods can be used to describe the characteristics of multiple oil-bearing sand bodies or individual sand layers within the same development system. Fu et al. focused on the heterogeneity of reservoirs, selecting parameters such as porosity, clay content, and sandstone thickness [11]. They used cluster analysis to divide the Fu Xin uplift South Qian 4th section reservoir into four categories, good, fairly good, poor, and bad reservoirs and quantitatively analyzed the classification criteria for these four types using Bayesian discrimination. Benham et al. established a multi-layer heavy oil reservoir interlayer quality index based on thickness, lithology, and reservoir plane continuity, which is used to analyze the impact of thin layers and interlayers on heavy oil thermal recovery [12]. Francesconi et al. carried out rock classification in the Kashagan oilfield based on core data and extended the analysis to include well logging and reservoir plane characteristics [13]. However, these reservoir classification methods are not suitable for the development needs of offshore thick–thin interbedded oilfields.

In recent years, machine learning methods such as neural networks and support vector machines have been widely applied in reservoir classification due to their strong generalization ability and ease of operation [14–19]. Bai et al. established an oilfield analog system using data mining technology and selected six machine learning algorithms, ultimately choosing the Light Gradient Boosting Machine algorithm to predict oilfield production capacity [20]. Wang et al. replaced manual methods with a BP neural network model for comprehensive reservoir evaluation and classification, achieving a prediction accuracy greater than 90% [21]. Lv et al. proposed a classification method for carbonate fracture–cavity reservoirs based on multilayer perceptron neural networks, using reservoir quality (physical properties and micro-porous structures) as the classification basis [22]. Rahimi and Riahi used random forest algorithms and geological statistical modeling for reservoir classification, achieving an average accuracy of 95% [23]. Koray et al. used a combination of unsupervised and supervised machine learning algorithms to establish the relationship between porosity and permeability in different regions, then relied on logging data for reservoir classification and geological modeling [24]. Nie et al. developed a machine learning classification prediction model based on large-scale real-time drilling data, which, when combined with different clustering algorithms, can be used for reservoir classification prediction [25]. Qiao et al. developed an efficient classification method for drilling pattern classification by combining graph attention mechanisms with encoder layers [26].

Although the aforementioned methods have achieved certain results in reservoir classification, they still face issues such as poor adaptability to multi-layer system combinations, an inability to fully capture the complex interactions between classification parameters, and low accuracy in the classification results. Therefore, this study takes the S oilfield as an example, integrating small-layer and sandstone structure features and combining single-well encountered sandbody combination characteristics. We introduce the graph attention mechanism to achieve accurate classification of different thick–thin reservoir combination patterns. The proposed approach not only represents an innovation in reservoir combination classification based on existing data from the target oilfield but also enables the prediction of reservoir combinations in newly drilled infill wells within the target field. Furthermore, it facilitates the assessment of initial productivity performance for these infill wells based on the prediction results.

2. Characteristics of the Thick–Thin Interbedded Reservoirs

The Offshore S oilfield is situated in southeastern Bohai Bay, approximately 216 km from Tanggu, with an average water depth of 27 m. The geographic location of the S oilfield is shown in Figure 1. Regionally, it lies within the Tan-Lu Fault Zone at the northeastern tip of the central segment of the Bonan Lower Uplift. To further enrich the information on the S Oilfield, Figure 2 presents the planar distribution pattern map of sandbodies of the oilfield.

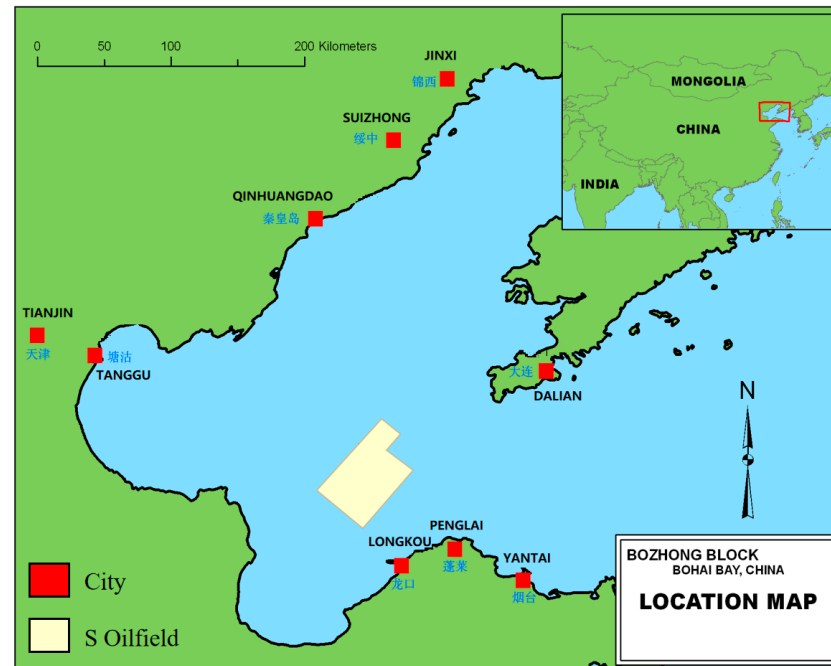


Figure 1. The geographic location of S oilfield.

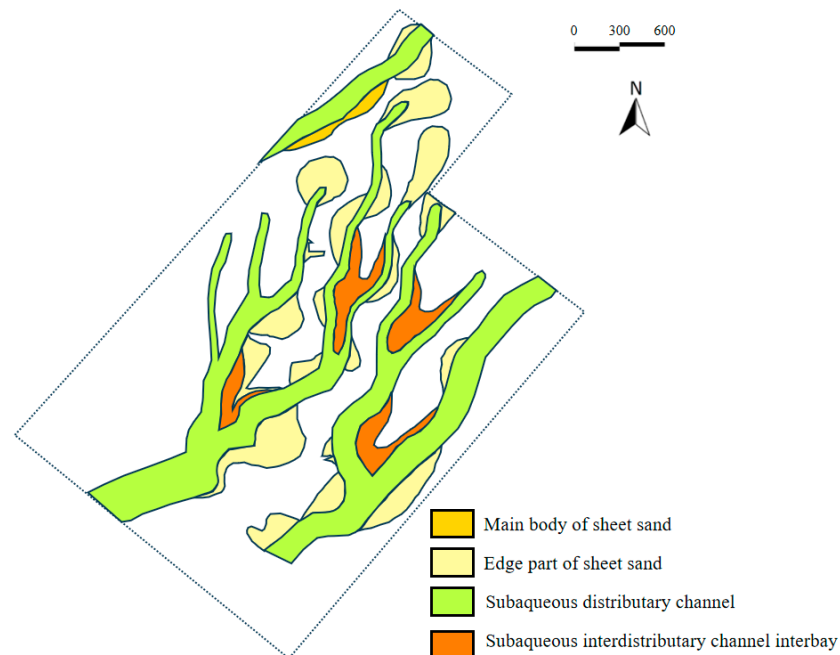


Figure 2. Planar distribution pattern map of sandbodies in S oilfield.

The Offshore S Oilfield has a vertical span of 500 m and a cumulative oil layer thickness of 100 m. The main oil-bearing layer, the Guantao Formation, is a shallow-water delta

sediment of the Miocene epoch in the Tertiary period, characterized by significant lateral variation in reservoir development. The well-tie profiles of the S oilfield are shown in Figure 3. This oilfield is a typical thick–thin interbedded reservoir. Due to the high proportion of sandstone reserves in small layers below 5 m, thick and thin reservoirs often develop simultaneously within the same small layer and are unevenly distributed within these layers. The economic efficiency of stratified development is poor, and under the same well network conditions, there is a significant disparity in the utilization degree of the thick and thin reservoirs, leading to prominent inter-layer conflicts.

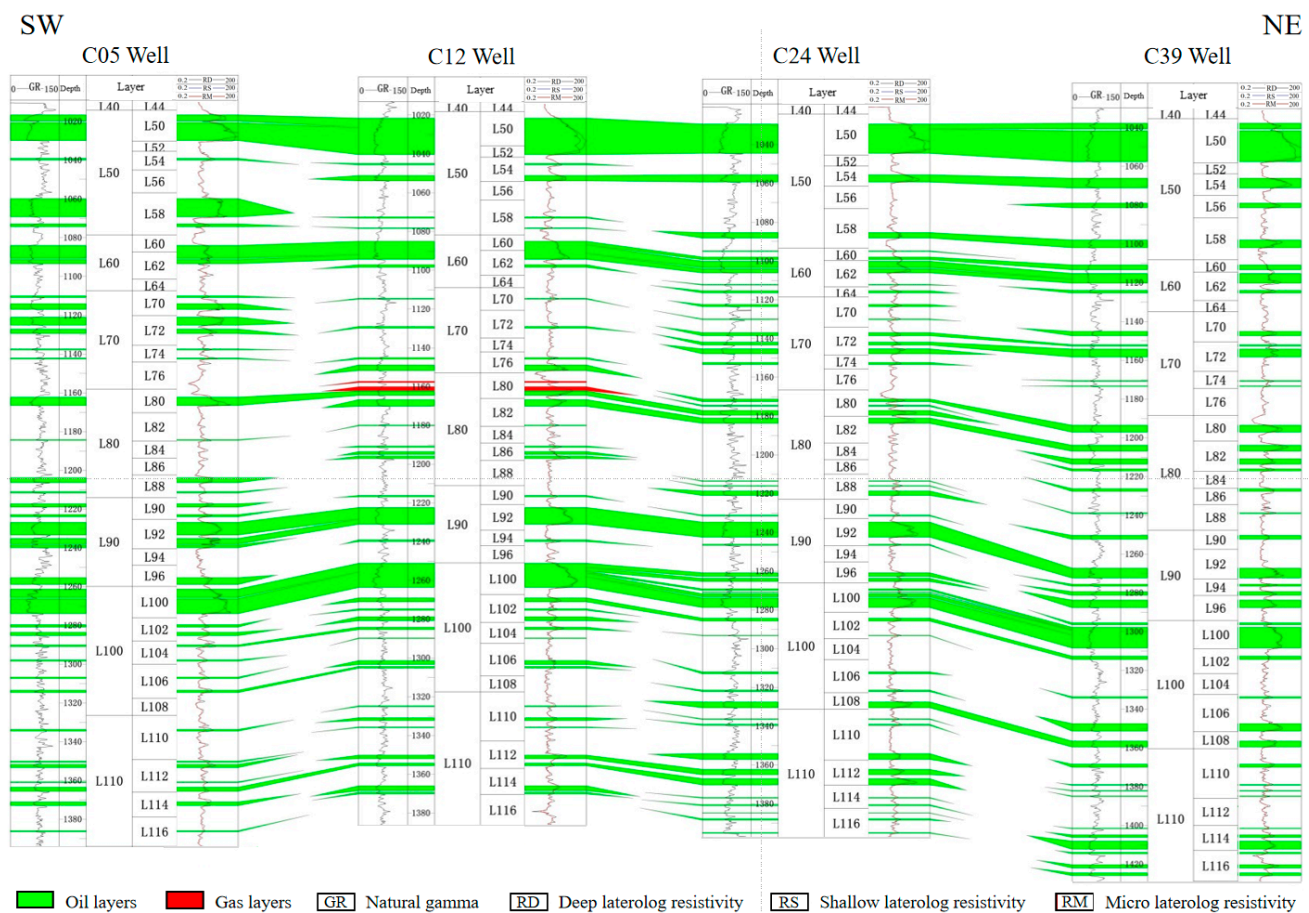


Figure 3. The well-tie profiles of the S oilfield from southwest to northeast.

