Petroleum Science and Engineering
2022; 6(1): 38-46
http://www.sciencepublishinggroup.com/j/pse
doi: 10.11648/j.pse.20220601.14
ISSN: 2640-4486 (Print); ISSN: 2640-4516 (Online)

Main Controlling Factors of the Flowback Effect for Volumetric Fracturing Horizontal Wells in Shale Oil Reservoir

Meng Feng[1], Weihong Xu[1], Hui Liu[1], Yu Liu[1], Zhihao Jiang[2], Feipeng Wu[2]

[1]Well Testing Company of XDEC CPTEX, Well Testing Technical Center, Karamay, China
[2]School of Petroleum Engineering, China University of Petroleum (East China), Qingdao, China

Email address:
2718628636@qq.com (Zhihao Jiang)

To cite this article:
Meng Feng, Weihong Xu, Hui Liu, Yu Liu, Zhihao Jiang, Feipeng Wu. Main Controlling Factors of the Flowback Effect for Volumetric Fracturing Horizontal Wells in Shale Oil Reservoir. *Petroleum Science and Engineering*. Vol. 6, No. 1, 2022, pp. 38-46.
doi: 10.11648/j.pse.20220601.14

Received: April 15, 2022; **Accepted**: May 5, 2022; **Published**: May 12, 2022

Abstract: The flowback system after fracturing is a key factor affecting the development effect of shale oil horizontal wells. This paper systematically analyzes the actual data of post-fracturing productivity in the study area, and preliminarily evaluates the main controlling factors and sensitivities that affect the development effect. By means of the reservoir numerical simulation method, the mining field data is fitted, and then the influence rule of the main control factors selected by the systematic simulation calculation on the development effect is calculated. Developed a data mining optimization model for the volume fracturing flowback system in shale oil horizontal wells, and carried out the main controlling factors and sensitivity evaluations that affect the production effect. The results show that the fitting accuracy of the fracturing flowback effect evaluation and prediction model formed in this paper to the actual data of the target area can reach more than 89%; The sensitivity of the main controlling factors affecting the post-fracturing productivity in the study area are: fracturing construction parameters, compressibility parameters, flowback system and geological factors; among them, there is an obvious positive correlation trend between productivity, flowback time and flowback amount, and the cumulative flowback volume has the greatest influence on the flowback system of oil well productivity. The optimization method based on data mining can better guide the optimal design of the fracturing flowback system for shale oil horizontal wells in the target area, and provide support for improving the fracturing production effect of shale oil horizontal wells in the target area.

Keywords: Shale Oil, Horizontal Well Volume Fracturing, Optimization of Flowback System, Data Mining Method

1. Introduction

At present, unconventional reservoirs represented by shale oil and gas have gradually become the focuses of exploration and development [1-4]. Due to the harsh reservoir conditions of shale oil, large-scale volume fracturing is generally used for development. In the process of development, there are great differences in oil production of single wells, and the main control factors of production capacity in the early stage of production are unknown. Therefore, the analysis of production influencing factors after volume fracturing and the establishment of drainage and production system optimization model are very important to improve the benefits of shale oil development [5-8].

At present, the domestic research on the optimization of flowback system of shale oil volume fracturing horizontal wells is in the preliminary stage. With the breakthrough of understanding and the need for concept innovation, some experts and scholars have gradually carried out relevant research and achieved a series of useful understanding. Liu Gang [9] and others explored and optimized the well-plugging control and drainage system after fracturing for Gulong shale oil in Songliao Basin, and initially formed the optimization method of well plugging time after fracturing for Gulong shale oil. Based on the flowback optimization scheme in the formation stage of deep shale horizontal wells, Du Yang [10] and others established the guidance chart of post fracturing production, which has good guiding significance for guiding the post fracturing production management and drainage production technology of deep shale gas wells. Gao Zhanwu [11] and others carried out the improved stress sensitivity experiment, defined the permeability change law of shale reservoir in Chang 7 member of Ordos Basin under the action of stress sensitivity, and optimized the reasonable flowback intensity and flowback time of horizontal wells. It can be found that the optimization of shale oil flowback system is very important to fully release the productivity of shale oil horizontal wells, and a large number of relevant studies focusing on the impact of flowback system on development effect are relatively rich. However, with the deepening of research, it is increasingly recognized that there are many factors affecting the productivity of shale oil wells, including geological conditions, fracturing technology and well bore characteristics, which have a great impact, that is, the optimization of shale oil horizontal flowback system cannot be analyzed as an isolated factor, and the relationship between various influencing factors should be deeply analyzed to fully consider the correlation between factors; At the same time, most of the current studies focus on the control measures and optimization design methods in the process of drainage after fracturing in specific regional reservoirs, which have not yet formed a mature and widely used theory and application system, and the mine application is still based on field experience [12-14].

Based on this, based on the field example oil well data, from the perspective of developing reservoir physical parameters, rock mechanics parameters, fracturing construction parameters, flowback system and other factors, this paper uses a variety of weight analysis methods to clarify the main control factors affecting the productivity after shale oil pressure fracturing. Then, through the research on the multi-field coupling seepage fitting method of industrialized fracturing shale oil production and drainage curve, after the production history fitting, the influence of various factors on productivity is systematically calculated. Finally, based on the actual data samples of the mine, BP neural network and multivariate nonlinear polynomial are used to analyze the main control factors, establish the calculation model, and analyze the applicability of each algorithm. Aiming at the highest initial oil production and the highest cumulative oil production, different production and drainage system optimization models are established to provide support for the optimization of flowback system of shale oil volume fracturing horizontal wells.

