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Single Well Productivity Prediction Model for Fracture-Vuggy Reservoir Based on Selected Seismic Attributes

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Abstract: Single well productivity is an important index of oilfield production planning and economic evaluation. Due to fracture-vuggy reservoirs being characteristically strongly heterogeneous and having complex fluid distribution, the commonly used single well productivity prediction methods for fracture-vuggy reservoirs have many problems, such as difficulty in obtaining reservoir parameters and producing large errors in the forecast values of single well productivity. In this paper, based on the triple medium model, the Laplace transform and Duhamel principle are used to obtain the productivity equation of a single well in a fracture-vuggy reservoir. Secondly, the seismic attributes affecting the productivity of a single well are selected using the Spearman and Pearson correlation index calculation method. Finally, the selected seismic attributes are introduced into the productivity equation of the triple medium model through the interporosity flow coefficient and the elastic storativity ratio, and the undetermined coefficients under different karst backgrounds are determined using multiple nonlinear regression. From these, a new method for predicting single well productivity of fracture-vuggy reservoir is established. In order to verify the feasibility of the new method, based on the actual production data of a fracture-vuggy reservoir in Xinjiang, the new single well productivity prediction method is used to predict the productivity of 134 oil wells. The results show that the new productivity prediction method not only reduces calculation workload, but also improves the accuracy of productivity prediction, which contributes to a good foundation for future oilfield development.

Keywords: single well productivity prediction; fracture–vuggy reservoir; triple medium model; three-dimensional seismic attribute; multivariate nonlinear regression

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1. Introduction

Carbonate oil–gas fields account for more than 50% of the world's total oil and gas reserves, and carbonate oil and gas production account for more than 60% of the world's total oil and gas production. Therefore, carbonate oil–gas fields are a primary area of research [1,2]. China's Xinjiang oil field is a typical fracture-vuggy carbonate reservoir, located in the Kuche and Luntai counties of the Xinjiang Uygur Autonomous Region. It is the largest oil field in the Tarim Basin, and its main exploration and development strata are Ordovician fracture-vuggy carbonate reservoirs [3,4]. Fracture-vuggy carbonate reservoirs are characterized by extremely complex, porous caverns and fracture structures, large scale differences, and serious heterogeneity in the reservoir space [5–7]. Relying on traditional methods of reservoir productivity prediction, when a single well productivity prediction is carried out for a carbonate reservoir, the resulting prediction produces significant error.

There are a number of commonly used prediction methods for single well productivity in fracture-vuggy carbonate reservoirs. One, machine learning, mainly utilizes support vector machines and neural networks, etc. This approach is based on learning the underlying patterns between an individual well's productivity and its influencing factors, utilizing them to predict and judge unknown sample points, and in turn predict the well's productivity [8–12]. A second is the discrete medium numerical simulation method; this model can accurately describe the connectivity of karst caves and fractures and the flow law of fluid in various flow channels [13]. However, discrete media numerical simulation has strict requirements with respect to computer hardware and numerical simulation technology, leaving it unsuitable for large scale use in oil fields [14–19]. A third method, equivalent continuum numerical simulation, is based on continuum theory. The fractured reservoir is simulated as anisotropic equivalent continuum with symmetric permeability tensor [20–22]. However, this method is not applicable to all fracture-vuggy reservoirs, and the equivalent continuum model cannot accurately describe the local seepage characteristics of fractures and caves, nor accurately reflect the real state of water drive in reservoirs [23]. All of the above methods are based on reservoir-related parameters such as permeability, porosity, capillary pressure, and relative permeability curves. The accuracy of productivity prediction depends on the accuracy of these parameters. However, there are certain errors in the acquisition of relevant parameters for fracture-vuggy reservoirs, which lead to large errors in the calculated results of such methods. Allen G. Hunt et al. [24] proposed a prediction model to describe the seepage in porous media, and Eric J R Parteli et al. [25] presented a self-organized model for the growth of two- and three-dimensional percolation clusters in multi-layered structures.