To further describe the impact of thick–thin reservoirs on the distribution of reservoir sand bodies, this paper introduces factors such as vertical periodicity and lateral continuity. Cumulative single-sandbody thickness, thickness variation coefficient, and vertical periodicity are used as the basis for reservoir classification. The thickness variation coefficient is defined as the ratio of the standard deviation of cumulative sandbody thickness at well points within a single small layer to the average cumulative sandbody thickness. A smaller lateral thickness variation coefficient indicates that the reservoir is more laterally continuous and stable. Conversely, a larger coefficient reflects faster lateral changes and poorer continuity of the reservoir. Vertical periodicity represents the number of sand bodies developed within a single small layer, often expressed by the layering coefficient or the average number of sand layers encountered by a well. This mainly characterizes the inter-layer heterogeneity of the thick–thin interbedded sandstone reservoirs. A larger layering coefficient indicates more sand bodies within the small layer, suggesting stronger heterogeneity between layers. On the other hand, a smaller coefficient suggests that the small layer is more stable and the reservoir is relatively homogeneous.

2.1. Characteristics of Class I Reservoirs

Reservoirs with an average thickness greater than 5 m are defined as Class I reservoirs. Based on the control of sedimentary processes and differences in reservoir quality, Class I reservoirs are further categorized into multi-stage strong continuous thick layers and single-stage strong continuous thick layers. The main characteristics of multi-stage strong continuous thick layers are as follows: the average thickness of a single sand layer is 6.5 m, the layering coefficient is greater than 2, multiple stages of sands with varying thicknesses are developed, the coefficient of variation in lateral thickness is less than 0.5, and the reservoir exhibits stable lateral continuity. A typical interwell profile is shown in Figure 4.

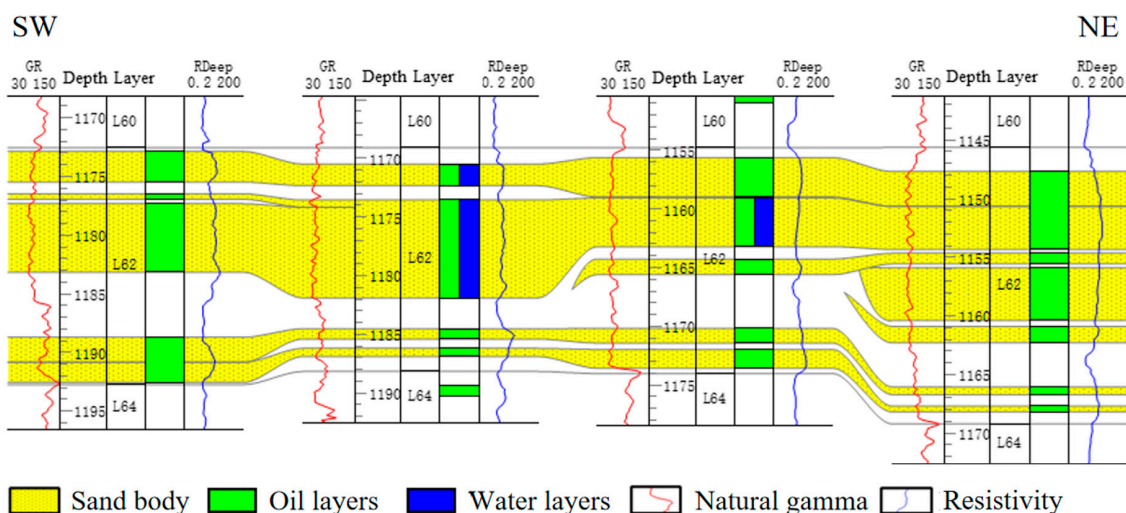


Figure 4. Typical interwell profile of multi-stage strong continuous thick layers from southwest to northeast.

The characteristics of single-stage strong continuous thick layers are as follows: the average thickness of a single sand layer is 6.2 m, the layering coefficient is less than 2, with single-stage sand bodies being predominant. The coefficient of variation in lateral thickness is 0.3, and the reservoir exhibits stable lateral continuity. A typical interwell profile is shown in Figure 5.

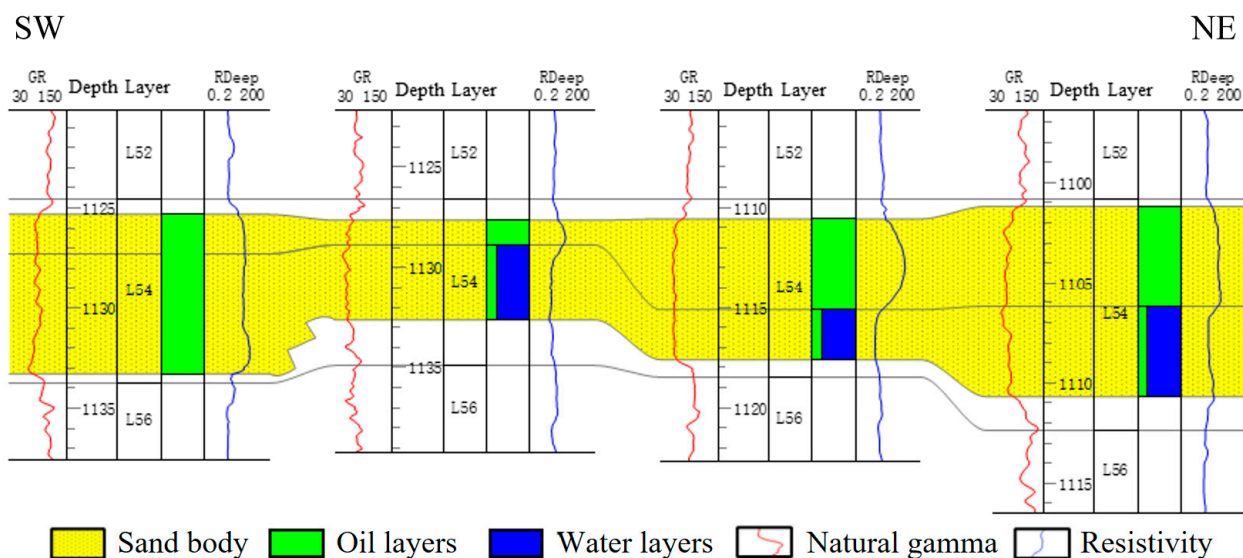


Figure 5. Typical interwell profile of single-stage strong continuous thick layers from southwest to northeast.

2.2. Characteristics of Class II Reservoirs

Class II reservoirs are medium-thick reservoirs with an average thickness ranging from 3 to 5 m. Based on the influence of sedimentary processes and reservoir quality differences on the parameters of the sand bodies within the layers, Class II medium-thick reservoirs are further subdivided into two subcategories: single-stage weak continuous medium-thick layers and multi-stage weak continuous medium-thick layers. The characteristics of single-stage weak continuous medium-thick layers are as follows: the average thickness of a single sand layer is 3.7 m, the layering coefficient is less than 2, with single-stage sand bodies being predominant. The coefficient of variation in lateral thickness is 0.8, and the reservoir exhibits rapid lateral changes with distinct facies zonation. The main facies zone shows stable lateral continuity, while the peripheral facies zones experience more rapid lateral variations. A typical interwell profile is shown in Figure 6.

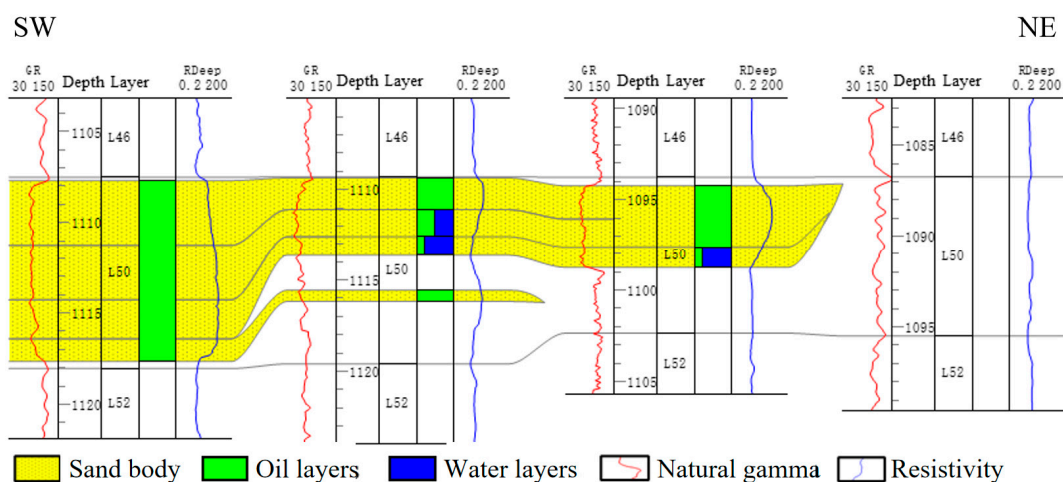


Figure 6. Typical interwell profile of single-stage weak continuous medium-thick layers from southwest to northeast.

The characteristics of multi-stage weak continuous medium-thick layers are as follows: the average thickness of a single sand layer is 3.0 m, the layering coefficient is greater than 2, and multiple stages of sands with unequal thicknesses are developed. The coefficient of variation in lateral thickness is greater than 0.5, and lateral reservoir variations are relatively rapid. A typical interwell profile is shown in Figure 7.

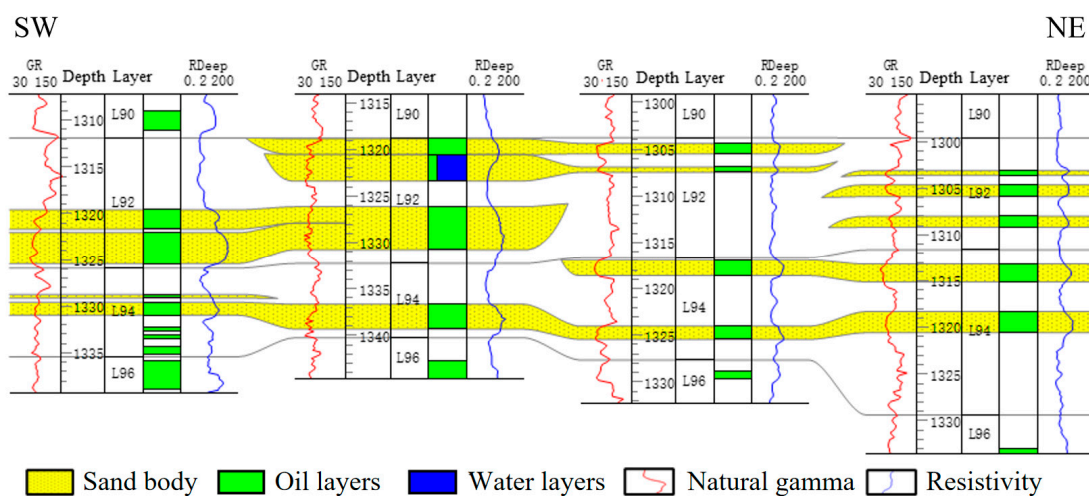


Figure 7. Typical interwell profile of multi-stage weak continuous medium-thick layers from southwest to northeast.