2. Analysis of Main Control Factors of Productivity After Fracturing Well Pressure Based on Field Data

Based on the data of 95 actual development wells in Jimsar shale oil reservoir, the physical parameters, reservoir compressibility parameters, fracturing construction parameters, flowback system and corresponding productivity data of each volume fracturing horizontal well are extracted. Then, the weight analysis methods such as grey correlation [15], entropy method [16], Pearson mic [17-18] and analytic hierarchy process [19] are used to evaluate the weight number of each major factor and every single factor on oil well productivity. The results are shown in Figure 1 and Figure 2.

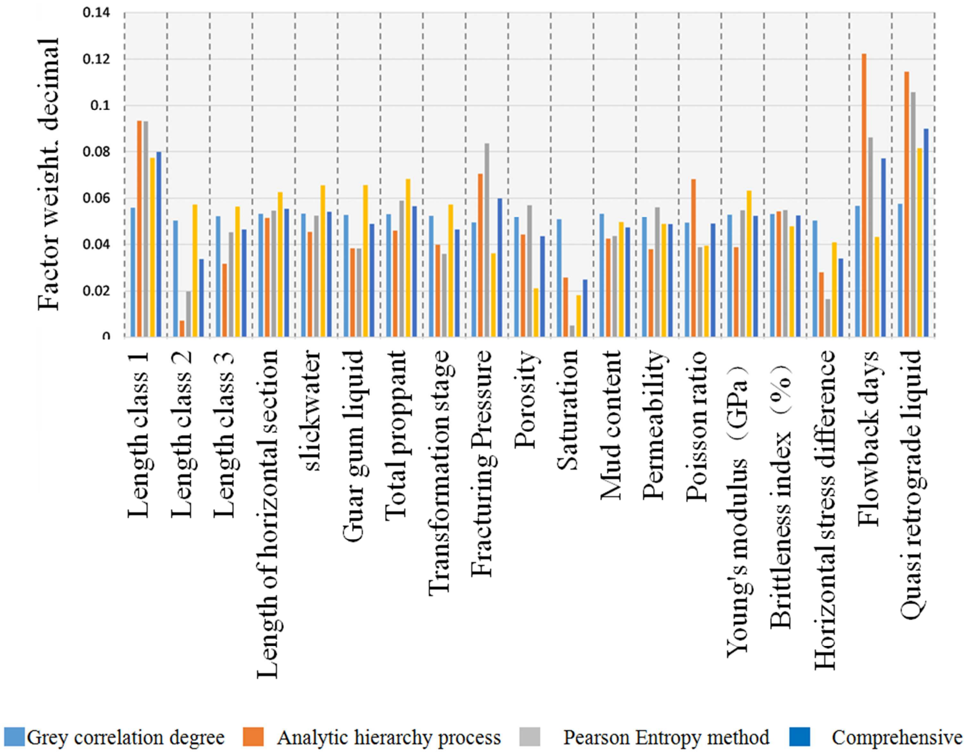


Figure 1. *Calculation results of influence weight of each method.*

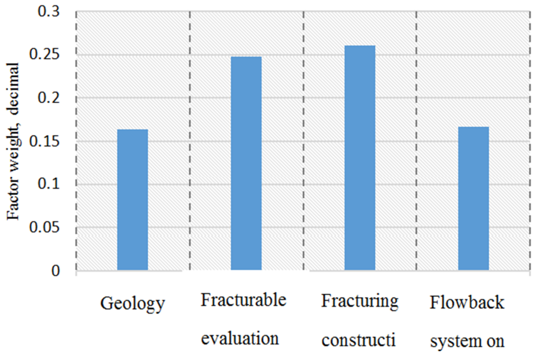


Figure 2. *Influence weight of various factors on production capacity.*

According to the above calculation results, it can be seen that the sensitivity of post fracturing production capacity to various types of parameters are: fracturing construction parameters, compressibility parameters, flowback system and geological factors; The priority order of the impact of each evaluation parameter on the post fracturing productivity is class 1 length, cumulative retrograde fluid, flowback days, fracture pressure, total supporting agent, horizontal section length, slick water, brittleness index, Young's modulus, Poisson ratio, guanidine gum solution, permeability, shale content, class 3 length, transformation stage, porosity, horizontal stress difference, class 2 length and saturation, The corresponding weight coefficients are 0.0799, 0.0898, 0.0772, 0.0599, 0.0565, 0.0554, 0.0542, 0.0525, 0.0524, 0.0489, 0.0487, 0.0486, 0.0472, 0.0464, 0.0464, 0.0435, 0.0339, 0.0337 and 0.0249 respectively; Among them, the three parameters such as class 1 length, cumulative liquid withdrawal and flowback days generally have great influence, and the weights are greater than 0.06, indicating that these three parameters are the key factors affecting the productivity after fracturing. Because Lucaogou Formation in Jimsar sag runs through different types of reservoir groups, the physical properties of each reservoir group are quite different, and shale oil is mostly concentrated in class I reservoirs with large thickness and high organic matter abundance. Therefore, when different reservoir groups are drilled in horizontal well section, their type and distribution range determine the reserve abundance and have the greatest impact on post fracturing productivity; At the same time, in the process of fracturing operation, the backflow system of fracturing fluid directly affects the damage degree of fracturing fluid to the formation and the conductivity of fracture and has a significant impact on the fracturing effect. Therefore, in the evaluation of fracturing drainage and production effect, priority should be given to the three parameters of class 1 length, cumulative retrograde fluid and flowback days.

