Hindawi
Geofluids
Volume 2022, Article ID 4324202, 10 pages
https://doi.org/10.1155/2022/4324202

Research Article

Prediction and Analysis of PDC Bit Wear in Conglomerate Layer with Machine Learning and Finite-Element Method

Li-qiang Wang,[1] **Ming-ji Shao**,[2] **Wei Zhang**,[2] **Zhi-peng Xiao**,[2] **Shuo Yang**,[2] **and Ming-he Yang**[3]

[1]*Department of Petroleum Engineering, Shengli College, China Petroleum University, Shandong Dongying 257061, China*
[2]*Exploration and Development Research Institute of TuHa Oilfield Company, CNPC, Xinjiang Hami 839009, China*
[3]*Department of Petroleum Engineering, Yangtze University, Hubei Wuhan 430000, China*

Correspondence should be addressed to Li-qiang Wang; 281035925@qq.com

Received 26 September 2021; Revised 21 November 2021; Accepted 6 December 2021; Published 10 January 2022

Academic Editor: Jinjie Wang

Polycrystalline diamond compact (PDC) bits experience a serious wear problem in drilling tight gravel layers. To achieve efficient drilling and prolong the bit service life, a simplified model of a PDC bit with double cutting teeth was established by using finite-element numerical simulation technology, and the rock-breaking process of PDC bit cutting teeth was simulated using the Archard wear principle. The numerical simulation results of the wear loss of the PDC bit cutting teeth, such as the caster angle, temperature, linear velocity, and bit pressure, as well as previous experimental research results, were combined into a training dataset. Then, machine learning methods for equal-probability gene expression programming (EP-GEP) were used. Based on the accuracy of the training set, the effectiveness of this method in predicting the wear of PDC bits was demonstrated by verifying the dataset. Finally, a prediction dataset was established by a Latin hypercube experiment and finite-element numerical simulation. Through comparison with the EP-GEP prediction results, it was verified that the prediction accuracy of this method meets actual engineering needs. The results of the sensitivity analysis method for the gray correlation degree show that the degree of influence of bit wear is in the order of temperature, back dip angle of the PDC cutter, linear speed, and bit pressure. These results demonstrate that when an actual PDC bit is drilling hard strata such as a conglomerate layer, after the local high temperature is generated in the formation cut by the bit, appropriate cooling measures should be taken to increase the bit pressure and reduce the rotating speed appropriately. Doing so can effectively reduce the wear of the bit and prolong its service life. This study provides guidance for predicting the wear of a PDC bit when drilling in conglomerate, adjusting drilling parameters reasonably, and prolonging the service life of the bit.

1. Introduction

With increasing oil and gas exploration in China, many glutenite reservoirs have been discovered, among which a representative oilfield is the Mahu oilfield in the Xinjiang oil region. At the bottom of the Badaowan Formation in the oilfield, the gravels are well developed, with a thickness of 100–350 m, and the ability to drill is poor. The formation lithology of the Karamay Formation changes greatly in the horizontal direction, there are many longitudinal intercalations, the glutenite particle size is uneven, and bit selection is difficult. Other glutenite reservoirs share this feature. The hard gravel makes it difficult to drill [1, 2].

Although polycrystalline diamond compact (PDC) bits have the advantages of high rock-breaking efficiency, strong wear resistance, and a long service life, when drilling in a conglomerate formation, the wear rate of the cutting teeth increases sharply, easily leading to bit failure. Therefore, to enhance the rock-breaking ability, accurately predicting the bit wear and reducing the adverse effects is important.

In research on the PDC bit wear law in conglomerate layers, experimental methods and numerical simulation