2.3. Characteristics of Class III Reservoirs

Class III reservoirs are influenced by the regulatory sedimentation of braided river delta early-late stages or isolated small-scale deposits. The average thickness of a single small layer is less than 3 m. They can be further subdivided into three types: multi-stage weak continuous thin layers, single-stage weak continuous thin layers, and single-stage discontinuous thin layers. The characteristics of multi-stage weak continuous thin layers are as follows: the average thickness of a single sand layer is 1.5 m, the layering coefficient is greater than 1.8, and the coefficient of variation in lateral thickness is less than 1.0. The reservoir exhibits rapid changes, with multiple stages of sand bodies superimposed, forming local dominant zones of a certain scale. A typical interwell profile is shown in Figure 8.

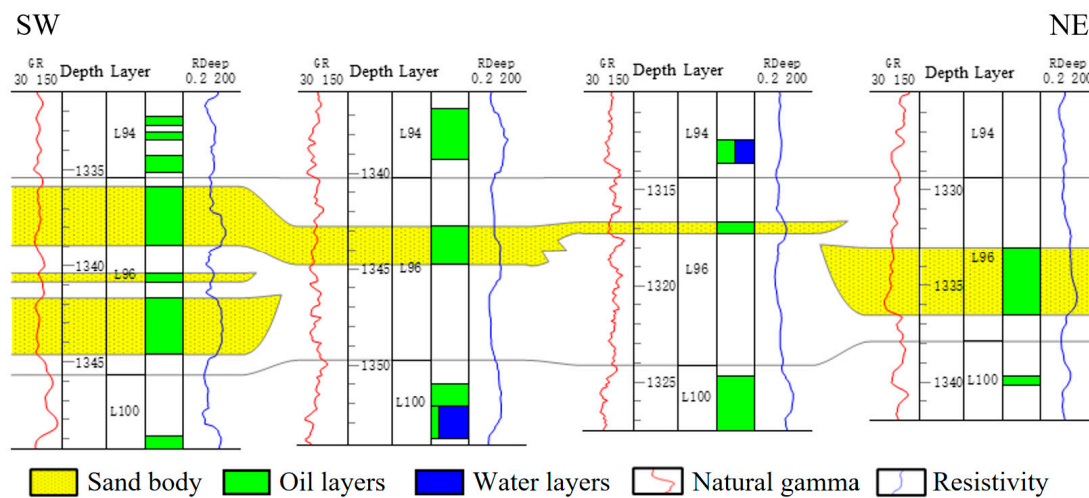


Figure 8. Typical interwell profile of multi-stage weak continuous thin layers from southwest to northeast.

The single-stage weak, continuous thin layer is characterized by an average thickness of the single sand layer of 1.4 m, a stratification coefficient of less than 1.8, and a lateral thickness variation coefficient of less than 1.0. The reservoir changes rapidly, and small-scale advantageous areas are locally developed. Its typical correlated well profile is shown in Figure 9.

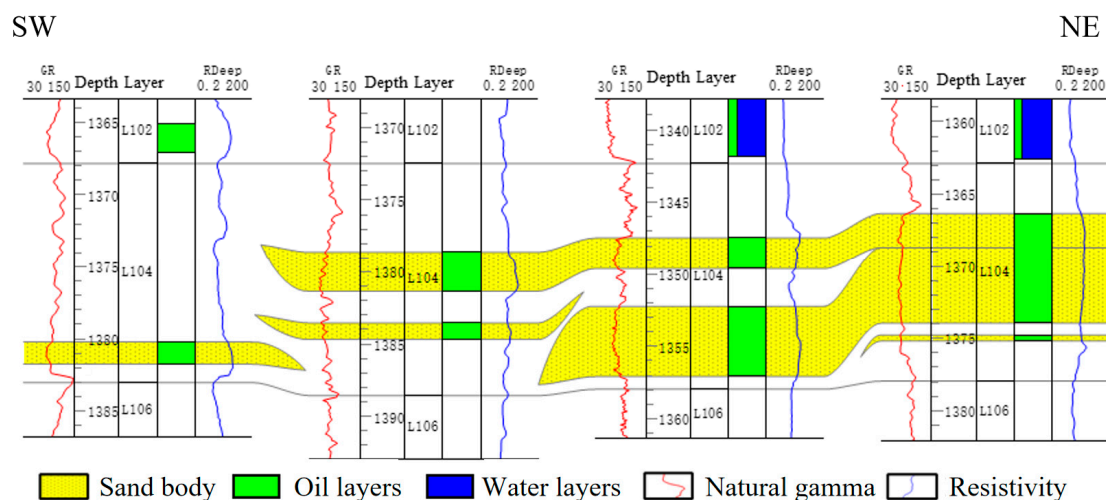


Figure 9. Typical interwell profile of single-stage weak continuous thin layers from southwest to northeast.

The single-stage discontinuous thin layer is characterized by an average thickness of the single sand layer of 0.9 m, a stratification coefficient less than 1.8, and a lateral thickness variation coefficient greater than 1.0. The reservoir exhibits extremely rapid lateral changes and mostly consists of isolated sand bodies. Its typical correlated well profile is shown in Figure 10.

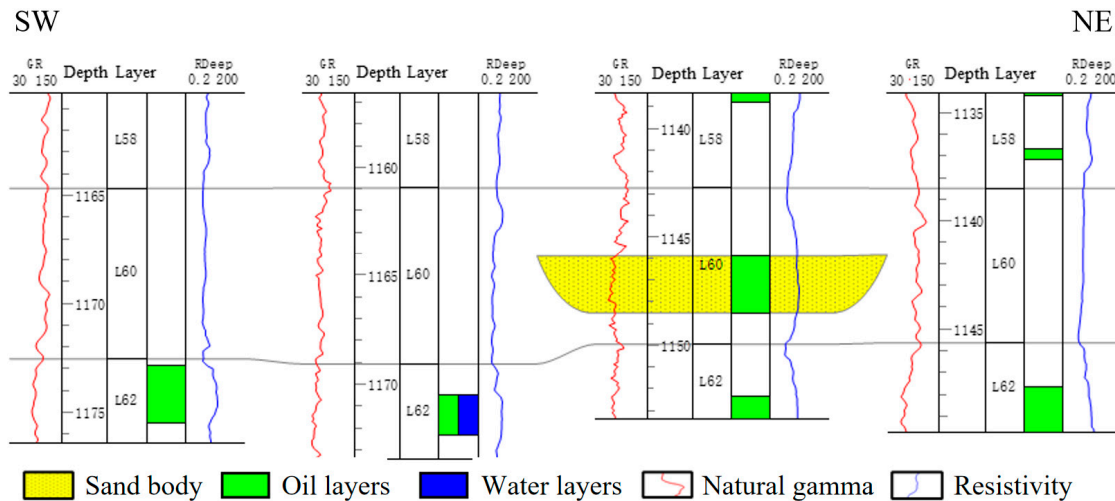


Figure 10. Typical wellbore profile of single-phase discontinuous thin layer from southwest to northeast.

In summary, by further combining seven sublayer parameters, including the average thickness of sand bodies, the sandstone/shale ratio of sublayers, the average permeability, the average porosity, and the mobility coefficient, the classification parameter table for the thick–thin interbedded sandstone reservoirs in S Oilfield is formed, as shown in Table 1.

Table 1. Parameters for classification of thick–thin interbedded reservoir in S oilfield.

Reservoir Classification	I	II	III
Average thickness of single sand layer (m)	>5	2~5	0.9~2
Sand ratio	>0.30	0.25	≤0.2
Average porosity (%)	>26	25~28	22~26
Average permeability (mD)	>500	400	<400
Stratification coefficient	1.7~2.5	1.7~2.3	1.2 < 2.4
Lateral variation coefficient (%)	0.3~0.5	0.5~0.8	0.6~1.4
Flow coefficient (mD·m/mPa·s)	>200	150	<100

3. Research on the Combination Modes of Thick–Thin Reservoir Layers

3.1. Parameter Analysis of Reservoir Combination Pattern

Based on the above reservoir classification results, a total of 14 characteristic parameters are considered, including the total thickness of sand bodies encountered by typical wells, the total number of sand bodies, the thickness of Class I sand bodies, the thickness of Class II sand bodies, the thickness of Class III sand bodies, the proportion of the thickness of Class I sand bodies, the proportion of the thickness of Class II sand bodies, the proportion of the thickness of Class III sand bodies, the number of Class I sand bodies, the number of Class II sand bodies, the number of Class III sand bodies, the proportion of the number of Class I sand bodies, the proportion of the number of Class II sand bodies, and the proportion of the number of Class III sand bodies. The reservoir combination patterns of typical thick–thin interbedded oil reservoirs are classified into four types: strong continuous thick-layer combination, weak continuous thick-layer combination, thick–thin

alternating combination, and weak continuous thin-layer combination. The typical well profile is shown in Figure 11, and the statistical values of parameter ranges for the four types of wells are shown in Table 2.

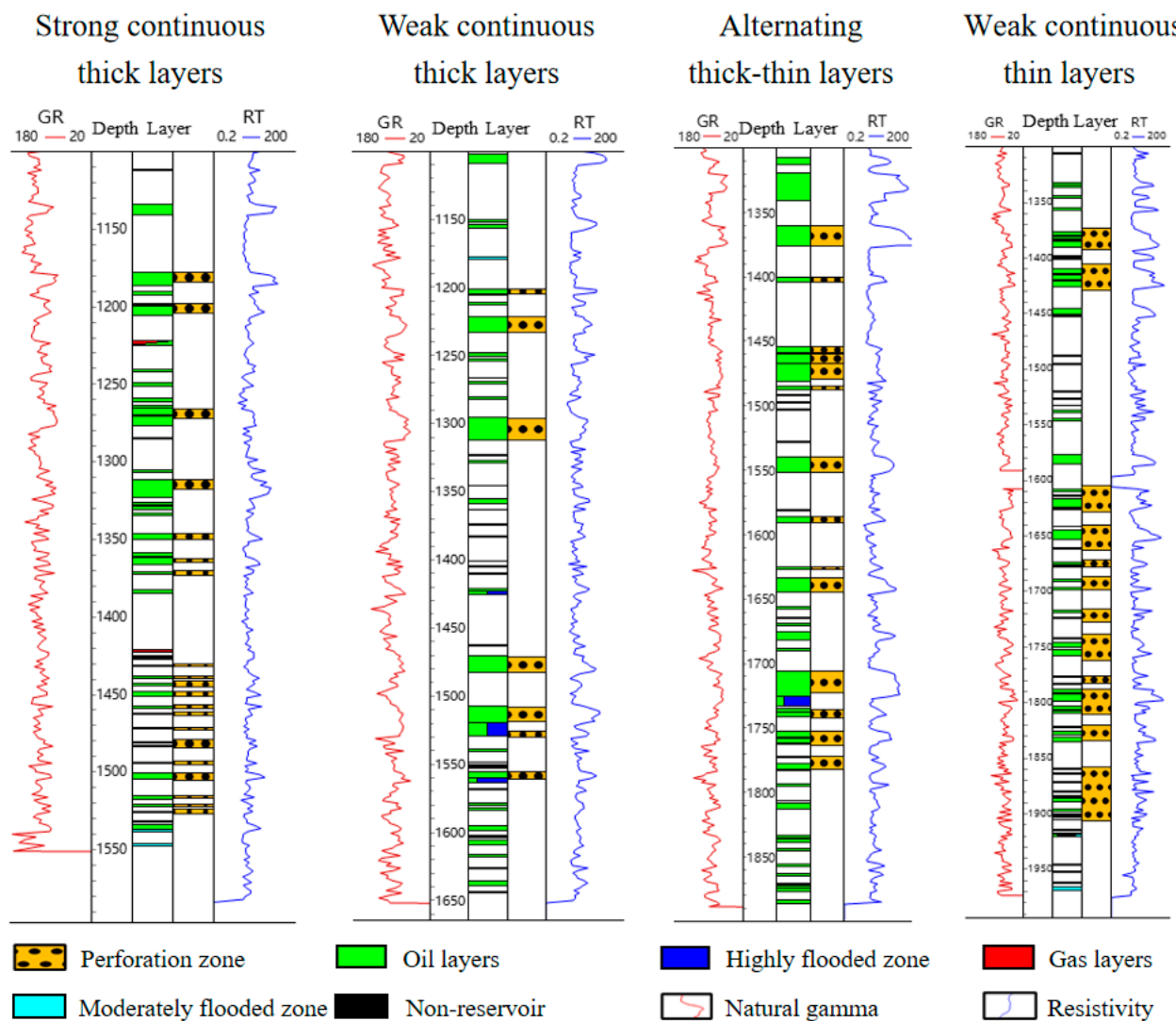


Figure 11. Typical well profiles of the combination modes of thick and thin reservoirs in S oilfield.