In this paper, a new method of single well productivity prediction, based on its seismic attributes, is proposed for the first time. In the high precision, three-dimensional seismic exploration of fracture-vuggy carbonate reservoirs, there are a lot of "beaded" seismic reflection waves. According to previous drilling data from the Xinjiang oilfield, there are also a lot of beaded seismic responses deep in the middle of such fields. The high precision 3D seismic reflection of earthquakes can be divided into beaded reflection, disordered strong reflection, flake reflection and weak reflection. Of these, beaded reflection is the strongest in terms of reflected energy and amplitude, and it characteristically has a small lateral extension range and large difference in vertical distribution. Beaded reflections occur when the properties of rock inside a reservoir (containing large amounts of oil and gas, large karst caves, and substantial porosity) differ significantly from those of surrounding rock. This variable density in seismic profile appears as a red and black beaded or granular shape [26]. The locations of high-producing wells in fracture-vuggy carbonate reservoirs are correspondent with "beaded-reflection" in seismic attribute [27], so "beaded—reflection" is an important reference for selecting well locations in fracture-vuggy carbonate reservoirs [28]. Although high precision 3D seismic methods can determine such well locations, it cannot predict the productivity of a single well. If a correlation formula interrelating the 3D seismic attributes and the productivity of a single well were established, prediction accuracy of the productivity of a single well would be greatly improved.

With respect to circumstances such as those shown in Figure 1 and based on the triple medium model proposed by Wu Yushu et al. [29], the productivity equation of a single well for prediction in fracture-vuggy reservoirs was obtained by using the Laplace transform and the Duhamel principle. Then, the Spearman and Pearson correlation index calculation methods were used to select the seismic attributes that effect the productivity of a single well; the selected seismic attributes were introduced to the productivity equation for triple media by the interporosity flow coefficient and the elastic storativity ratio. Multivariate nonlinear regression was used to determine the undetermined coefficients under different karst background conditions, establishing a new method for predicting single well productivity in fracture-vuggy reservoirs. Finally, multiple linear regression and BP neural networks, support vector machines (SVM), and similar methods are compared with the proposed new productivity calculation method; the results show that the proposed method can more accurately predict single well productivity, and is thus better suited to carbonate reservoir development, providing cost-effective technical support for planning future oilfield development.

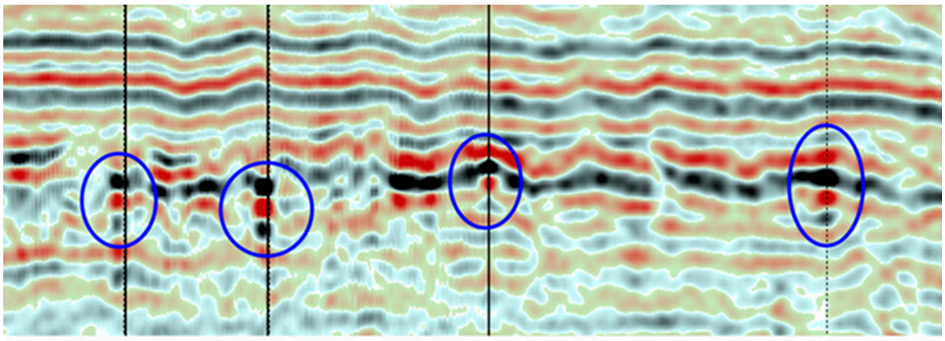

Figure 1. Beaded reflection.

2. Construction of Productivity Prediction Model for Fracture-Vuggy Reservoir

The triple medium model mainly includes karst caves, fractures, and bedrocks, as shown in Figure 2. The presuppositions and conditions of the fracture-vuggy reservoir productivity prediction model are as follows:

(1) The reservoir is infinitely homogeneous and has isotropic permeability;
(2) The well is produced at constant pressure;
(3) The reservoir fluid is single phase;
(4) The seepage law satisfies Darcy's law and the compressibility coefficient is constant.

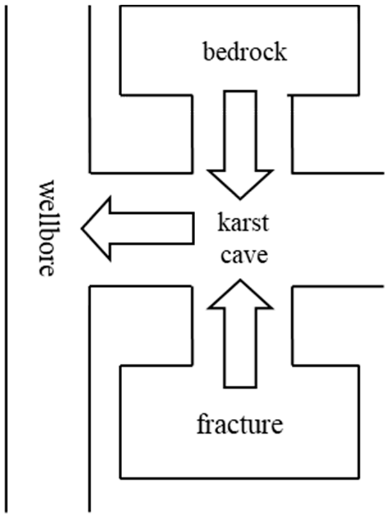

Figure 2. Triple medium reservoir model.

