Research on the Prediction of Natural Gas Single-Well Operation Cost Based on Machine Learning

Zhuohan Guo[1], Ying Tian[1,*], Yuhan Ma[1], Yinan Chen[2], Lin Liang[2]
[1]*Exploration and Development Research Institute, PetroChina Southwest Oil and Gas Field Company, Chengdu, Sichuan, China*
[2]*Key Laboratory of Energy Security and Low-carbon Development, Southwest Petroleum University, Chengdu, Sichuan, China*
**Corresponding Author*

Abstract: In order to overcome the current problem of large amount of data required in the measurement of single well development and operation cost, the calculation process is complicated, and it is difficult to make fast and accurate prediction. By searching for many factors affecting the operating costs of natural gas wells, six machine learning algorithms, including linear regression, decision tree, AdaBoost, XGBoost, Support Vector Machine (SVM) and Artificial Neural Network (ANN), are used to construct a model to verify the usability of machine learning algorithms in the prediction of operating costs of single wells for natural gas development. Combined with the actual sample data, it is found that most of the machine learning models run with a high degree of fit to the real data, among which the elastic network regression model in the linear regression model has a prediction accuracy of 98%, which demonstrates the model's superiority in the prediction of natural gas single-well operating costs.

Keywords: Machine Learning; Single-Well Operating Cost; Cost Components; Prediction Method; Elastic Network Regression

1. Introduction

Under the guidance of China's macro-strategy of constructing a modern energy system that is both clean and efficient, safe and sustainable, natural gas, as a particularly high-quality and low-carbon choice among fossil energy sources, has attracted a lot of attention for its future development. However, along with the rapid growth in demand for natural gas, the contradiction between supply and demand in this field is becoming more and more obvious in China. According to statistics, from 2010 to 2024, China's natural gas consumption has surged from 106.9 billion cubic meters (bcm) to 426.05 bcm, while production, though rising, has only increased from 96 bcm to 246.4 bcm, resulting in a high external dependence of 40.9%, which undoubtedly poses a challenge to national energy security. In view of this, China's oil companies are focusing on boosting their efforts in oil and gas exploration and development, striving to make substantial progress in ensuring national energy security. In this process, how to invest scientifically and rationally plan the input and output of oilfields has become a practical problem that oil companies need to solve. Single well, as an indispensable basic element of oil and gas field capacity construction, the data of its production and operation cost is crucial for benefit evaluation, which directly affects the scientific decision-making and benefit analysis of oilfield managers. Currently, oilfield enterprises are facing many difficulties in single well cost management. On the one hand, the complexity of centralized data management makes the integration of effective information difficult; on the other hand, the production conditions of single-well are different, coupled with the complexity of factors affecting production and operating costs, which further increases the management difficulty. Under this circumstance, how to accurately predict the operating cost of single well development and rationally set the investment amount for different types of natural gas wells, so as to support geologic, engineering and other professionals to carry out multiple rounds of technical and economic evaluation, has become a bottleneck that needs to be broken through urgently.

2. Literature Review

At present, the study of operating cost prediction for oil and gas field development usually involves a series of steps, including identifying the study object, collecting relevant material information, selecting appropriate prediction models and evaluating the prediction results, etc. These steps help to better identify and utilize the potential change patterns of production and cost to derive the prediction results. In the oilfield development stage, production is unstable or fluctuates greatly due to various reasons, so forecasting techniques are needed to guide production. Forecasting techniques include a variety of methods, such as exponential smoothing method, input-output method, fuzzy system forecasting method, time series analysis, energy consumption elasticity coefficient method, econometric model forecasting, gray system forecasting, regression analysis, artificial neural network and support vector machine. Each method has its specific data application scenario. Finding the most suitable prediction model for each oil field according to its characteristics and conducting a large number of data modeling and analysis experiments are the core problems that scholars need to solve. Various methods and research results adopted in this field at home and abroad mainly focus on the following areas.

First, the gray model. Gray prediction method is an important mathematical method that can accurately predict the development trend in the future period and adjust the results according to the actual situation. This technique is mainly applied in the fields related to modeling research, predictive analysis, and decision control of systems. For example, Sun et al. used the gray prediction method in the prediction of operating costs in the Karamay oil field; Wang used three different prediction models, Hubbert, Weng Cycle Model, and HCZ, based on the most recent statistical data of China's petroleum production during the period of 1990-2013 to estimate China's annual petroleum production and peak value [1]. Zhang et al. used a modified version of the gray neural network model in the production forecasting of Daqing oil field, thus constructing a modified version of the combined gray-neural network model [2]. Jian et al. chose M oilfield as the research target and used the gray correlation method to analyze its operation cost [3].