3. Horizontal Well Parameters - Flowback Effect - Production Big Data Learning and Fitting

The seepage law of shale reservoir is complex. The establishment of an accurate productivity prediction model can better reveal the production and development law, so as to accurately and effectively predict the productivity of oil wells. Therefore, based on the analysis results of the main factors controlling the productivity after shale oil pressure, the calculation models are established by using BP neural network [20] and multivariate nonlinear polynomial [21], and the applicability of each model is evaluated to screen out the energy production prediction model more suitable for the reservoir characteristics of Lucaogou formation in Jimusar depression.

3.1. BP Neural Network

The evaluation parameters are selected as the input parameters, the post fracturing productivity as the output parameters, and the minimum prediction error of the test data set as the evaluation index to optimize the structural parameters of the hidden layer, to establish the neural network prediction model of each influencing parameter and the productivity of horizontal wells. Finally, 95 groups of the sampled data are training data, and the remaining 26 groups of data are used to test the calculation model. The verification results are shown in Figure 3:

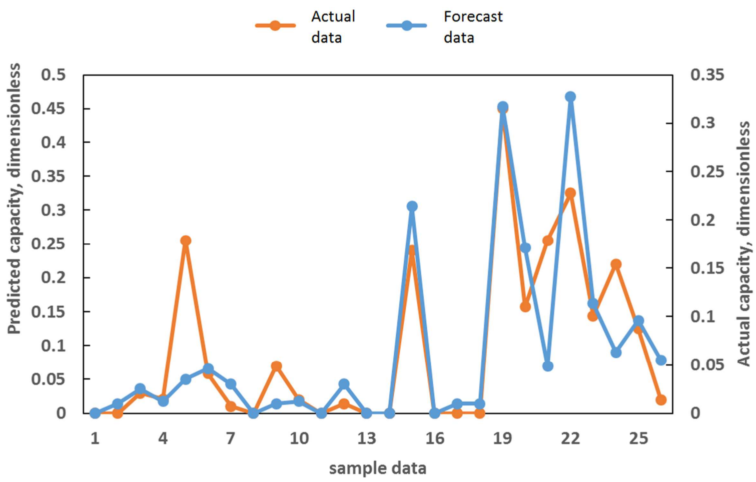


Figure 3. *Comparison of prediction and calculation results of BP neural network.*

It can be seen that the correlation between the predicted capacity and the actual capacity is poor, and the correlation degree is only 0.68, indicating that the training result of BP neural network model is poor under the current sample data set.

3.2. Multivariate Nonlinear Polynomial Regression

Based on the idea of least square method, the influence of evaluation parameters on post-compaction productivity is regressed and analyzed. Using the matrix solution method, the coefficients of the equation can be solved and the multivariate nonlinear fitting model can be obtained. The calculation model test is carried out by using the sample data, and the verification results are shown in Figure 4:

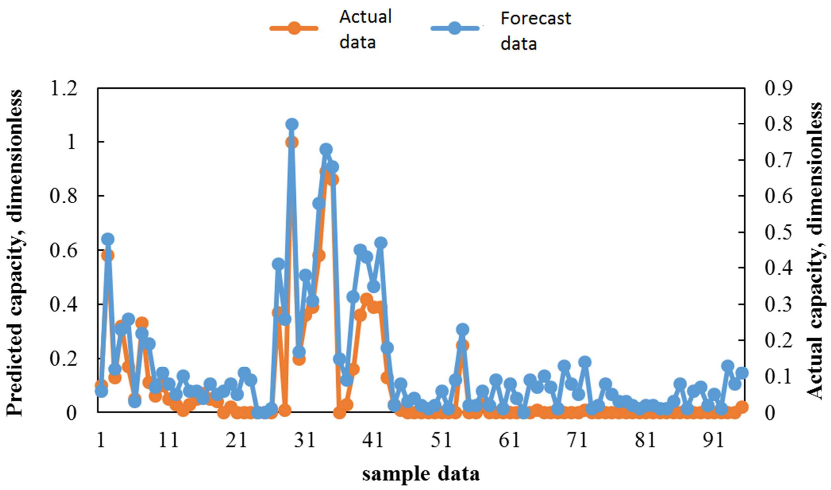


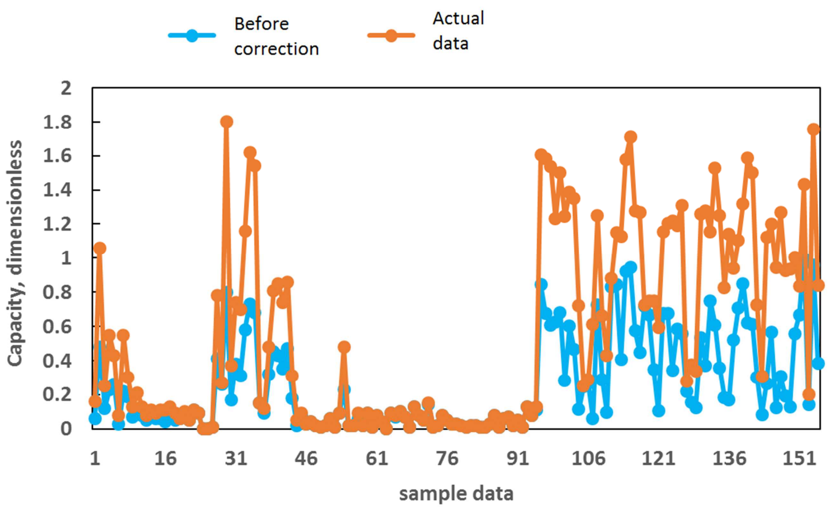
Figure 4. *Comparison of calculation results of multivariate nonlinear polynomial regression.*