The triple medium mathematical model was established on the basis of fractured-vuggy reservoir proposed by Wu Yushu et al. [29]. The governing equations of the three seepage media are as follows:

$$\text{fracturesystem: } \frac{K_3}{\mu}\nabla^2 p_3 = \phi_3 C_3 \frac{\partial p_3}{\partial t} + q_1^* + q_2^* \tag{1}$$

$$\text{bedrocksystem: } \frac{K_1}{\mu}\nabla^2 p_1 = \phi_1 C_1 \frac{\partial p_1}{\partial t} - q_1^* \tag{2}$$

$$\text{Karstcavesystem: } \frac{K_2}{\mu}\nabla^2 p_2 = \phi_2 C_2 \frac{\partial p_2}{\partial t} - q_2^* \tag{3}$$

We define a dimensionless variable:

$$r_D = \frac{r}{r_w}; t_D = -\frac{K_3 t}{\mu r_w^2(\phi_3 C_3 + \phi_1 C_1 + \phi_2 C_2)}$$

$$p_{Dj}(r_D, t_D) = \frac{2\pi K_3 h}{\mu}[p_i - p_j(r,t)](j = 1,2,3)$$

In the formula:

t_D − dimensionless time; p_{Dj} − dimensionless pressure;
p_i − initial formation pressure, MPa; q_j − inter − porosity flow factor;
$P_j(r,t)$ − instantaneous formation pressure, MPa;
r_D − dimensionless radius;
K_j − permeability, μm^2; ϕ − porosity; μ − fluidviscosity, MPa•s;
r_w − wellboreradius, m; h − reservoirthickness, m; ω_j − elasticstorativityratio.

When the stratum is infinite, the Laplace transformation of t_D is simplified as follows:

$$\frac{\partial^2 \overline{P}_{D3}}{\partial r_D^2} + \frac{1}{r_D}\frac{\partial \overline{P}_{D3}}{\partial r_D} - \left[\frac{\omega_1 s \lambda_1}{\omega_1 s + \lambda_1} + \frac{\omega_2 s \lambda_2}{\omega_2 s + \lambda_2} + (1-\omega_1-\omega_2)s\right]\overline{P}_{D3} = 0 \tag{4}$$

At the bottom of the well (r_D = 1), when s is small, the solution is asymptotic when t_D is large (t_D > 50):

$$p_{D3}(1, t_D) = \frac{1}{2}[\{\ln t_D + Ei(-\xi_1 t_D) + Ei(-\xi_2 t_D) - Ei(-\delta_1 t_D) - Ei(-\delta_2 t_D) + 0.809\}] \tag{5}$$

According to Duhamel's principle, the product of the production solution under constant pressure and the pressure solution under constant pressure is:

$$\widetilde{q}_D = \frac{\sqrt{sf(s)}K_1\left[\sqrt{sf(s)}\right]}{sK_0\left[\sqrt{sf(s)}\right]} \tag{6}$$

simplified as

$$\widetilde{q}_D = \frac{\sqrt{sf(s)}K_1}{sK_0} \tag{7}$$

When s is very small, the equation of the relationship between the production and the elastic storativity ratio of fractures and karst cave and the interporosity flow coefficient are obtained:

$$\widetilde{q}_D = -\left\{ s\ln\left[\sqrt{s\frac{(1-\omega_1-\omega_2)\left(s+\left(\frac{1}{2(1-\omega_1-\omega_2)}\left[\left(\frac{\lambda_2}{\omega_2}(1-\omega_1)+\frac{\lambda_1}{\omega_1}(1-\omega_2)\right)-\sqrt{\left(\frac{\lambda_2}{\omega_2}(1-\omega_1)+\frac{\lambda_1}{\omega_1}(1-\omega_2)\right)^2-4(1-\omega_1-\omega_2)\left(\frac{\lambda_1\lambda_2}{\omega_1\omega_2}\right)}\right]\right)\right)}{(s+\frac{\lambda_1}{\omega_1})}} \sqrt{\frac{\left(\left(s+\left(\frac{1}{2(1-\omega_1-\omega_2)}\left[\left(\frac{\lambda_2}{\omega_2}(1-\omega_1)+\frac{\lambda_1}{\omega_1}(1-\omega_2)\right)+\sqrt{\left(\frac{\lambda_2}{\omega_2}(1-\omega_1)+\frac{\lambda_1}{\omega_1}(1-\omega_2)\right)^2-4(1-\omega_1-\omega_2)\left(\frac{\lambda_1\lambda_2}{\omega_1\omega_2}\right)}\right]\right)\right)\right)}{(s+\frac{\lambda_2}{\omega_2})}}\right] + 0.5772 - \ln 2\right\}^{-1} \tag{8}$$