Second, regression analysis method. It belongs to the typical mathematical and statistical analysis method, by creating a regression prediction model with appropriate data analysis and processing, then calculating the predicted value in combination with the actual situation, and finally checking the accuracy of the model by the error in the prediction model with simple characteristics. However, if the appropriate equation cannot be found, this will directly lead to the poor accuracy of the prediction results of the final analysis. Wang analyzed the historical data of operation cost in Dagang Oilfield, pointed out the factors affecting the operation cost, and then predicted the operation cost based on the corresponding change trend [4]. Dong used the PCA method to select the regression model as the independent variable indicator, and applied it to the empirical study of oilfield operating cost prediction, obtaining the indicator variables that have a significant impact on the operating cost [5]. Li analyzed three aspects of the principal component regression model based on production control, development stage and macro system, and proposed nine influencing indicators such as liquid production, number of wells in the population consumption index, and so on, to predict the operating costs of oilfields with controlled water-drive development [6]; Li et al. used three methods such as reject-by-exclusion, optimal subset, and principal component regression in multiple linear regression analysis to predict the operating costs, respectively. operation cost prediction [7]. Chen et al. used the actual data of DX oilfield from 2010 to 2016 to establish a regression prediction model to analyze the partial least squares regression analysis of the respective variable indicators [8]. Hu studied the method of determining operating costs based on the composition of variable and fixed costs, and used a single well in a regional fractured block reservoir as a typical case to measure [9].

Third, the neural network approach. Creating mathematical models or computational models to estimate or approximate functions by simulating the structure and function of biological brains has made the evolution of neural networks the main reason for the current research hotspots. In terms of oil and gas field cost prediction, Wu et al. established a linear regression prediction model based on multiple factors and a nonlinear error back-propagation (BP) neural network prediction model to predict the operating cost of water-driven oilfields with exceptionally high water content [10]. Zhou established an operation cost prediction model with support vector machine, and predicted the current operation cost of high water content oilfield development better [11]. Feng established a PSO-RBF optimization network to predict the operating cost of a single well [12].

The accuracy of the prediction results of the above research methods depends on the researcher's combination of the actual production situation, the experience and quality of the oilfield management personnel, as well as the accurate collection and pre-processing of information and data. Due to the large number of complex mathematical calculations between various influencing factors in natural gas development, this processing directly increases the time of calculations and at the same time creates the result of large errors. The applicability of the various methods needs to be improved due to the different scopes and stages of natural gas development, and the actual complexity and conditions used.

With the rapid development in the field of artificial intelligence, researchers have found that machine learning algorithms perform better and have a certain degree of accuracy when analyzing and processing complex nonlinear data sets, i.e., classifying and predicting, and can be used to build relevant models for classification or prediction activities. The main research content of machine learning algorithms is that the computer uses the existing sample data set, summarizes a certain law, produces a model algorithm corresponding to the function of the law, and uses the output algorithm model for numerical classification and prediction. Machine learning algorithms accept input data rather than accepting input instructions to work, will be trained to learn the ability of the algorithmic model can be applied to a new sample set is called the ability to generalize, combined with the knowledge of mathematical statistics, the choice of the loss function, to ensure that the algorithmic model fits the data sample set of the appropriateness of the algorithmic model. In this paper, we will use machine learning algorithms, select the corresponding regression prediction model and loss function to carry out comparative experiments of natural gas single well operating cost prediction for research, in order to achieve the purpose of selecting better performance machine learning algorithms for fast and accurate prediction of natural gas single well operating cost.