As can be seen from Figure 11 and Table 2, for the strong continuous thick-layer combination pattern, the number of single sand layers is relatively small vertically. The sand bodies are mainly Class I thick-layer sand bodies and the heterogeneity between sand bodies is weak. For the weak continuous thick-layer combination pattern, the sand bodies encountered in a single well are mainly Class II and Class III single sand bodies. Although thick-layer sand bodies predominate vertically, there are also thin-layer sand bodies, resulting in relatively strong heterogeneity. Under the weak continuous thin-layer combination pattern, weak continuous thin sand bodies are well developed in the sand bodies encountered in a single well, and the total thickness of the sand bodies is not large. For the thick–thin alternating combination pattern, due to the alternating distribution of thick–thin reservoirs vertically, the heterogeneity is stronger than that of the other three combination patterns.

Table 2. Discrimination parameters of reservoir combination patterns for typical wells in S oilfield.

Parameters	Range of Thick–Thin Alternation	Range of Weak Continuous Thin Layer	Range of Weak Continuous Thick Layer	Range of Strong Continuous Thick Layer
Thickness of Class I Sand Bodies (m)	20~75	0~35	18~35	18~49
Thickness of Class II Sand Bodies (m)	6~37	14~38	10~25	2~7
Thickness of Class III Sand Bodies (m)	8~26	10~30	2~9	0~2
Proportion of Class I Sand Bodies (%)	43~69	0~41	44~69	68~92
Proportion of Class II Sand Bodies (%)	15~35	32~73	21~41	8~25
Proportion of Class III Sand Bodies (%)	15~25	18~46	5~15	0~7
Number of Class I Sand Bodies	3~10	0~5	2~4	2~5
Number of Class II Sand Bodies	2~11	4~13	3~8	1~2
Number of Class III Sand Bodies	6~22	8~27	2~6	0~1
Proportion of the Number of Class I Sand Bodies (%)	8~15	0~14	22~40	40~83
Proportion of the Number of Class II Sand Bodies (%)	17~31	24~50	30~50	17~40
Proportion of the Number of Class III Sand Bodies (%)	50~58	46~73	17~33	0~25
Total Thickness of Sand Bodies (m)	44~137	34~101	31~61	26~53
Total Number of Sand Bodies	12~43	13~43	7~18	4~6

3.2. Discrimination Model of Multilayer Perceptron Based on Graph Attention Networks

Due to the large number of parameters involved in the identification of thick–thin reservoir combination patterns and the complex relationships between them, manual identification is challenging and labor-intensive. Therefore, in this paper, a reservoir combination pattern identification model based on artificial neural networks is developed, leveraging the ability of the graph attention mechanism to mine complex relationships and the powerful nonlinear mapping capability of multilayer perceptrons. This model is designed to replace manual identification for determining reservoir combination patterns. The multilayer perceptron (MLP) consists of multiple layers of neurons and can learn the complex mapping relationships between data input and output through training, storing the connection relationships of neurons in the form of weights [27]. Its structure is simple and includes an input layer, hidden layers, and an output layer, with the hidden layers containing two or more layers. The process of the multilayer perceptron model is as follows: the training set is fed into the hidden layer through the input layer. The neurons in the hidden layer perform logical operations on the received data to obtain deeper features, which are then passed to the output layer. The data from the output layer represent the final judgment of the entire neural network. In the neural network, the hidden layer plays a crucial role in feature extraction and is a critical component of the network.

Due to the potential interdependencies among the 14 input attributes in the reservoir combination pattern identification, the standard multilayer perceptron network may fail to accurately capture these dependencies, which in turn affects the model's performance. Therefore, based on the standard MLP model, this paper proposes a graph attention-based MLP classification model [28] that dynamically adjusts the dependency weights between input features, enhancing the ability to mine the relationships between features. This allows the network to more precisely construct the mapping between input features and the classification results, thereby improving classification accuracy. As shown in Figure 12, the process begins by extracting the feature values of each input attribute individually. Then, each attribute's feature value is treated as a node in a fully connected graph with sixteen nodes. The feature vector of node i is denoted as h_i . Using the attention mechanism,

the association degree between neighboring node j and node i can be calculated with the following formula:

$$e_{ij} = \sigma_1 \left(\alpha^T [Wh_i || Wh_j] \right) \quad (1)$$

where α and W are the learnable parameters of the network, σ_1 represents the LeakyReLU activation function, and $||$ denotes the concatenation operation. To further standardize the measurement of the association weights between different nodes, the degree of association between each node and its neighboring nodes needs to undergo a Softmax normalization process, yielding the final attention coefficients. The calculation formula is as follows:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})} \quad (2)$$

where α_{ij} is the attention coefficient of the neighboring node j with respect to node i , and N_i represents the set of neighboring nodes of node i , and $\exp$ denotes the exponential function with base e . Using Equation (3), the final associated features of each node are calculated. These features are then passed through two fully connected layers to output the classification result. The specific formula for calculating the associated features is as follows:

$$h'_i = \sigma_2 \left(\sum_{k \in N_i} \alpha_{ik} Wh_k \right) \quad (3)$$

where σ_2 represents the ELU activation function.

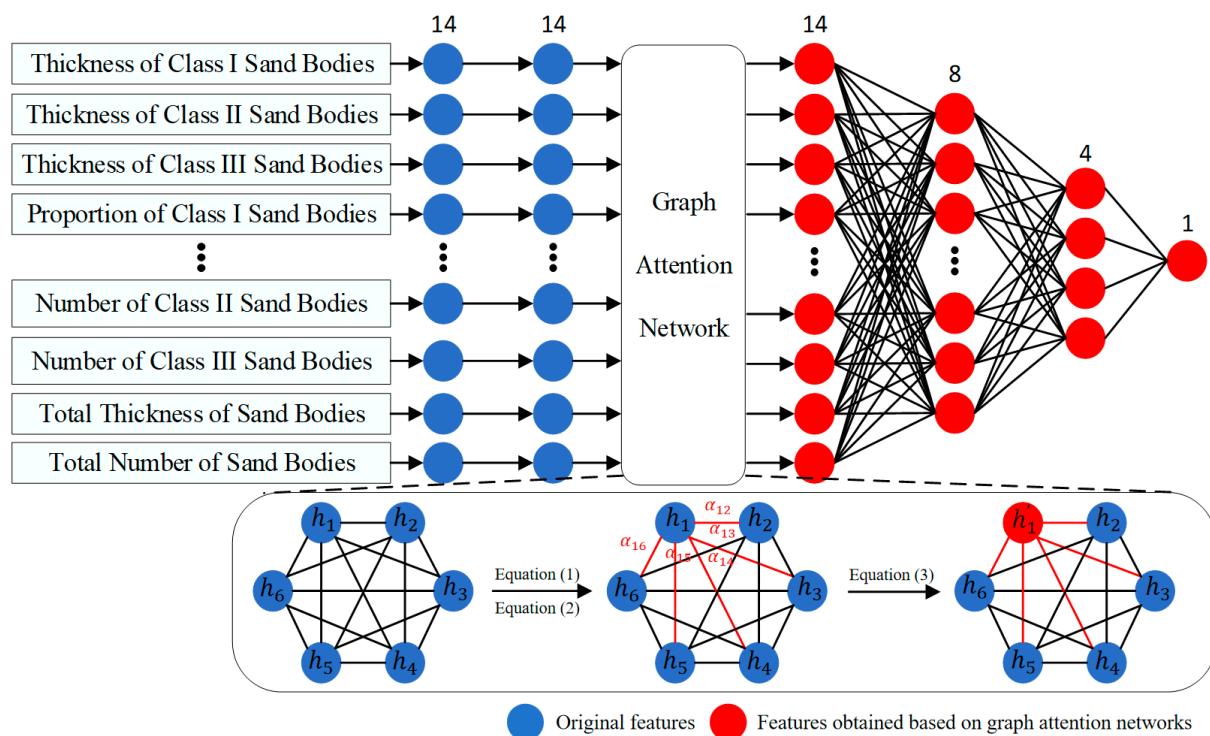


Figure 12. Structure of graph attention-based multilayer perceptron model.

3.3. Analysis of Classification Results

The cross-entropy function is used as the loss function in this paper. The principle of cross-entropy is to multiply the probability distribution of the actual measurements by the probability distribution of the predicted values element-wise, take the logarithm, and finally sum all elements and take the negative. The cross-entropy function has the advantage of faster network convergence, effectively encouraging the model to make its predicted

probability distribution approach the actual distribution more quickly. Its mathematical expression is as follows:

$$L = -\frac{1}{N} \sum_i \sum_{c=1}^M y_{ic} \log(p_{ic}) \quad (4)$$

where M is the number of reservoir combination pattern categories, i is the i -th input sample, and y_{ic} represents the label of the i -th sample for the reservoir combination pattern category c . When the true class of i is c , y_{ic} takes the value 1, otherwise, it takes the value 0, p_{ic} is the probability of the i -th sample belonging to the reservoir combination pattern category c .

In order to conduct research on the reservoir combination pattern classification model, data from 278 development wells were collected as the training and testing data for the neural network. A balanced selection of 250 wells was divided into a training set and a validation set in a 7:3 ratio, with the remaining 28 wells used as test samples. Due to the presence of multiple different dimensions and varying magnitudes among the 14 feature attributes in the dataset, the data distribution is inconsistent, making it difficult to correctly learn the proportional weights of each attribute. To enhance data consistency and improve the model's classification accuracy, the maximum–minimum normalization method will be applied to the feature attributes in the dataset. This method maps the data to the $[0, 1]$ range. The specific formula is as follows:

$$Y_i = \frac{X_i - (X_i)_{\min}}{(X_i)_{\max} - (X_i)_{\min}} \quad (5)$$

where $(X_i)_{\min}$ is the minimum value of the i -th feature, $(X_i)_{\max}$ is the maximum value of the i -th feature, and Y_i is the normalized value of the i -th feature attribute.