It can be seen that the prediction results of the multivariate nonlinear polynomial regression model fit well with the real results, and the correlation degree is as high as 0.85, indicating that the model established by this method has high practicability. Compared with the results of BP neural network prediction model, it can be found that using multiple nonlinear regression method to establish a comprehensive evaluation model has higher feasibility.

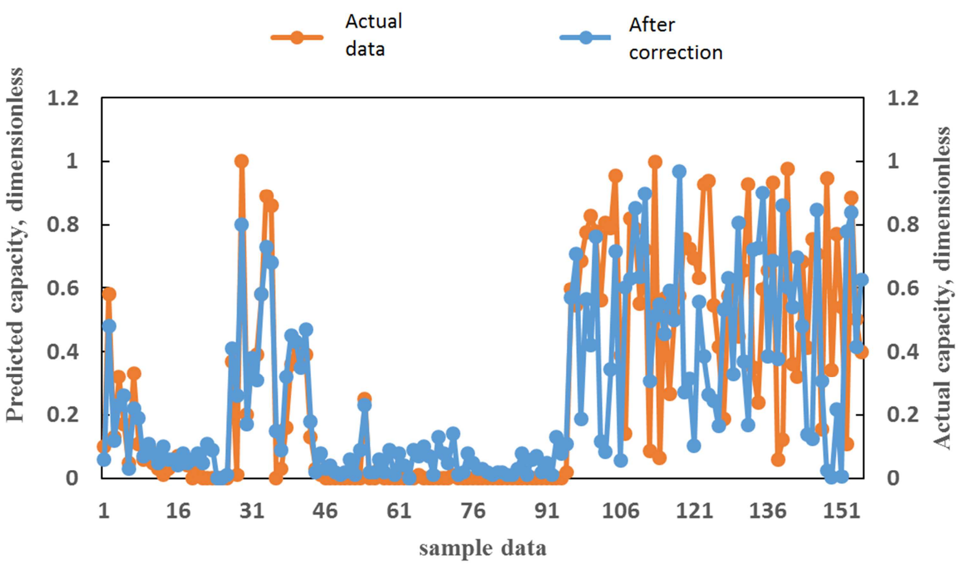
In order to further improve the calculation accuracy of the oil test capacity fitting model and obtain the capacity data closer to the actual conditions, the final oil test capacity prediction model is formed by using the actual production data of the mine to carry out machine learning and calibrating the comprehensive evaluation model established by the multiple nonlinear regression method (see Formula 1). Through verification and comparison, the relationship curve between predicted and fitted yield and actual yield before and after model calibration is shown in Figure 5.

$$y = \theta_0 + \sum_{i=1}^{19} \theta_i x_i + \sum_{j=1}^{19} \theta_j x_j^{\,2} \tag{1}$$

Where, x_i is each evaluation parameter; θ_i is the constant coefficient of the primary term and θ_j is the constant coefficient of the secondary term respectively; θ_0 is -0.3645;



(1) Error curve before correction



(2) Error curve after correction

Figure 5. *Comparison curve of production capacity prediction model before and after correction.*

Table 1. *Statistical table of constant coefficient of oil test productivity prediction model.*

Evaluation parameters	Primary term Constant coefficient	Constant coefficient of quadratic term	Evaluation parameters	Primary term Constant coefficient	Constant coefficient of quadratic term
Length class 1	0.6340	-0.2930	Saturation	0.0202	-0.6014
Length class 2	-0.6961	0.3996	Mud content	0.2100	0.3253
Length class 3	-0.0173	-0.3625	Permeability	-1.5807	-0.2384
Length of horizontal section	0.0871	0.2604	Poisson ratio	1.7077	0.1450
slickwater	-0.0769	-0.4351	Young's modulus (GPa)	0.2967	-0.2305
Guar gum liquid	0.1513	0.2082	Brittleness index (%)	-0.3269	1.7832
Total proppant	-0.1312	-0.1147	Horizontal stress difference	-0.6360	-1.1879
Transformation stage	-0.1686	0.3132	Flowback days	0.5115	0.3787
Fracturing Pressure	0.2925	-0.2125	Quasi retrograde liquid	0.3149	-0.5544
Porosity	-0.1712	0.8177			

As can be seen from Figure 5, the average relative error between the calculated results of the calibrated productivity prediction model and the actual productivity of the mine is smaller. Compared with the model before calibration, the prediction accuracy of the calibrated model is improved by 34.8% ~ 45.2%. The results show that the calibrated productivity prediction model can obtain more accurate prediction results, and can effectively guide the flowback system design and productivity prediction of shale oil fractured horizontal wells.

4. Optimization Simulation of Drainage and Production System with Different Objectives

At present, to solve the main problems in the process of shale oil drainage and production, we mainly start with optimizing the drainage and production system. It can be seen that formulating a reasonable drainage and production system is the key to ensure its mining quality and efficiency. Therefore, based on the above productivity prediction model, the flowback rate and production oil pressure after fracturing are optimized respectively. Using the multivariate nonlinear fitting method, the optimization models of drainage and production system are established respectively with the goal of the highest initial oil production and the highest cumulative oil production, and the optimization simulation is carried out.