3. Natural Gas Single Well Operation Cost Composition and Influencing Factors

Single well costing is to group all the costs directly and indirectly incurred on wells in the production process into single wells through certain methods, and calculate the cost and profit and loss of each well based on its output. Tracking the cost and expense of a single well through the Early Warning Module can realize a good early warning function. Comparative analysis of costs can be performed on a daily, monthly, quarterly and yearly basis. Single well operation cost mainly consists of extraction operation fee, downhole operation fee, logging and testing fee, maintenance and repair fee, light hydrocarbon recovery fee, oil and gas treatment fee, natural gas purification fee, transportation fee, late production pressurization fee, other auxiliary operation fee and plant and mine management fee. Combining China National Petroleum Corporation's “Methods and Parameters for Economic Evaluation of Oil and Gas Exploration and Development Construction Projects of China National Petroleum Corporation”, “Classification and Evaluation Methods for Benefits of Developed Oil and Gas Fields Blocks and Single-well” (Q/SY 01035-2020) and the actual natural gas development, the method of accounting for single-well operation costs and the core influencing factors are as Table (1) shown.

4. Experimental Design and Data Sources

4.1 Experimental Design

This experiment is to use six different machine learning algorithms to predict the operating cost of natural gas single wells, in which the input values use each factor that affects the cost of single wells, and the ultimate goal is to find out that better machine learning algorithms can be applied to the field of predicting the operating cost of natural gas single wells by comparing the predictions of the different machine learning algorithms, and to screen the divisional engineering of the weighted higher features and make optimization suggestions. The basic steps of the experiment are as follows: first, collect the sample data set. In this paper, the data of single well operation cost and influencing factors of a gas field are selected as the sample data set and data preprocessing is carried out.

Second, regression prediction. Six classical machine learning algorithms, such as linear regression, decision tree, AdaBoost, XGBoost, support vector machine (SVM) and artificial neural network (ANN), are selected to train and predict the sample data set. Finally, the five different algorithms models are evaluated to find out one of the five algorithms with better performance of regression prediction model.

Table 1. Operating Cost Components and Influencing Factors of Natural Gas Single Wells

Operating cost breakdown	Accounting method	Influencing factors
Material Costs	Material costs directly incurred on a single well + costs apportioned to a single well according to the start-up time of the well to which it belongs Production time	Production Time Production
Fuel Costs	Fuel costs incurred directly on a single well + fuel costs apportioned to a single well according to the time of startup of the oil (gas) well to which it belongs Time of production	Production Time Production
Power Costs	Power costs incurred directly on single-well + costs apportioned to single-well based on the volume of fluid (gas) produced by the oil (gas) wells to which they belong Yield	Production
Personnel Costs	Personnel costs incurred directly on a single well + costs apportioned to a single well based on when the oil (gas) well to which it belongs was opened	Production Time Production
Other Fees	Other fees incurred directly on single-well + apportioned to single-well according to the time of start-up of the oil (gas) wells to which they are attached	Production Time Production
Fee for Injection of Oil Repellents	Driver injection costs incurred by the block are apportioned to block-effective oil and gas wells on the basis of the volume of fluids produced	Production
Downhole Operation Cost	well workover costs incurred on a single well + costs apportioned to block-effective oil (gas) wells based on the volume of fluids (gas) produced.	Production Wellhead Pressure
Logging and Testing Cost	Logging and testing fee incurred for a single well + apportioned to block recipient oil (gas) wells based on the volume of fluids (gas) produced.	Gas Reservoir Type Production
Maintenance and Repair Cost	Maintenance and repair fee incurred for a single well + apportioned to a single oil (gas) well according to the opening time of the oil (gas) well to which it belongs.	Gas Reservoir Type Production Time
Transportation Costs	transportation costs incurred directly on a single well + costs apportioned to a single well according to the opening time of the oil (gas) well to which it belongs, and oil pulling costs according to the amount of fluid produced.	Production Time Production
Plant and Mine Management Fees	apportioned to single-well according to the start-up time of the oil (gas) wells to which they belong Production time	Production Time Production
Oil And Gas Treatment Fee	apportioned to single-well on the basis of annual liquid (gas) production	Production

4.2 Data source and Processing

4.2.1 Data source and indicator division

The data set of this experiment is selected from 353 single wells related data of a domestic oil field, and according to the analysis in Table (1), wellhead gas production, wellhead pressure and production time are selected as the core explanatory variables, in addition, for the purpose of predicting the operation cost more accurately, the type of natural gas reservoirs and whether or not gas wells are reinjected and pressurized are taken as the characteristic variables. The specific indicators are shown in Table (2).