S is the complex variable of Laplace in the formula

$$f(s) = a(s+\xi_1)(s+\xi_2)/[(s+\delta_1)(s+\delta_2)]$$

$$a = 1 - \omega_1 - \omega_2; b = \frac{\lambda_2}{\omega_2}(1 - \omega_1) + \frac{\lambda_1}{\omega_1}(1 - \omega_2); c = \lambda_1\lambda_2/\omega_1\omega_2$$

$$\xi_j = \frac{1}{2a}\left[b + (-1)^j \sqrt{b^2 - 4ac}\right]; \delta_j = \lambda_j/\omega_j (j = 1, 2)$$

The elastic storativity ratio of the cave is ω_1, and the interporosity flow coefficient is λ_1. The elastic storativity ratio of the fracture is ω_2, and the interporosity flow coefficient is λ_2. Elastic storativity ratio and interporosity flow coefficient are two important variables in the productivity equations of fracture-vuggy reservoirs; in this paper, the seismic attribute is introduced into the productivity equation of fracture-cavity reservoirs by establishing the functional relationship between the seismic attribute, elastic storativity ratio and interporosity flow coefficient. Assuming:

$$\omega_1 = a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \tag{9}$$

$$\omega_2 = b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \tag{10}$$

$$\lambda_1 = c_1 x_1 + c_2 x_2 + \cdots + c_n x_n \tag{11}$$

$$\lambda_2 = d_1 x_1 + d_2 x_2 + \cdots + d_n x_n \tag{12}$$

In the formula: $x_1, x_2 \ldots x_n$ is the preferred seismic attribute, and $a_1, a_2 \ldots a_\mathrm{n}, b_1, b_2 \ldots b_n, c_1, c_2 \ldots c_n, d_1, d_2 \ldots d_n$ is the undetermined coefficient in the equation. Substituting the four hypothesized Equations (9)–(12) into Equation (8), the productivity evaluation equation of fracture-vuggy reservoir is obtained: $q = f\ (x_1, x_2 \ldots x_n, a_1, a_2 \ldots a_n, b_1, b_2 \ldots b_n, c_1, c_2 \ldots c_n, d_1, d_2, \ldots d_n)$.

3. Productivity Prediction Method for a Single Well

With respect to differences in a reservoir's geological background, the Xinjiang oil field can be divided into four areas: fault area, Ming river area, under river area, and complex karst area. Because the main controlling factors for different geological backgrounds differ, seismic attributes also differ when predicting the productivity of a single well in its respective area. In order to optimize the seismic attributes suitable for each area, we adopt a statistical correlation coefficient method in this paper. The Pearson product moment correlation coefficient, sometimes referred to as PMCC, is used to measure the correlation between two variables, X and Y, and its value range is [−1, +1]. The Spearman correlation coefficient, often expressed by the Greek letter ρ, uses the monotone equation to evaluate the correlation between two statistical variables. When there are no duplicate values in the data and both variables are completely monotonically correlated, the Spearman correlation coefficient is +1 or −1.

The main seismic attributes that affect the productivity of a single well are: distance, RMS, frequency attenuation percentage, beading area, frequency attenuation coefficient, sweet spot minimum, and sweet spot maximum. Spearman correlation coefficient calculations and Pearson correlation coefficient calculations were used to analyze the degree of influence from seismic attributes on oil well productivity. In this paper, the data of 134 oil wells were statistically analyzed, and the correlation between seismic attributes and oil well productivity was analyzed. Finally, the three seismic attributes with the strongest correlation to the fault, Ming river, under river, and complex karst areas were selected as the seismic attributes of the prediction method established in this paper.

The Pearson and Spearman methods were used to analyze the correlation between dynamic data and seismic parameters of four regions of the Xinjiang oil field, and the results, shown in Table 1, were obtained. In Table 1, the closer the absolute value of the correlation coefficient is to one, the stronger is the correlation between the two.

Table 1. Correlation analysis table of seismic attributes and dynamic data.