To obtain the optimal classification model, it is necessary to select the best activation function and optimizer. The activation function maps the input of the neuron to the output, representing complex nonlinear relationships. In this paper, three types of activation functions are compared. The Sigmoid function has an input range from negative infinity to positive infinity, an output range of $(0, 1)$, and is a continuous function centered at 0.5. Its mathematical expression is as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (6)$$

The Tanh function also has an input range from negative infinity to positive infinity. The output values are centered at 0, with a range of $(-1, 1)$. Its mathematical expression is as follows:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (7)$$

Due to the issues of gradient vanishing and high computational complexity associated with the Sigmoid function, and the fact that the derivative of the Tanh function approaches 0 at the extremes, which can also lead to gradient vanishing and high complexity caused by exponentiation, an increasing number of researchers tend to use the ReLU function. The input range of the ReLU function is also infinite, with an output range of $[0, +\infty)$. Its mathematical expression is as follows:

$$f(x) = \max(0, x) \quad (8)$$

Optimizers can adjust the trainable parameters in a way that minimizes the objective function. This paper primarily compares two algorithms: Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam). SGD is a commonly used first-order

optimizer in deep learning. Its basic principle is to randomly select a small batch of samples during each iteration to compute the gradient of the loss function and then use the gradient to update the parameters. The expression is as follows:

$$\theta_{t+1} = \theta_t - \eta \nabla f(\theta_t) \quad (9)$$

where θ_{t+1} represents the model parameters at the $t + 1$ -th iteration, η is the learning rate, and $\nabla f(\theta_t)$ is the gradient of the objective function with respect to the parameters θ_t .

The adaptive matrix estimation method uses both first- and second-order moment estimates of the gradient to dynamically adjust the learning rate of the parameters within a certain range, allowing it to adapt to the update speed of different parameters and making the parameter changes smoother. The comparison results of different activation functions and optimizer settings are shown in Table 3. The training loss and validation accuracy results for the SGD and Adam models are shown in Figures 13 and 14.

Table 3. Comparison of discrimination model training details with different activation functions and optimizers for classification accuracy.

Activation Function and Optimizers	SGD $\eta = 0.1$ (%)	SGD $\eta = 0.01$ (%)	SGD $\eta = 0.001$ (%)	Adam (%)
Sigmoid	50.8	54.2	69.5	96.6
Tanh	49.2	45.8	54.2	69.5
ReLU	22.0	42.4	20.3	35.6

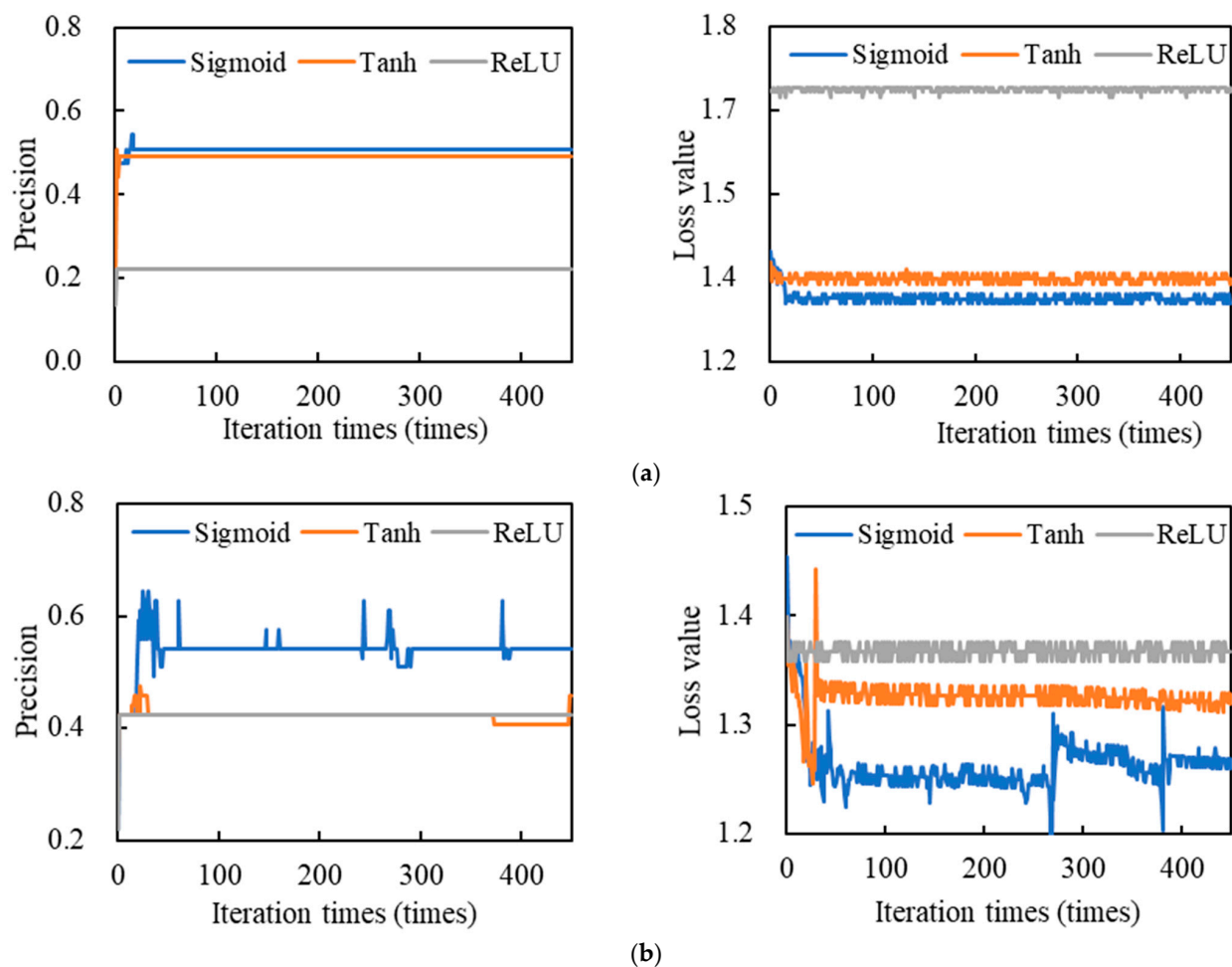


Figure 13. Cont.

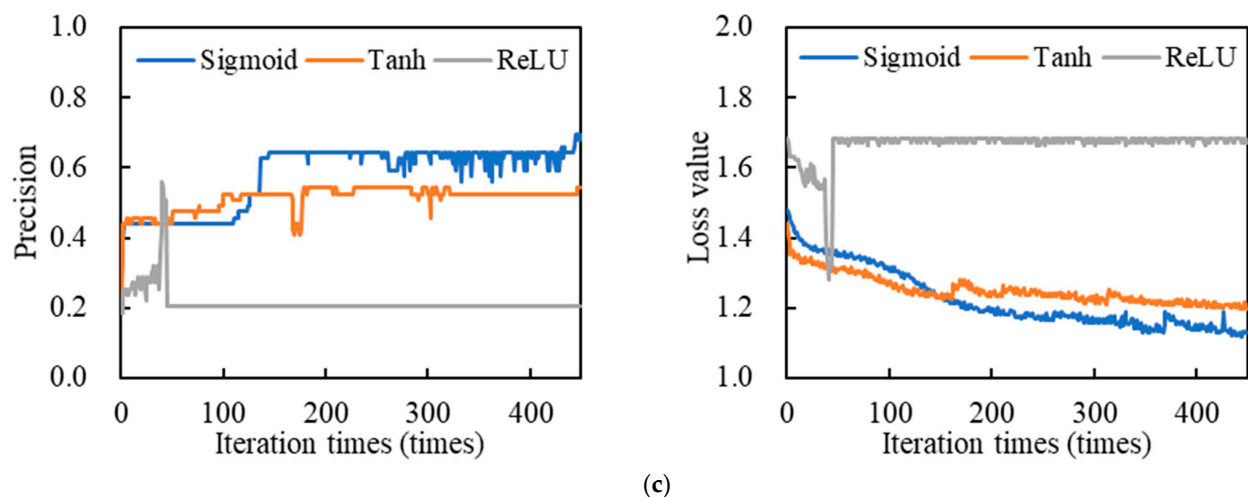


Figure 13. Results of model experiments with SGD algorithm. (a) The precision and loss value of SGD algorithm with $\eta = 0.1$. (b) The precision and loss value of SGD algorithm with $\eta = 0.01$. (c) The precision and loss value of SGD algorithm with $\eta = 0.001$.

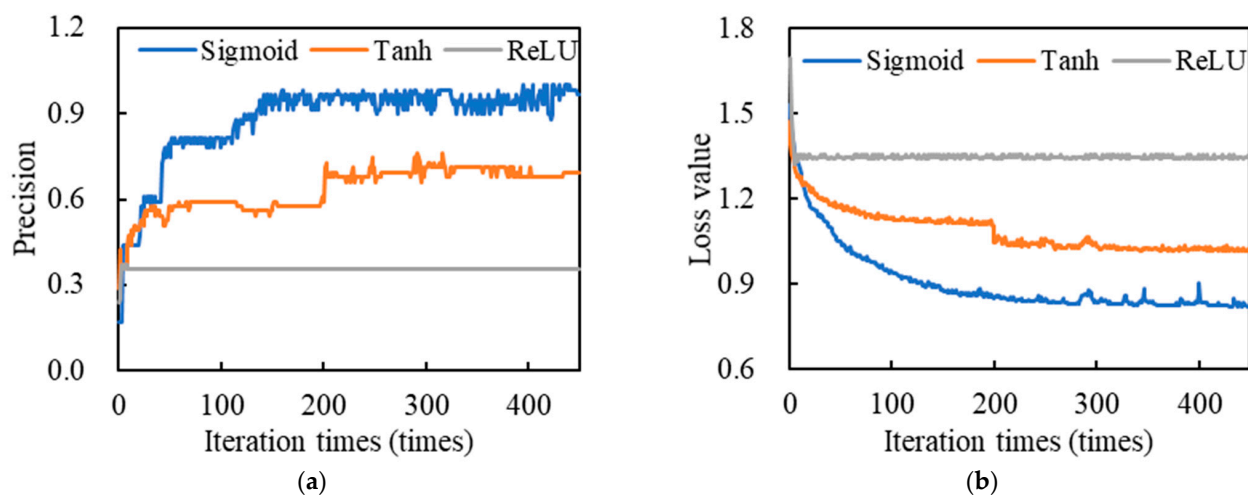


Figure 14. Results of model experiments with the Adam algorithm. (a) The precision of the Adam algorithm. (b) The loss value of the Adam algorithm.

The results from the three activation functions with different optimizer settings show that, when the activation function is the Sigmoid function and the optimizer is Adam, the classification accuracy reaches a maximum of 96.6%. It can be concluded that the Sigmoid function, with its smooth curve characteristics and good gradient propagation ability, is well-suited for handling nonlinear relationships in classification problems. The Adam optimizer, as an adaptive learning rate algorithm, adjusts the learning rate based on the gradient of the parameters, which effectively improves the training efficiency and accuracy of the model. Therefore, we chose the Sigmoid function and the Adam algorithm as the activation function and optimizer for the final classification model, respectively.

To validate the effectiveness of the method presented in this paper, the classification results of the Graph Attention Multilayer Perceptron (GMLP) are compared with the prediction results of other classification models, including Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), Adaptive Boosting (AdaBoost), and Random Forest (RF). The comparison metrics are accuracy, precision, and recall. Accuracy is the most basic evaluation metric, representing the proportion of correctly classified samples among the total number of samples. Precision refers to the proportion of true positive samples among all samples predicted as positive by the model. High precision means that most of the

samples predicted as positive by the model are indeed true positives. Recall refers to the proportion of true positive samples among all actual positive samples. High recall means that the model is able to identify most of the true positives. The comparison results are shown in Table 4.