Table 2. Classification of Variable Indicators

Classification of Indicators	Indicator name	Indicator number	Indicator description
Target data	Cost	Y	Ordered variables
Influencing factors	Gas reservoir type	X1	characteristic variable: with water and no Sulphur = 1, with water and Sulphur = 2
	Whether or not to re-inject pressure	X2	Characteristic variable: with no re-injection and no pressure = 0, with re-injection and pressure = 2,

			with re-injection and no pressure = 1, without re-injection and with pressure = 1.
	Wellhead Pressure	X3	Ordered Variable
	Production Time	X4	Ordered Variable
	Wellhead Gas Production	X5	Ordered Variable

4.2.2 Data processing

In the regression prediction algorithm, all the features of the sample data heap samples produce the same level of influence, if the difference in the range of values is too large then it will lead to the distance of the sample space points will be dominated by the characteristics of the indicators with larger values, thus reducing the influence of the characteristics of the other indicators with a small range of values, which affects the results of the regression prediction model. After the statistics of the original data, it was found that the range of the original data values of the indicators varies greatly, so it is necessary to normalize the sample dataset, using the minimum-maximum normalization, i.e., the discrete normalization, to map all the data between [0,1], and the principle formula is shown in Equation (1).

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

Where: x' --Feature data after normalization; $x_{\max}$ --Maximum value of sample feature data; $x_{\min}$ --Minimum value of sample feature data.

5. Experimental Process and Results Analysis

5.1 Experimental Process

This experiment is firstly by extracting the input values of the relevant influencing factors of the required single-well operation cost, and the output is the single-well operation cost, and the ideas of the training model and the prediction model are shown in Figure 1 and Figure 2.

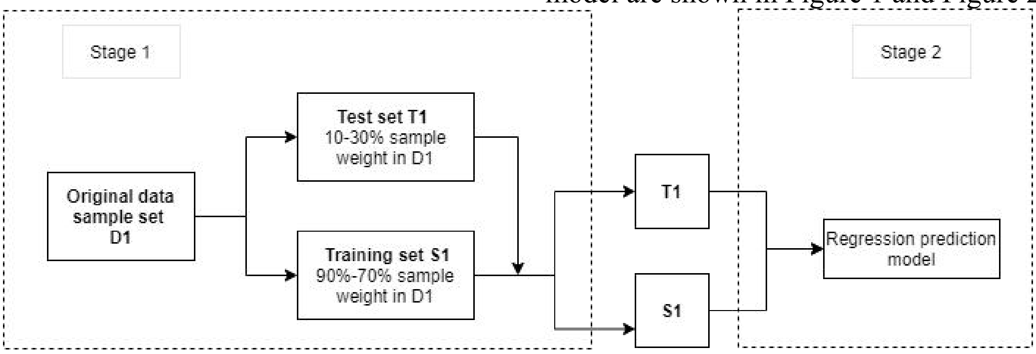


Figure 1. Machine Learning Regression Algorithm Training Model Framework Diagram

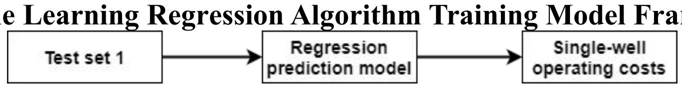


Figure 2. Machine Learning Regression Algorithm Prediction Framework Diagram

The specific steps of the experiment are as follows:

(1) Data set generation

Using the known single-well operation cost and influencing factors to construct a single-well operation cost regression prediction model, to get rid of the previous time-consuming and labor-intensive situation of calculating single-well cost, and to speed up the process of cost control of single-well development. Firstly, relevant information is obtained from the data, and a part of the single-well operation cost dataset to be studied is drawn as a training set, and the remaining part and negative samples are used as a test set. In the preliminary experiment, 75% (264 sets) will be used for training and 25% (89 sets) will be used for testing, and the ratio of the training set and test set will be adjusted accordingly during the experiment based on the experimental results in order to obtain the prediction results with the highest accuracy. The data of the initial training set and test set are shown in Table (3) and Table (4).

(2) Construction of regression prediction model

The functions of regression prediction model of different algorithms are different, but all of them need to use the positive samples in the corresponding sample data set as the training set, and take the input values of the relevant influencing factors and the cost of a single well as the output value for training, and get the values of various correlation coefficients in the regression prediction function of the algorithms after a certain cycle of algorithmic training, so as to complete the construction of regression prediction model.