4.1. Construction of Optimal Model for Maximum Initial Oil Production

Taking the maximum initial oil production as the goal, the evaluation parameter data volume is established, and the optimization model of the maximum initial oil production is established by using the method of multivariate nonlinear polynomial fitting (see equation 2).

$$\hat{y}_\theta\left(x_1, x_2, \ldots x_{18}\right) = \theta_0 + \sum_{i=1}^{18} \theta_i x_i + \sum_{j=1}^{18} \theta_j x_j^{\,2} \tag{2}$$

Where, y_θ is the initial oil production, t/d; x_i is each evaluation parameter; θ_i is the constant coefficient of the primary term and θ_j is the constant coefficient of the secondary term respectively; θ_0 takes -5.4863.

Table 2. *Optimum model coefficient of maximum initial yield.*

Evaluation parameters	**Primary term Constant coefficient**	**Constant coefficient of quadratic term**	**Evaluation parameters**	**Primary term Constant coefficient**	**Constant coefficient of quadratic term**
Length class 1	0.6855	12.5864	Porosity	21.4582	1.3946
Length class 2	-9.0635	-17.0561	Saturation	-3.5818	6.3046
Length class 3	-9.6167	4.1678	Mud content	-0.8388	-10.4211
Length of horizontal section	2.0034	1.9836	Permeability	-1.6365	-5.2196
slickwater	-3.7604	3.4850	Poisson ratio	-4.9207	8.6962
Guar gum liquid	2.0510	-4.9966	Young's modulus (GPa)	-3.7179	-9.5200
Total proppant	8.6017	12.8737	Brittleness index (%)	-0.0147	7.5009
Transformation stage	6.9728	-9.3237	Horizontal stress difference	12.5481	2.5045
Fracturing Pressure	-15.2838	0.4414	Average oil pressure	-11.1292	-1.2524

According to the model, carry out inverse calculation, comparison and fitting, and the specific results are shown in Figure 6:

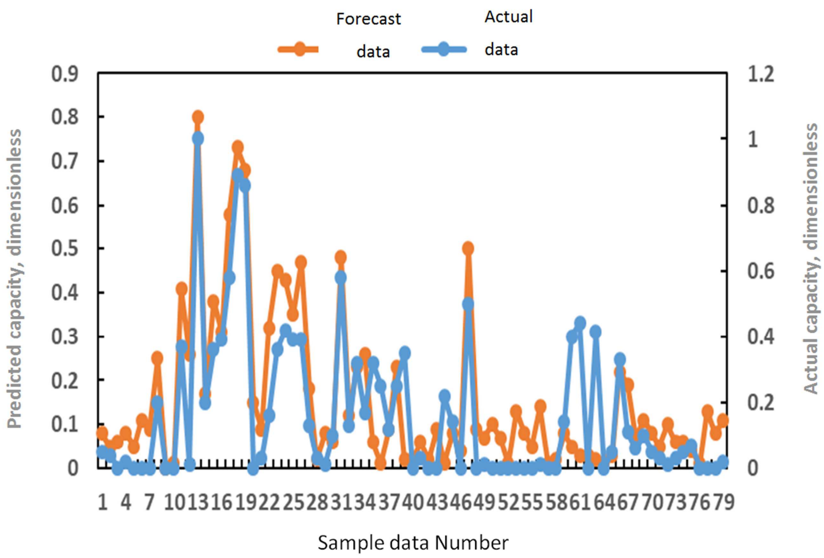


Figure 6. *Comparison of calculation results of the optimization model with the highest initial yield.*

It can be seen from Figure 6 that the prediction results of the multivariate nonlinear polynomial regression model for the initial oil production are in good agreement with the real results, indicating that the model establishment method has high practicability.

4.2. Construction of Optimal Model for Maximum Cumulative Oil Production

Taking the maximum cumulative oil production as the goal, establish the corresponding evaluation parameter set, and construct the maximum cumulative oil production optimization model by using the method of multivariate nonlinear polynomial fitting (see equation 3).

$$\hat{y}_\theta\left(x_1, x_2, \ldots x_{20}\right) = \theta_0 + \sum_{i=1}^{19} \theta_i x_i + \sum_{j=1}^{19} \theta_j x_j^{\,2} \tag{3}$$

Table 3. *Maximum cumulative yield optimization model coefficient.*

Evaluation parameters	**Primary term Constant coefficient**	**Constant coefficient of quadratic term**	**Evaluation parameters**	**Primary term Constant coefficient**	**Constant coefficient of quadratic term**
Length class 1	0.2343	11.3688	Porosity	19.1565	2.3659
Length class 2	-8.1563	-18.7329	Saturation	-3.5818	5.3259
Length class 3	-8.5279	3.0078	Mud content	-0.7546	-12.9581
Length of horizontal section	3.1568	2.1592	Permeability	-3.5695	-3.8562
slickwater	-4.8947	3.4625	Poisson ratio	-5.8122	7.5315
Guar gum liquid	3.6914	-4.2257	Young's modulus (GPa)	-4.2595	-14.003
Total proppant	8.0227	11.3564	Brittleness index (%)	-2.8654	6.8622
Transformation stage	7.5541	-2.6553	Horizontal stress difference	15.2369	3.5621
Fracturing Pressure	-13.2584	4.2656	Average oil pressure	-10.5594	-9.5983