Table 4. Comparison of discrimination results of six different methods.

Methods	Accuracy (%)	Precision (%)	Recall (%)
SVM	0.864	0.891	0.864
XGBoost	0.898	0.920	0.898
AdaBoost	0.932	0.933	0.932
RF	0.847	0.887	0.847
MLP	0.915	0.927	0.915
GMLP	0.966	0.967	0.966

From the data in Table 4, it can be seen that the GMLP method outperforms other models in four key performance indicators: accuracy, precision, recall, and F1 score. Its classification accuracy reaches as high as 96.6%, which is a 3.4% improvement over the AdaBoost algorithm. This demonstrates the efficient ability of the Graph Attention-based Multilayer Perceptron in capturing the complex relationships between reservoir attributes, enabling the model to more accurately identify and utilize the interactions between reservoirs. This proves the adaptability of the method in the reservoir combination pattern classification scenario. Furthermore, through an ablation study comparing the identification accuracy of the GMLP model with that of the standard Multilayer Perceptron (MLP) model, the contribution of the graph attention mechanism to improving the performance of the MLP model is further explored. From the comparison results, it can be observed that, after introducing the graph attention mechanism, the training accuracy of the model can reach 96.6%, while the classification training accuracy of the standard MLP algorithm only reaches 91.5%, as shown in Figure 15. It can be seen that the GMLP model not only improves identification accuracy but also accelerates the model's fitting speed during the training process. The reason for this is that the graph attention mechanism can effectively extract the attention of each feature by enhancing the main informative features and reducing the interference from irrelevant information, which accelerates the computational efficiency of the algorithm and results in high-accuracy classification.

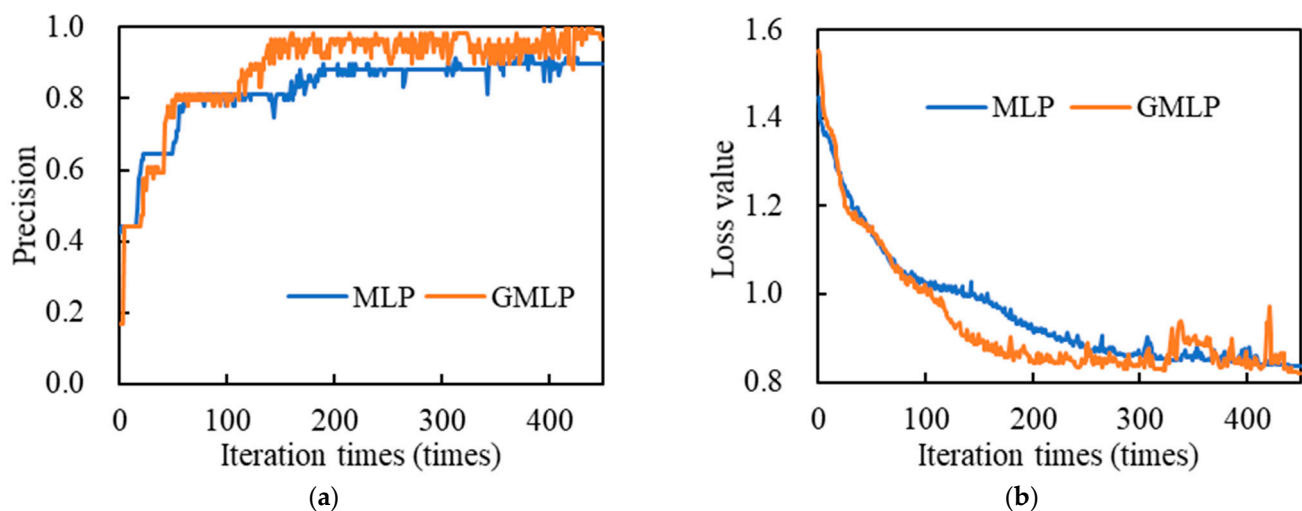


Figure 15. The comparison result of graph attentioned multi-layer perceptron model and multi-layer perceptron model. (a) The precision of MLP and GMLLP. (b) The loss value of MLP and GMLLP.

4. Productivity Evaluation for Different Reservoir Combinations

4.1. Interlayer Interference Diagnostic Plot for Different Reservoir Combinations

Nagao's indoor experimental study showed that the interlayer interference coefficient is correlated with factors such as water content and permeability grade difference [29], and established the corresponding functional relationship as follows:

$$\alpha = \frac{0.275 \left[\lambda + \sum_{i=1}^n (-1)^{i+1} f_w^i \right] \left(\ln \frac{K_{max}}{K_{min}} \right)^\omega}{[\ln(1 + K_{min})]^\gamma} \quad (10)$$

where K_{max} is the maximum permeability value among the small layers and K_{min} is the minimum permeability value among the small layers.

The permeability grade difference is replaced by the average stratigraphic coefficient grade difference between the injection and production wells in each small layer. Using multiple linear regression, the interlayer interference characteristic curves of typical wells in the four reservoir combination models are fitted, as shown in Figure 16. The correlation relationship between the interlayer interference coefficient, water content, and the average stratigraphic coefficient grade difference is as follows:

$$\alpha = \kappa \left[\lambda + f_w^3 - f_w^2 + f_w \right] \left(\frac{(\overline{KH})_{max}}{(\overline{KH})_{min}} \right)^\omega [\ln(1 + (\overline{KH})_{min})]^\gamma \quad (11)$$

where $(\overline{KH})_{max}$ is the maximum average stratigraphic coefficient value for a certain injection-production well across all small layers and $(\overline{KH})_{min}$ is the minimum average stratigraphic coefficient value for the same well. The correlation coefficients κ , λ , γ , and ω obtained through the fitting are shown in Table 5.

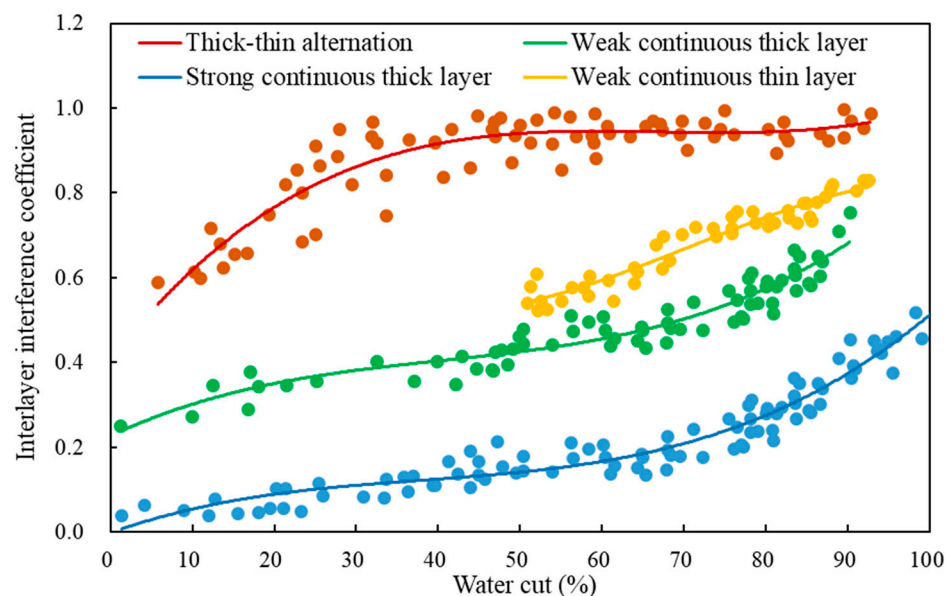
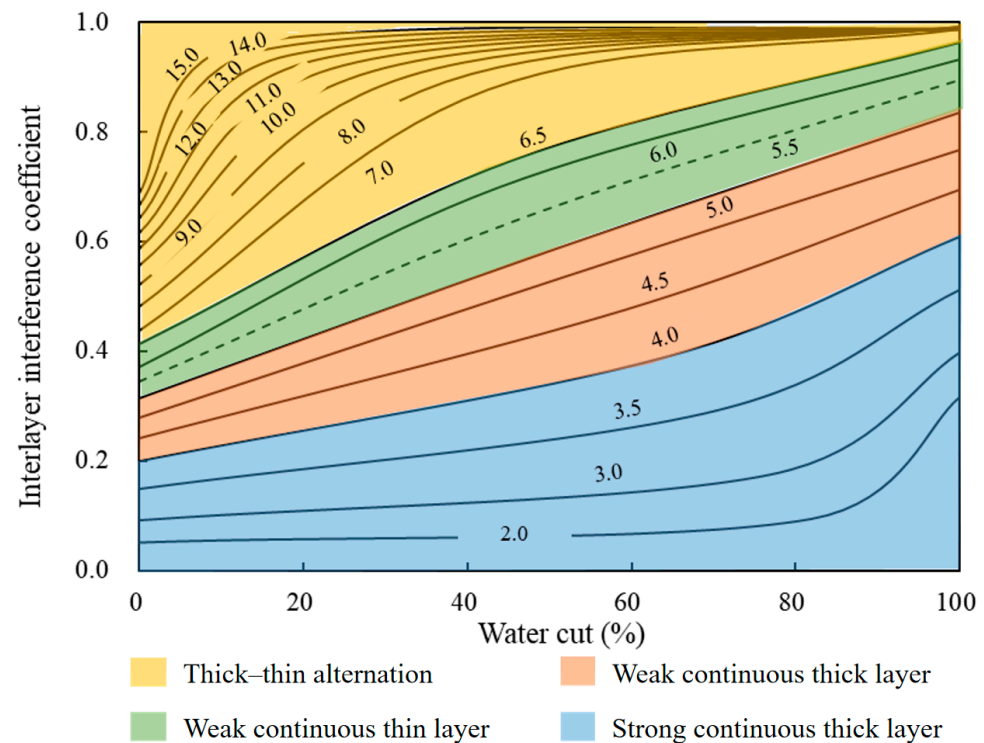


Figure 16. The matching of changes of interlayer interference coefficient with water content in typical wells with four combination patterns.

Using Equation (10), the variation pattern of the interlayer interference coefficient for typical wells is extended to different reservoir combination models. This allows for the plotting of the relationship between the interlayer interference coefficient and water content under different stratigraphic coefficient grade differences for each reservoir combination model, as shown in Figure 17.

Table 5. The correlation coefficient value of interlayer interference coefficient.

Parameter Range	κ	λ	γ	ω
$2.0 < \frac{(KH)_{max}}{(KH)_{min}} \leq 4.0$	0.21	0.47	2.07	0.74
$4.0 < \frac{(KH)_{max}}{(KH)_{min}} \leq 5.0$	0.35	0.69	0.97	0.41
$5.0 < \frac{(KH)_{max}}{(KH)_{min}} \leq 7.0$	0.35	0.69	0.97	0.41
$7.0 < \frac{(KH)_{max}}{(KH)_{min}} \leq 16.0$	0.69	2.44	0.21	0.43

**Figure 17.** Type curve of interlayer interference coefficient and water cut under different reservoir combinations.

It can be seen that the diagram is divided into four regions. In region 1, the range of stratigraphic coefficient grade differences is approximately 2.0–4.0. The main feature of this region is that, during the low-to-medium water content stage, the interlayer interference is relatively weak and changes slowly. As the water content increases and reaches the high water content stage, the interlayer interference increases significantly. This region primarily corresponds to the strong, continuous, thick-layer combination model. In region 2, the range of stratigraphic coefficient grade differences is roughly 4.0–5.0. The main feature here is that interlayer interference is observed during the no-water oil production period, and the interlayer interference coefficient gradually increases with the rising water content. The suppressive effect on production capacity continues to intensify. This region mainly corresponds to the weak continuous thick-layer combination model. In region 3, the range of stratigraphic coefficient grade differences is roughly 5.0–7.0. The main feature of this region is that the interlayer interference coefficient is slightly stronger than that of region 2. As the water content increases, the interlayer interference coefficient first rises quickly, then the rate of increase slows down. This region primarily corresponds to the weak continuous thin-layer combination model. Region 4 corresponds to the production wells in the thick–thin interactive combination model, with stratigraphic coefficient grade

differences greater than 7.0. The main feature of these production wells is that interlayer interference appears earlier, reaching a high level during the low-to-medium water content stage. Compared to other combination models, the production capacity of oil wells is significantly suppressed.