(3) Cost prediction and performance evaluation

Eventually, after completing the construction of the regression prediction model, the test set can be used to test the prediction model, i.e., to detect whether the prediction effect of the prediction model is accurate. Firstly, according to the characteristics composed of the values in the test set, then using the single well characteristics as the input value of the prediction model, the predicted value of the development cost of each single well is obtained according to the trained regression prediction model. In order to select objective and effective evaluation criteria to judge the estimation effect of the above estimation simulation outputs, this experiment adopts three indexes, namely, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Coefficient of Determination (R Squared (R^2), to judge the fitting degree and estimation accuracy of the model estimation outputs and the actual outputs, of which the Mean Squared Error (MSE), the Coefficient of Determination (R^2), and the Coefficient of Determination (R^2) are used. The Mean Absolute Error (MAE) is the average of the absolute errors between the predicted values and the real values, which directly reflects the average level of prediction errors, and the smaller the MAE value, the higher the prediction accuracy; the Mean Squared Error (MSE) is the average of the squares of the prediction errors, which is used to measure the magnitude of the model's errors in predicting the future data; and the Coefficient of Determination (R^2) is used to determine the closeness of the data and the fitting regression line, and the R^2 is used to determine the accuracy of the data and the accuracy of the model. regression line, the closer $R^2$is to 1 the better the explanatory power of the regression equation. Finally, the variance and R^2 are explained by the evaluation metrics, and the predicted values obtained and the true values in the sample dataset are calculated to evaluate the performance of the prediction model.

Table 3. Description of Training Set Data

	count	mean	std	min	25%	50%	75%	max
Wellhead pressure X3	264	0.1666	0.1683	0	0.0475	0.1066	0.2284	1
Production time X4	264	0.7036	0.3213	0	0.4715	0.8761	0.9681	1
Industrial gas production X5	264	0.0755	0.1469	0	0.0055	0.0187	0.0733	1
Gas Reservoir Type X1_2	264	0.5303	0.5	0	0	1	1	1
Pressure Boosting Reinjection X2_1	264	0.2765	0.4481	0	0	0	1	1
Pressure Boosting Reinjection X2_2	264	0.3182	0.4667	0	0	0	1	1

Table 4. Description of Test Set Data

	count	mean	std	min	25%	50%	75%	max
Wellhead pressure X3	89	0.1851	0.1876	0.0029	0.0453	0.126	0.2663	0.8639
Production time X4	89	0.7494	0.3231	0.0014	0.6282	0.9203	0.9711	1
Industrial gas production X5	89	0.1036	0.1601	0	0.0049	0.0303	0.1344	0.6349
Gas Reservoir Type X1_2	89	0.5056	0.5028	0	0	1	1	1
Pressure Boosting Reinjection X2_1	89	0.2584	0.4403	0	0	0	1	1
Pressure Boosting Reinjection X2_2	89	0.2472	0.4338	0	0	0	0	1

5.2 Result Analysis

Construct and write the regression prediction model code based on six algorithmic principles on Anaconda 3 open source platform using Python3.8 platform in Spyder software, and conduct regression prediction model training and testing experiments using normalized sample dataset, and get the experimental results as shown in Table (5).

From Table (5), it can be seen that all six machine learning algorithms have good performance in regression fit, and the coefficients of determination (R2) of the five models except the decision tree model are more than 0.9, with the linear regression model having the highest R2 of 0.97. The linear regression model also has the highest accuracy in terms of the Mean Absolute Error (MAE) and the Mean Square Error (MSE). Therefore, it can be concluded that the linear regression model in machine learning has the best performance in predicting natural gas operating costs through parameters such as reservoir type, reinjection pressurization, wellhead pressure, wellhead gas production, and cumulative years of extraction.