Individual Well Producing Rate	Correlation Coefficient	X_1	X_2	X_3	X_4	X_5	X_6	X_7
fault area	Pearson	−0.401	−0.095	−0.064	0.718	0.692	0.294	−0.222
	Spearman	−0.473	−0.132	0.037	0.676	0.475	0.434	−0.278
under river area	Pearson	−0.11	0.116	−0.247	0.875	0.853	0.815	0.012
	Spearman	−0.113	0.139	−0.167	0.725	0.743	0.745	0.001
Ming river area	Pearson	−0.11	0.116	−0.247	0.875	0.853	0.815	0.012
	Spearman	−0.113	0.139	−0.167	0.725	0.743	0.745	0.001
complex karst area	Pearson	−0.38	0.805	0.75	0.829	0.527	−0.354	0.000
	Spearman	−0.411	0.791	0.612	0.737	0.237	−0.335	0.000

According to Table 2, the distance, the bead area, and the frequency attenuation coefficient were selected as the seismic attribute parameters to predict the production of a single well in the fault area. The bead area, frequency attenuation coefficient, and sweet spot minimum were selected as the seismic attribute parameters to predict the production of a single well in both the under river and Ming areas. Frequency attenuation percentage, bead area and frequency attenuation coefficient were selected as the seismic attribute parameters to predict the production a of single well in the complex karst area.

Table 2. Seismic attribute corresponding table.

fault area	X_1	distance	Ming river area	X_1	distance
	X_2	RMS		X_2	RMS
	X_3	frequency attenuation coefficient		X_3	Frequency attenuation coefficient
	X_4	beaded area		X_4	beaded area
	X_5	rate of amplitude change		X_5	rate of amplitude change
	X_6	sweet spot minimum		X_6	sweet spot minimum
	X_7	sweet spot maximum		X_7	sweet spot maximum
under river area	X_1	distance	complex karst area	X_1	RMS
	X_2	RMS		X_2	frequency attenuation coefficient
	X_3	frequency attenuation coefficient		X_3	beaded area
	X_4	beaded area		X_4	rate of amplitude change
	X_5	rate of amplitude change		X_5	sweet spot minimum
	X_6	sweet spot minimum		X_6	sweet spot maximum
	X_7	sweet spot maximum			

In order to verify the accuracy of the new single well productivity prediction model, 134 oil wells in the Xinjiang oilfield were forecasted. Table 3 shows the regression results of the undetermined coefficients of the nonlinear equation of single well productivity in the fault area, the under river area, the Ming river area and the complex karst area. The results obtained from the new well productivity prediction equation were compared with actual production data. As can be seen in Figure 3, the prediction data of 33 sampled wells selected from the fault area were 85% accurate compared with actual field data; 48 sampled wells selected from the under river area were 87% accurate in comparison; 23 sampled wells selected from the Ming river area were 80% accurate in comparison; 30 sampled wells selected from the complex karst area were 80% accurate in comparison.

Table 3. Production calculation results.

Area	Parameter	Estimated Value	Parameter	Estimated Value
fault area	a1	−2.50015	c1	1.090775
	a2	−13.2065	c2	−1.92896
	a3	20.33426	c3	−85.7551
	b1	0.047811	d1	−0.00572
	b2	0.060151	d2	−0.00717
	b3	0.008436	d3	−0.00086
under river area	a1	−2.50015	c1	1.0907751
	a2	−13.2065	c2	−1.928956
	a3	20.33426	c3	−85.75511
	b1	0.047811	d1	−0.005718
	b2	0.060151	d2	−0.007175
	b3	0.008436	d3	−0.000859
Ming river area	a1	3.29385	c1	59.76628
	a2	−0.05509	c2	3.13136
	a3	−3.80572	c3	5.747533
	b1	3.732016	d1	−0.75274
	b2	1.359635	d2	−0.19553
	b3	−2.70759	d3	0.55742
complex karst area	a1	3.29385	c1	59.76628
	a2	−0.05509	c2	3.13136
	a3	−3.80572	c3	5.747533
	b1	3.732016	d1	−0.75274
	b2	1.359635	d2	−0.19553
	b3	−2.70759	d3	0.55742