4.2. Calculation of Interlayer Interference Oil Productivity Index

From the variation pattern of the interlayer interference coefficients in different thick–thin reservoir combinations, it can be concluded that the interlayer interference coefficient is one of the key factors influencing the prediction of oil productivity index for new wells [30]. Based on the definition of the oil productivity index and the calculation formula for interlayer interference coefficient, the following oil productivity index calculation formula for offshore typical thick–thin interlayer reservoirs, considering interlayer interference, can be derived:

$$J_{\alpha o(f_w)} = \frac{Q_o}{p_e - p_{wf}} (1 - \alpha_{f_w}) = J_{o(f_w)} (1 - \alpha_{f_w}) \quad (12)$$

$$J_{\alpha o(f_w)} = J_{o(f_w=0)} \cdot J_{Do(f_w)} \times (1 - \kappa[\lambda + f_w^3 - f_w^2 + f_w] \left(\frac{(\overline{KH})_{max}}{(\overline{KH})_{min}} \right)^\omega [\ln(1 + (\overline{KH})_{min})]^\gamma) \quad (13)$$

where $J_{\alpha o(f_w)}$ represents the oil recovery index at a production water cut f_w considering interlayer interference, $J_{o(f_w)}$ represents the oil productivity index at the same water cut f_w without considering interlayer interference, and α_{f_w} represents the interlayer interference coefficient at water cut f_w . $J_{o(f_w=0)}$ represents the no-water oil productivity index, $J_{Do(f_w)}$ represents the dimensionless oil productivity index at water cut f_w .

By combining the basic parameters such as the initial water cut f_w and the stratigraphic coefficient grade difference for production wells in different reservoir combination models of the S oilfield, the following are calculated: the interlayer interference coefficient $\alpha_{(f_w=0)}$ for the no-water oil production period, the oil productivity index $J_{\alpha o(f_w)}$ at water cut f_w considering interlayer interference, and the dimensionless oil productivity index $J_{Do(f_w)}$ at water cut f_w considering interlayer interference. Additionally, by using Equation (13), the no-water oil productivity index $J_{o(f_w=0)}$ without interlayer interference is calculated, as shown in Table 6.

Table 6. Calculation parameter for oil productivity index of production wells of typical oilfield.

Composite Pattern	Thick–Thin Alternation	Weak Continuous Thin Layer	Weak Continuous Thick Layer	Strong Continuous Thick Layer
Oil well	A1	B1	C1	D1
Effective thickness (m)	100.2.	40.8	78.9	86.8
f_w (%)	80	85	80	90
Formation coefficient gradient	4.5	3.8.	3.5	2.5
α_{f_w}	0.24	0.22	0.20	0.09
$J_{Do(f_w)}$	0.29	0.25	0.29	0.19
$J_{o(f_w)}$ (m ³ /(d·MPa))	10.9	2.8	9.7	16.0
$J_{o(f_w=0)}$ (m ³ /(d·MPa))	48.7	14.4	16.0	91.4

A diagnostic plot showing the relationship between the no-water oil recovery index and the mobility coefficient, after correction for interlayer interference in the four reservoir combination models, is plotted as shown in Figure 18. After the correction for interlayer interference, the correlation between the no-water oil recovery index and the mobility coefficient for the four combination models significantly improved, with all reaching over 98%.

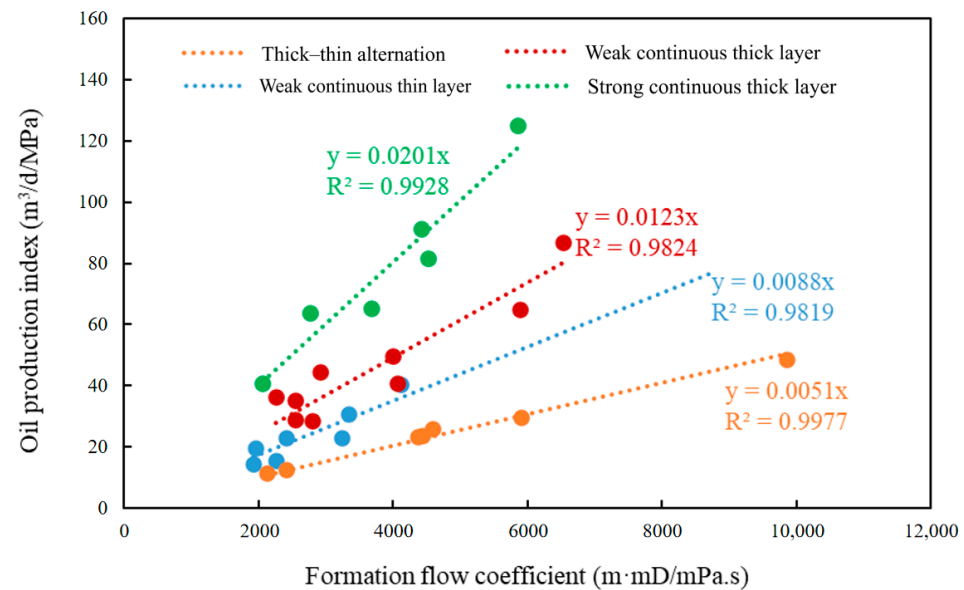


Figure 18. Diagram of the relationship between oil recovery index with no water production and flow coefficient under different reservoir combinations.

4.3. Case Application

To further verify the effectiveness of the methodology proposed in this paper, nine potential infill well locations planned for drilling in the pilot test area for infill adjustment of S Oilfield were selected for initial productivity evaluation. The basic parameters for each well are shown in Table 7.

Table 7. Basic parameters of infill well combinations in pilot block.

Oil Well	Composite Pattern	Average Permeability (mD)	Perforation Thickness (m)	Formation Factor (mD·m)	Formation Coefficient Grade Difference	Initial Water Cut (%)
P22	Weakly continuous thick Layer	1500	40	60,000	3.4	40
P42	Weakly continuous thick Layer	1000	50	50,000	3.4	40
P32	Weakly continuous thin Layer	1000	50	50,000	3.4	85
P14	Weakly continuous thick Layer	880	40	35,200	3.4	80
P13	Weakly continuous thin Layer	840	40	33,600	4	40
P15	Weakly continuous thin Layer	830	40	33,200	4	40
P16	Weakly continuous thin Layer	760	40	30,400	4	70
P18	Weakly continuous thick Layer	964	50	48,200	4	60
P19	Weakly continuous thick Layer	798	40	31,920	4	60

By classifying the reservoir combination pattern types, and referring to the relationship diagram in Figure 11 of the interlayer interference coefficient and formation coefficient level difference with water cut variation for different reservoir combination patterns, the inter-layer interference coefficient $\alpha_{(f_w=0)}$ for the no-water production period of each infill well is obtained. Combining the dimensionless oil productivity index, the oil productivity index considering interlayer interference $J_{\alpha o(f_w)}$ for the potential well group of nine infill wells is calculated using Equation (13) and compared with the field-measured oil productivity index during the initial production period, as shown in Figure 19.

As shown in Figure 16, the oil productivity index calculated using the method in this paper is similar to the field-measured oil productivity index, with an average error of 10%. The relative error is relatively large for wells P32 and P14, mainly due to the higher actual water cut at the time of production compared to the predicted value.

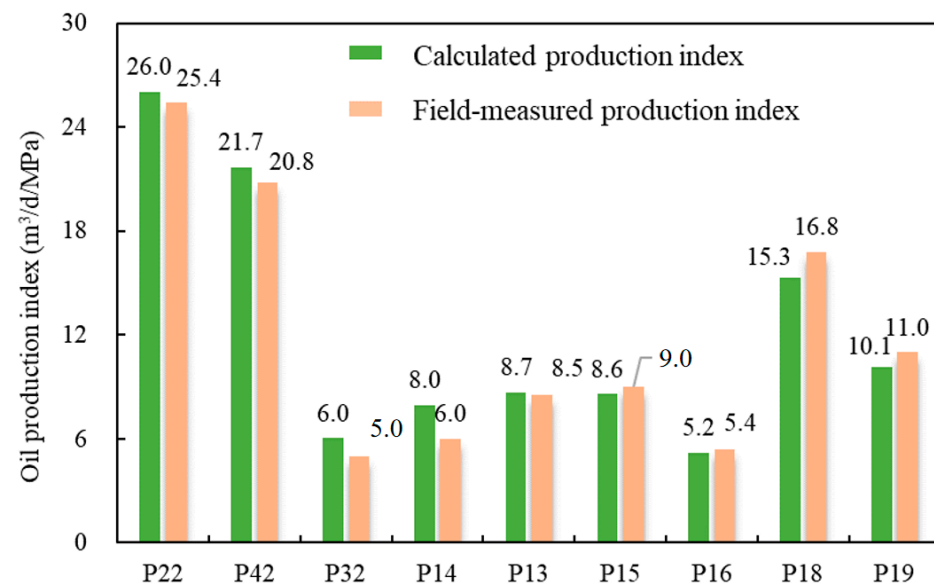


Figure 19. Comparisons of calculated production index and field-measured production index for infill wells.

5. Conclusions

- (1) Through statistical analysis of single-well sand body combination characteristics, reservoir combination modes were classified into four categories: strong continuous thick-layer combination, weak continuous thick-layer combination, thick–thin intercalated combination, and weak continuous thin-layer combination. A multi-layer artificial neural network discrimination model based on the graph attention mechanism was established, improving the classification accuracy. This study shows that the prediction accuracy of this classification method can reach 96.6%, with prediction results significantly better than other methods.
- (2) A relationship diagram of interlayer interference coefficients with water cut variation was established for different reservoir combination modes. The strong, continuous, thick-layer combination generally exhibits a relatively low degree of interference. In the weak continuous thick-layer combination, the interlayer interference coefficient increases gradually with the rise in water cut. In the weak continuous thin-layer combination, the interlayer interference coefficient increases rapidly with water cut initially, and then the increase slows down. The thick–thin intercalated combination mode exhibits a relatively high overall interlayer interference coefficient.
- (3) A method for calculating the oil production index based on different reservoir combination modes was established. The results show that the correlation between the oil production index without water cut and the flow capacity is significantly improved for different reservoir combination modes. Furthermore, in actual oilfield applications, the production capacity calculations exhibit a small deviation from the actual values.