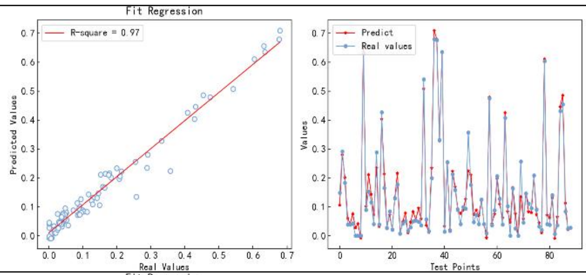
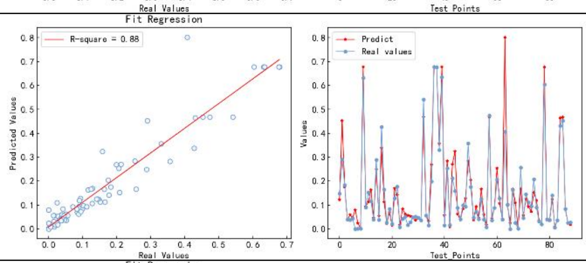
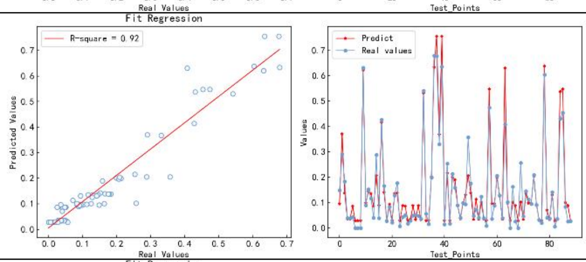
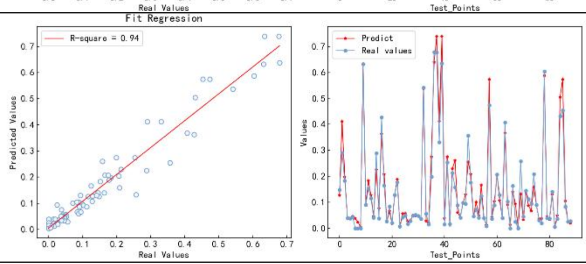
On the basis of identifying the linear regression model as the optimal machine learning prediction model, this experiment further compares the accuracy of various types of linear regression models based on different regularization techniques in order to select the optimal regression model. The experimental results are shown in Table (6).

As can be seen from Table (6), the three evaluation indexes of the elastic network regression model are optimal among all linear regression models. Therefore, according to the elastic network regression model, the regression equation for the prediction of the operating cost of a single natural gas well is as Equation (2):

$$Y = -3643337.10924 + 1350597.88893x_1 + 183512.25152x_2 + 176762.05086x_3 + 29153.61560x_4 + 369.30383x_5 \quad (2)$$

where: Y is the annual operating cost of a single well (RMB 10,000,000); is the type of natural gas reservoir; is whether to pressurize or re-inject; is the wellhead pressure; is the production time (days); and is the production volume of the wellhead (kcf).

Table 5. Machine Learning Prediction Results

Predictive Modelling	MAE	MSE	R^2	Evaluation Curve Chart
Linear Regression	0.021	0.001	0.969	
Decision Trees	0.031	0.003	0.884	
AdaBoost	0.031	0.002	0.918	
XGBOOST	0.025	0.001	0.944	

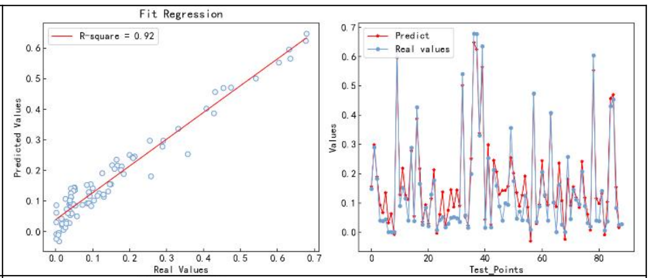
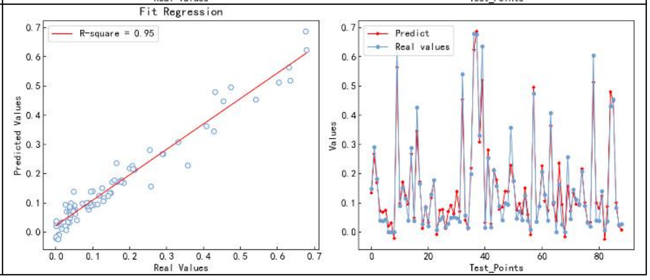
Support Vector Machines(SVM)	0.037	0.002	0.924	
Artificial Neural Networks(ANN)	0.029	0.001	0.947	