According to the model, carry out inverse calculation, comparison and fitting. The specific results are shown in Figure 7:

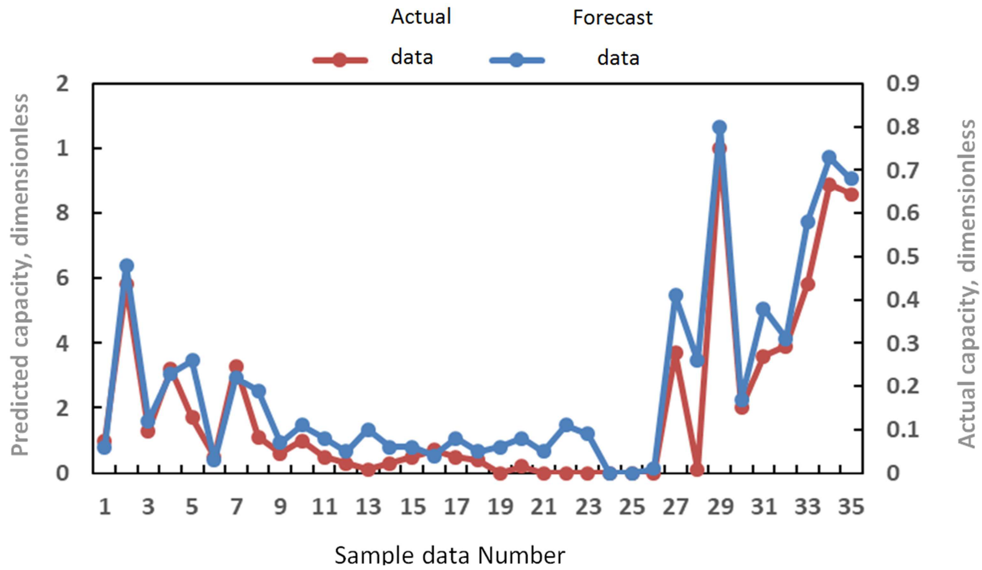


Figure 7. *Comparison of calculation results of maximum cumulative yield optimization model.*

As can be seen from Figure 7, the prediction results of the multivariate nonlinear polynomial regression model on the initial oil production are basically the same as the real results, and the correlation degree can reach more than 0.89, indicating that the model establishment method has high practicability.

4.3. Optimization Simulation of Drainage System

4.3.1. Optimization Simulation of Drainage System Aiming at the Highest Initial Oil Production

Using the established initial oil production optimization model, the oil pressure corresponding to the maximum initial oil production under different oil saturation is analyzed and determined, and the optimization curve is shown in Figure 8.

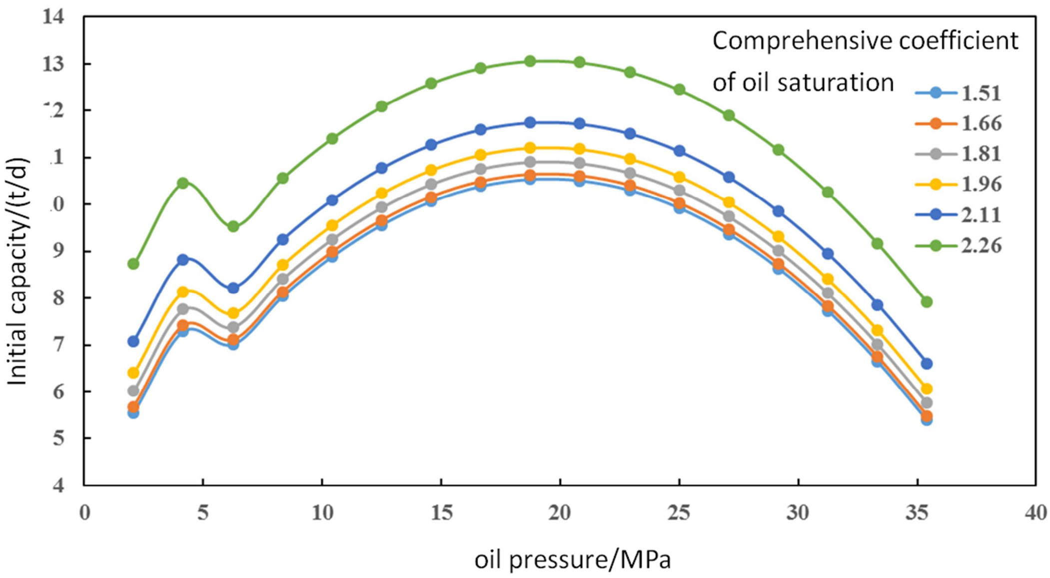


Figure 8. *Optimization curve aiming at the maximum initial oil production.*

As can be seen from figure 8, the changing trend of initial production capacity under different oil saturation conditions is the same, while the maximum initial oil production first increases and then decreases with the increase of oil pressure. When the oil pressure is about 20MPa, the initial production capacity reaches the maximum.

4.3.2. Optimization Simulation of Drainage and Production System Aiming at the Highest Cumulative Oil Production

Using the established initial oil production optimization model, analyze and determine the cumulative liquid volume corresponding to the maximum cumulative oil production under different flowback times, and the optimization curve is shown in Figure 9.