Compared to previous studies, the core contribution of this paper lies in the efficient development potential assessment of offshore thick–thin interbedded reservoirs through a systematic classification of reservoir combination patterns and an evaluation method for productivity. Traditional reservoir classification methods mainly rely on geological statistics and empirical formulas, which struggle to effectively capture the complex heterogeneity of thick–thin interbedded reservoirs and are insufficient in characterizing dynamic production features. In contrast, this paper establishes a classification and productivity evaluation system based on reservoir combination patterns by comprehensively considering the structural characteristics of reservoirs and dynamic production data. This system can not

only accurately identify different types of reservoir combination patterns but also provide a scientific basis for dynamic reservoir development through the variation patterns of interlayer interference coefficients. Moreover, this method has demonstrated high accuracy and adaptability in practical oilfield applications.

Although the method proposed in this paper performs well in the classification and productivity evaluation of offshore thick–thin interbedded reservoirs, it is primarily applicable to offshore multi-layer sandstone reservoirs, especially those with complex, thick–thin interbedded structures. However, in carbonate reservoirs or other non-sandstone reservoirs, due to lithological differences and reservoir structural complexity, the method may require further adjustment and optimization. Future research will focus on the following aspects: (1) integrating more geological and geophysical data to enrich the model’s input features and improve prediction accuracy; (2) exploring the application of this method to other complex reservoir types, such as shale oil reservoirs and tight sandstone reservoirs, to verify its universality.

Author Contributions: Conceptualization, B.J. and S.C.; methodology, B.J.; software, Y.S. and R.D.; validation, B.J., S.C., Y.S. and R.D.; formal analysis, R.D.; investigation, B.J.; resources, S.C.; data curation, S.C.; writing—original draft preparation, B.J.; writing—review and editing, S.C.; visualization, Y.S. and R.D.; supervision, B.J.; project administration, B.J.; funding acquisition, B.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Technology Projects of China National Offshore Oil Corporation: KJGG-2024-15-0501.

Data Availability Statement: All data included in this study are available upon request by contact with the corresponding author.

Conflicts of Interest: Authors Bin Jiang and Ruikai Duan were employed by CNOOC Research Institute Co., Ltd. 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.

References

1. Li, G.; Qin, Y.; Zhang, H.; Song, X.; Wang, B.; Wang, Z.; Mi, W. Quantitative Characterization of Thin-Interbedded Coal Measure Reservoir Configurations in the Wujiu Depression, Inner Mongolia: Sedimentary Controlling Mechanisms. *Mar. Pet. Geol.* **2024**, *164*, 106852. [\[CrossRef\]](#)
2. Xie, J.; Hou, B.; He, M.; Liu, X.; Wei, J. Fracture-Controlled Fracturing Mechanism and Penetration Discrimination Criteria for Thin Sand-Mud Interbedded Reservoirs in Sulige Gas Field, Ordos Basin, China. *Pet. Explor. Dev.* **2024**, *51*, 1327–1339. [\[CrossRef\]](#)
3. Ni, C.; Su, M.; Yuan, C.; Liu, H.; Cui, X. Thin-Interbedded Reservoirs Prediction Based on Seismic Sedimentology. *Pet. Explor. Dev.* **2022**, *49*, 851–863. [\[CrossRef\]](#)
4. Wei, C.; Li, H.; Luo, H.; Li, Y.; Cheng, S. Generalized Analytical Solutions of Vertically Fractured Wells in Commingled Reservoirs: Field Case Study. *SPE J.* **2024**, *29*, 1419–1433. [\[CrossRef\]](#)
5. Shi, W.; Cheng, J.; Liu, Y.; Gao, M.; Tao, L.; Bai, J.; Zhu, Q. Pressure Transient Analysis of Horizontal Wells in Multibranch Fault-Karst Carbonate Reservoirs: Model and Application in SHB Oilfield. *J. Pet. Sci. Eng.* **2023**, *220*, 111167. [\[CrossRef\]](#)
6. Bai, W.; Cheng, S.; Wang, Y.; Cai, D.; Guo, X.; Guo, Q. A transient production prediction method for tight condensate gas wells with multiphase flow. *Pet. Explor. Dev.* **2024**, *51*, 172–179. [\[CrossRef\]](#)
7. Li, H.; Yue, D.; Zhang, X. Characteristics of pore structure and reservoir evaluation of low permeability reservoir in Sulige gas field. *Earth Sci. Front.* **2012**, *19*, 133–140.
8. Zhao, J.; Cao, G.; Wu, Y. Application of multivariate membership function for tight sandstone reservoir classification. *Nat. Gas Geosci.* **2018**, *29*, 1553–1558.
9. Wang, S.; Gao, X.; Lu, J. Heterogeneity of sandstone reservoir with alternating thin layers and oiliness distribution: A case study of K1h26 reservoir in LU9 well area. *J. Northeast. Pet. Univ.* **2016**, *40*, 26–34.
10. Yuan, W.; He, S.; Jiao, X.; Tan, W.; Yang, D. Evaluatin method for the permeabilities of low permeability and ultra-low permeability pebbly sandstone reservoirs in Beibuwan Basin. *Pet. Geol. Oilfield Dev. Daqing* **2020**, *39*, 127–134.
11. Fu, D.; Xu, J.; Wang, G. Reservoir classification and evaluation based on Q cluster analysis combined with bayesian discrimination algorithm. *Sci. Technol. Rev.* **2011**, *29*, 29–33.

12. Benham, P.; Freeman, M.; Zhang, L.; Choudhary, P.; Spring, L.; Warrlich, G.; Ahmed, K.; Shen, C.; Sanwoolu, A.; Jha, M.; et al. The function of baffles within heavy oil reservoir and their impact on field development: A case study from kuwait. In Proceedings of the SPE International Heavy Oil Conference and Exhibition, Kuwait City, Kuwait, 10–12 December 2018. [\[CrossRef\]](#)
13. Francesconi, A.; Bigoni, F.; Balossino, P.; Bona, N.; Marchini, F.; Cozzi, M. Reservoir rock types application-Kashagan. In Proceedings of the SPE/EAGE Reservoir Characterization and Simulation Conference, Abu Dhabi, United Arab Emirates, 19–21 October 2009. [\[CrossRef\]](#)
14. Manzoor, U.; Ehsan, M.; Radwan, A.; Hussain, M.; Iftikhar, M.; Arshad, F. Seismic Driven Reservoir Classification Using Advanced Machine Learning Algorithms: A Case Study from the Lower Ranikot/Khadro Sandstone Gas Reservoir, Kirthar Fold Belt, Lower Indus Basin, Pakistan. *Geoenergy Sci. Eng.* **2023**, *222*, 211451. [\[CrossRef\]](#)
15. Özdoğan-Sarıkoç, G.; Sarıkoç, M.; Celik, M.; Dadaser-Celik, F. Reservoir Volume Forecasting Using Artificial Intelligence-Based Models: Artificial Neural Networks, Support Vector Regression, and Long Short-Term Memory. *J. Hydrol.* **2023**, *616*, 128766. [\[CrossRef\]](#)
16. Asedegbega, J.; Ayinde, O.; Nwakanma, A. Application of Machine Learning For Reservoir Facies Classification in Port Field, Offshore Niger Delta. In Proceedings of the Nigeria Annual International Conference and Exhibition, Lagos, Nigeria, 2–4 August 2021. [\[CrossRef\]](#)
17. Bellal, A.; Khetib, Y. Prediction of Discrete and Continuous Wellbore Logs Values Using Artificial Neural Network, Decision Trees and Support Vectors Machine Algorithms. In Proceedings of the 56th US Rock Mechanics/Geomechanics Symposium, Santa Fe, NM, USA, 26–29 June 2022. [\[CrossRef\]](#)
18. Katterbauer, K.; Marsala, A.; Zhang, Y.; Hoteit, I. Artificial Intelligence Aided Geologic Facies Classification in Complex Carbonate Reservoirs. In Proceedings of the SPE Middle East Oil & Gas Show and Conference, Manama, Bahrain, 28 November–1 December 2021. [\[CrossRef\]](#)
19. Ma, Z.; Ou, X.; Zhang, B. Development of a Convolutional Neural Network Based Geomechanical Upscaling Technique for Heterogeneous Geological Reservoir. *J. Rock Mech. Geotech. Eng.* **2024**, *16*, 2111–2125. [\[CrossRef\]](#)
20. Bai, W.; Cheng, S.; Guo, X.; Wang, Y.; Guo, Q.; Tan, C. Oilfield Analogy and Productivity Prediction Based on Machine Learning: Field Cases in PL Oilfield, China. *Pet. Sci.* **2024**, *21*, 2554–2570. [\[CrossRef\]](#)
21. Wang, J.; Feng, G.; Wang, X. Evaluation method and application of glutenite reservoir in steep slope zone of lacustrine basin in Dongying depression—By taking E2s41 in LA block as an example. *Pet. Geol. Eng.* **2022**, *36*, 61–68.
22. Lv, L.; Wang, X.; Dong, J.; Yu, W.; Liu, Y. MLP neural network-based carbonate seam-hole reservoir type classification and application—An example from the Cretaceous Mishrif Formation of the M oilfield, Iraq. The Second Annual Meeting of Petroleum Geophysics in China. In *Petroleum Geophysicists Society of the Chinese Petroleum Society*; Geophysical Research Institute of BGP Inc.: Hebei, China; CNPC: Hong Kong, 2024; Volume 5.
23. Rahimi, M.; Riahi, M.A. Reservoir Facies Classification Based on Random Forest and Geostatistics Methods in an Offshore Oilfield. *J. Appl. Geophys.* **2022**, *201*, 104640. [\[CrossRef\]](#)
24. Koray, A.-M.; Bui, D.; Kubi, E.A.; Ampomah, W.; Amosu, A. Machine Learning Based Reservoir Characterization and Numerical Modeling from Integrated Well Log and Core Data. *Geoenergy Sci. Eng.* **2024**, *243*, 213296. [\[CrossRef\]](#)
25. Nie, Y.; Xian, C.; Luo, J.; Zhang, J.; Wang, Y.; Li, C. Bagging Machine Learning Algorithms for Rapid Identification, Classification, Evaluation and Upscaling in Unconventional Reservoir. *Geoenergy Sci. Eng.* **2025**, *246*, 213545. [\[CrossRef\]](#)
26. Qiao, Y.; Luo, Y.; Shang, X.; Zhou, L. An Efficient Drilling Conditions Classification Method Utilizing Encoder and Improved Graph Attention Networks. *Geoenergy Sci. Eng.* **2024**, *233*, 212578. [\[CrossRef\]](#)
27. Taud, H.; Mas, J. Multilayer perceptron (MLP). In *Geomatic Approaches for Modeling Land Change Scenarios*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 451–455. [\[CrossRef\]](#)
28. Velickovic, P.; Cucurull, G.; Casanova, A.; Romero, A.; Lio, P.; Bengio, Y. Graph attention networks. *Stat* **2017**, *1050*, 10–48550. [\[CrossRef\]](#)
29. Nagao, M.; Datta-Gupta, A.; Onishi, T.; Sankaran, S. Reservoir connectivity identification and robust production forecasting using physics informed machine learning. In Proceedings of the SPE Reservoir Simulation Conference, Galveston, TX, USA, 28–30 March 2023. [\[CrossRef\]](#)
30. Ore, T.; Davudov, D.; Malkov, A.; Venkatraman, A.; Al-Aulaqi, T.; Singh, G.; Dindoruk, B.; Djanuar, Y.; Huang, Q.; Adnan, I.; et al. A Comprehensive Analysis of Data Driven Techniques to Quantify Injector Producer Relationships. In Proceedings of the Gas & Oil Technology Showcase and Conference, Dubai, United Arab Emirates, 13–15 March 2023. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.