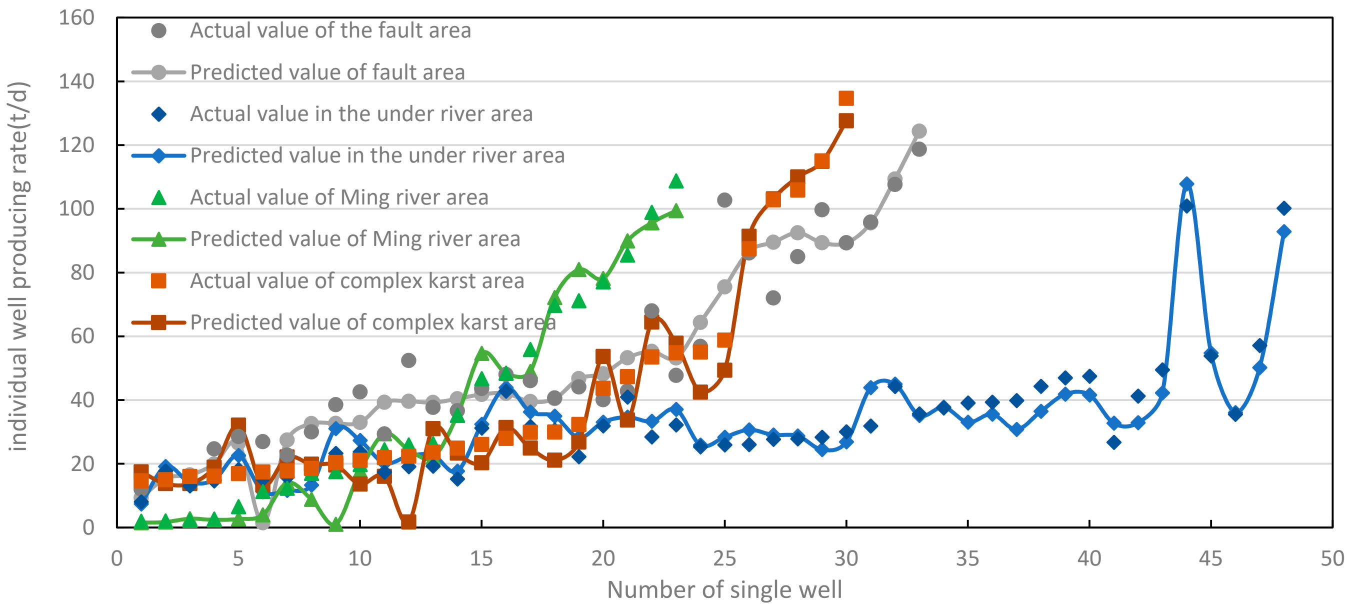

Figure 3. Comparison chart of production forecast.

4. Comparison with Other Methods

In this paper, three of the most commonly used methods were selected from the many methods of single well productivity prediction. First, multiple linear regression, that is, multiple influencing factors as independent variables for the linear representation of the dependent variable; second, nonlinear regression using BP neural networks that include an input layer, a hidden layer, and an output layer in which the upper and lower layers are fully connected and there is no connection between nodes in each layer [30]; third, support vector machines, which are based on statistical learning theory and seek the best trade-off between the complexity and learning ability of the model, based on limited sample information, in order to achieve the best promotion ability [31].

Modelled against actual data from the Xinjiang oilfield, when these three main methods (multiple linear regression, BP neural networks, support vector machines) were used to predict the productivity of a single well and their results were compared with the proposed new method of single well productivity prediction, it was apparent that the new method achieved the highest accuracy and widest application scope among the the Xianjiang oilfield's four areas (see Table 4).

Table 4. Comparison of various methods.

Oil Region		Precision	Oil Region		Precision
fault area	multiple linear regression	78.05%	under river area	multiple linear regression	69.17%
	BP neural network	62%		BP neural network	70.95%
	support vector machine	72.25%		support vector machine	82.46%
	multivariate nonlinear regression	85%		multivariate nonlinear regression	87%
Ming river area	multiple linear regression	75.57%	complex karst area	multiple linear regression	73.78%
	BP neural network	75.57%		BP neural network	71.08%
	support vector machine	72%		support vector machine	77.50%
	multivariate nonlinear regression	80%		multivariate nonlinear regression	80%

5. Conclusions

(1) In this paper, a new method for predicting single well productivity of fracture-vuggy reservoirs based on optimized seismic attributes was established by using multivariate nonlinear regression based upon the triple medium model.

(2) In this paper, the Spearman correlation index calculation method and the Pearson correlation index calculation method were used to screen seismic attributes of four reservoir areas in the Xinjiang oilfield, and three seismic attributes with the greatest influence on the productivity of a single well were selected from each area.

(3) In this paper, a new single well productivity prediction method was used to predict the productivity of 134 oil wells. Compared with actual production data, the fitting accuracy reached greater than 80%. Thus, it was shown that this new method of single well productivity prediction has higher fitting accuracy, reinforcing technical support for single well productivity prediction.

(4) The results of the new single well productivity prediction method were compared with those of similar methods, such as multiple linear regression, BP neural networks, and support vector machines. The results showed that the fitting accuracy of these other methods is weaker, with most failing to reach 80%. It was shown that the productivity prediction method proposed in this paper can more accurately predict the productivity of a single well and so contribute to a solid foundation for the planning future oilfield development.

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