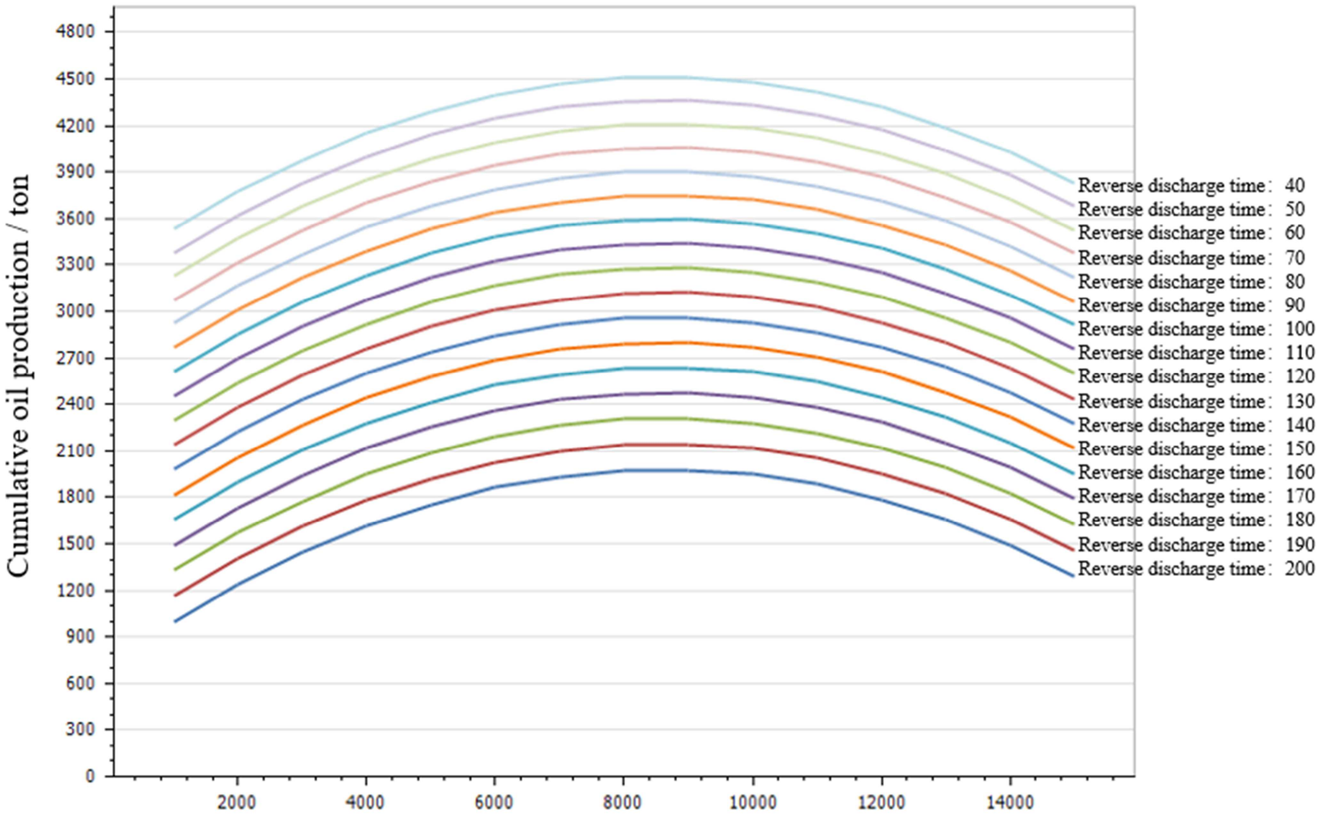


Figure 9. *Optimization curve aiming at maximum cumulative oil production.*

As can be seen from Figure 9, the changing trend of initial production capacity corresponding to different flowback time is the same, while the maximum cumulative oil production first increases and then decreases with the increase of flowback time. When the villain time is about 8000m^3, the maximum cumulative oil production reaches the highest value.

5. Conclusion and Suggestion

(1) Based on the statistical results of mine data, the influence weight is analyzed and calculated by using grey correlation analysis, Pearson mic correlation analysis, analytic hierarchy process and entropy analysis; From the geological point of view, the productivity of shale oil fracturing in the study area is mainly controlled by class I length and permeability; From the perspective of compressibility evaluation parameters, the productivity of shale oil fracturing in the study area is mainly affected by fracture pressure and brittleness index; From the point of view of shale production capacity and Horizontal Fracturing area, the main fracturing parameters are studied;

(2) Compared with BP neural network method, the model established by the multiple nonlinear regression method has higher prediction accuracy and carries out machine learning according to the actual production data of the mine to form the final oil test productivity prediction model. The results show that the fitting accuracy of the prediction model to the actual data of the target area can reach more than 89%.

(3) Based on the initial oil production optimization model and cumulative oil production optimization model, it is clear that the maximum initial oil production first increases and then decreases with the increase of oil pressure, and the maximum value is obtained when the oil pressure is about 20MPa; At the same time, the maximum initial oil production increases first and then decreases with the increase of oil saturation. The maximum value is obtained when the flowback time is about 8000m^3.

(4) At present, the research work only focuses on single-stage fracturing, and the research on the interference between each section under the condition of segmented fracturing needs to be deepened, such as the viscosity of guanidine gum liquid and the amount of proppant in different sections; At present, only the research on the influence law of the main control factors of the drainage effect of single well volume fracturing has been carried out. The effect of multi well volume fracturing at the same time should be better than that of single well, and the influence law is also different.