Table 6. Comparison of Prediction Accuracy of Different Linear

Regression models	MAE	MSE	R^2
Elastic network regression	13705641124930.20	2678081.495	0.98364
Lasso regression	52090165449981.00	3298029.432	0.93779
Ridge regression	52084185079738.50	3288032.111	0.93780
Non-negative linear regression	52090165313404.20	3298029.941	0.93779
Minimum angle regression	52090165313404.10	3298029.941	0.93779

6. Conclusion and Discussion

The paper mainly researches the application of machine learning algorithms on the prediction of natural gas single well operation cost, analyses and compares the prediction accuracy of six algorithms in the prediction of operation cost, and verifies the validity of machine learning algorithms in the experiment. The experimental results show that the accuracy of the prediction results of the five machine learning algorithms is greater than 90%, and there is a feasibility of the prediction results for the natural gas single-well operating cost index. The prediction results from the actual data are realistic, and the linear regression model, especially the elastic network regression model, has the best performance and the highest prediction accuracy.

Some shortcomings are also found in this experimental study:

(1) The sample data are only for some gas reservoir types of single wells for experimental prediction, the six machine learning algorithms used are not always the optimal algorithms, and the process of tuning the parameters has a certain degree of subjectivity and randomness, and it is not always the case that the parameters of the six machine learning algorithms are adjusted to the optimal state.

(2) Although the efficiency and accuracy of this experiment is improved compared with traditional cost prediction methods, it is only applicable to the data in this experiment, and the generalization ability of the regression prediction model of the machine learning algorithms may not be applicable to the prediction of operating costs of all single wells. The operating cost indicators are affected by many factors, and the operating costs of single wells of different types are not the same, so the operating cost prediction indicator system can be further expanded to increase the influencing factors.

Acknowledgements

This work was supported by a project grant from 2024 Petro China Youth Science and Technology Special Program ‘Natural Gas Reserve Evaluation and Optimization Model for Development Planning in Sichuan Basin’. (Grant No. 2024DQ03028).

References

[1] Ting-ting Wang, Cheng Huang, Qi-chen Zhang. The peak of China's oil production forecasting and strategies research. China Mining Magazine, 2015, 24(12):38-44.

[2] Fang-zhou Zhang, Hu-yong Yan, Li-quan Yang, et al. Application of Improved Grey

Neural Network Model to Oil Yields. Computer Technology and Development, 2013, 23(06):241-244+248.
[3] Dan Jian, Xi-yu Ren, Juan Yue, et al. Grey correlation analysis of oil and gas operating cost components. Economic & Trade, 2017, (14):116.
[4] Yan-ping Wang. Oil and Gas Operating Cost Prognostication Research of Da Gang Oil Field Company. China University of Petroleum, 2007.
[5] Shang-bin Dong. An empirical study of oil operating cost forecasting. Oil-Gas Field Surface Engineering, 2009, 28(10):21-23.
[6] Feng Li, Xiao-hui Zhang, De-bin Qu, et al. Prediction of operating costs in water-driven oilfields based on principal component regression modelling. Journal of Oil and Gas Technology，2012，34(9)：136-139.
[7] Ping Li, Qiong Mao, Xin-ying Wang, et al. Establishment and Application of the Operation Cost Prediction Model Based on Multivariate Linear Regression Analysis. Petroleum Planning & Engineering, 2018, 29(03):33-37+52.
[8] Wu Chen, Tao-hong Wu, Chen Chen, et al. Prediction of Oilfield Operation Cost Through Partial Least Squares Regression-A Case Study on DX Oilfield. Journal of Southwest Petroleum University (Social Sciences Edition), 2019, 21(01):8-13.
[9] Yan Hu, An-qi Gao, Yu-lu Tian. Discuss Determination Method and Application of Oil and Gas Operating Cost in Petroleum Enterprises. Modern Industrial Economy and Informationization, 2024, 14(07): 187-189+194.
[10] Xi-xi Wu, Chun-hua Hou, Wu Chen, et al. Study on Combined Forecast Method for Operating Cost of High Water-cut Water Flooded Oilfield. Technology &Economics in Petrochemicals, 2014, 30(06):5-9.
[11] Qing Zhou, Cheng-zuo Lin, Rong Li. Support Vector Machine Based Classification Prediction Method for Operational Costs. Petroleum and New Energy, 2016, 27(03):16-18.
[12] Jin-rong Feng. Research on Data Analysis Method of Single Well Production and Operation Cost Based on Neural Network. Xi’an Shiyou University, 2020.