Funding

This study was supported by the National Key R&D Program of China (No. 2020YFA0711800) and the Natural Science Foundation of China (NO. 51874339 and NO. 51904320).

References

[1] Zhang Kang. From tight oil and gas to shale oil and gas——an analysis of the development path of unconventional oil and gas in China [J]. International petroleum economy, 2012, 20 (03): 9-15+109.

[2] Wang Shuling, Wu Xishun, Zhang Wei, Tian qianning. Progress and trend o-f global exploration and development for shale resources [J]. China mining, 2016, 25 (02): 7-11+15.

[3] Peng Chengyong. FRACTURING TECHNOLOGIES USED FOR SHALE-OI-L AND SHALE-GAS HORIZONTAL WELLS [J]. Natural gas exploration and development, 2014, 37 (01): 68-71+100.

[4] Li Guoxin, Luo Kai, Shi Deloitte. Key technologies, engineering management and important suggestions of shale oil/gas development: Case study of a Duver-nay shale project in Western Canada Sedimentary Basin [J]. Petroleum exploration and development, 2020, 47 (04): 739-749.

[5] LEI Qun, XU Yun, CAI Bo, GUAN Baoshan, WANG Xin, BI Guoqiang, LI Hui, LI Shuai, DING Bin1, FU Haifeng, TONG Zheng, LI Tao, ZHANG Haoyu. Progress and prospects of horizontal well fracturing technology for shale oil and gas reservoirs [J]. Petroleum Exploration and Development, 2022, 49 (01): 166-172+182.

[6] LEl Qun, WENG Dingwei, XIONG Shengchun, LlU Hanbin, GUAN Baoshan, DENG Qiang, YAN Xuemei, LIANG Hongbo, MA Zeyuan. Progress and development directions of shale oil reservoir stimulation technology of China National petroleum Corporation [J]. Petroleum Exploration and Development, 2021, 48 (05): 1035-1042.

[7] Hou Bing, Chang Zhi, Wu An'an, Elsworth Derek. Simulation of competitive propagation of multi-fractures on shale oil reservoir multi-clustered fracturing in Jimsar sag [J]. Acta Petrolei Sinica, 2022, 43 (01): 75-90.

[8] Yang S, Han L, Wang J, et al. Laboratory study on casing deformation during multistage horizontal well fracturing in shale gas development and strain based casing design [J]. Journal of Natural Gas Science and Engineering, 2021, 89 (3): 103893.

[9] Liu Gang, Yang Dong, Mei Xianwang, Yu Shuxin, Ma weiqi, fan Xuejun. Method of well-soaking and controlled flowback after large-scale fracturing of Gulong shale oil reserviors in Songliao Basin [J]. Daqing Petroleum Geology and development, 2020, 39 (03): 147-154 DOI: 10.19597/J.ISSN.1000-3754.202004062.

[10] Du Yang, Lei Wei, Li Li, Zhao zhejun, Ni Jie, Liu Tong. Post-frac production control and drainage technology of deep shale gas wells [J]. Oil and gas reservoir evaluation and development, 2021, 11 (01): 95-101+116 DOI: 10.13809/j.cnki.cn32-1825/te.2021.01.013.

[11] Gao Zhanwu, Qu Xuefeng, Huang Tianjing, Xue Ting, Cao Peng. Stress sensitivity analysis and optimization of horizontal well flowback system for shale oil reservoir in Ordos Basin [J]. Natural Gas Geoscience, 2021, 32 (12): 1867-1873.

[12] J Wang, Xiong Y, Lu Z, et al. Influence of Volume Fracturing on Casing Stress in Horizontal Wells [J]. Energies, 2021, 14.

[13] Hang W, Wz C, Zs C, et al. Failure analysis of casing dropping in shale oil well during large scale volume fracturing [J]. Engineering Failure Analysis, 2020, 118.

[14] He L, Ma Y, Tan T, et al. Mechanisms of sulfur and nitrogen transformation during Longkou oil shale pyrolysis [J]. Energy, 2021, 232 (5): 120977.

[15] Tan xuerui, Deng Julong Grey correlation analysis: a new method of multivariate statistical analysis [J]. Statistical research, 1995 (03): 46-48 DOI: 10.19343/j.cnki.11-1302/c.1995.03.011.

[16] Wang Fuxi, Mao Aihua, Li Helong, Jia Minglu. Quality Measurement and Regional Difference of Urbanization in Shandong Province Based on the Entropy Method [J]. Geoscience, 2013, 33 (11): 1323-1329 DOI: 10.13249/j.cnki.sgs.2013.11.006.

[17] Liang Shan. Comparative study of MIC and traditional correlation analysis methods [J]. Shanxi youth, 2019 (09): 47 + 49.

[18] Zhang Yulei, Dang Yan, he Ping'an. Quantitative Analysis of the Relationship of Biology Species Using Pearson Correlation Coefficient [J]. Computer engineering and application, 2005 (33): 83-86 + 103.

[19] Deng Xue, Li Jiaming, Zeng Haojian, Chen junyang, Zhao Junfeng. Analysis of weight calculation method of analytic hierarchy process and its application [J]. Practice and understanding of mathematics, 2012, 42 (07): 93-100.

[20] Li Youkun. Analysis and Improvement Applications Of BP Neural Network [D]. Anhui University of technology, 2012.

[21] Xu Qun. The research on non-linear regression analysis methods [D]. Hefei University of technology, 2009.