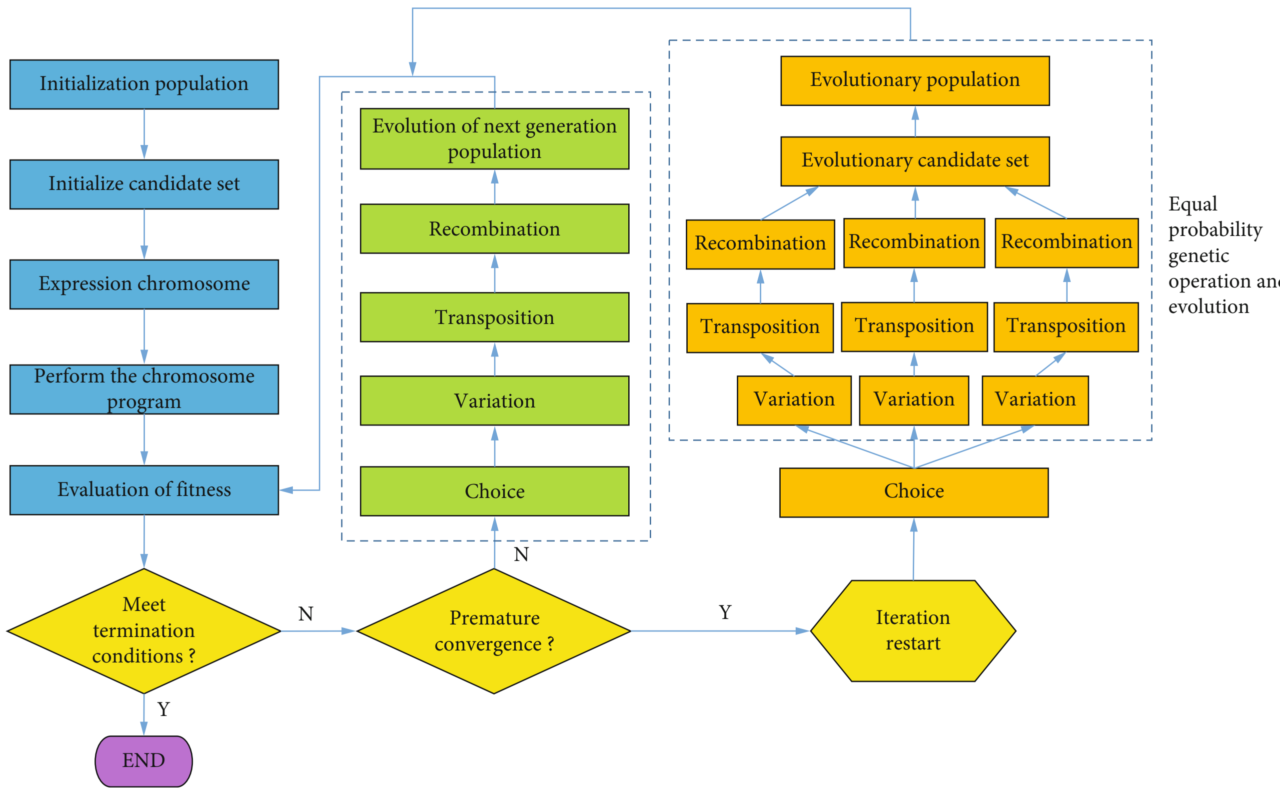

Figure 1: Flowchart of EP-GEP [19].

methods, such as the finite-element method, have mainly been used. In experimental research, standard wear parts or composite chips are generally used for grinding tests to obtain the wear laws of diamond bits in different rock media, such as the influences of rock properties, normal pressure, cutting line speed, and wear chord length on the amount of wear of the composite [3–7]. In comprehensive research through experiments and numerical simulations, the experimental method is generally used to study the influences of different factors, such as the cutting angle of the PDC coring bit, outcrop, linear velocity, and rock sample properties, on the wear law of composite cutting teeth. Then, the feasibility of wear law is verified using the numerical simulation method [8, 9]. The above research mainly addressed the wear law of the drill bit using the experimental method, which has played a positive role in promoting research in this field. However, the influence of temperature on bit wear has not been considered, and the experimental method or combined experimental and numerical simulation verification cannot accurately predict the wear of the PDC drill under the combined action of various factors in high-temperature and high-pressure environments. Therefore, not only is in-depth study of the bit wear law under different temperatures needed, but also it is particularly important to select appropriate prediction methods to predict bit wear under different working conditions to achieve efficient drilling and prolong the service life of bits.

Among the many prediction methods, machine learning has developed rapidly in recent years and has good development prospects [10–13]. Gene expression programming (GEP) is based on the genetic algorithm (GA) and genetic programming (GP), which has excellent performance in knowledge mining, function discovery, optimization, and prediction [14]. Using a machine learning modeling tool, an explicit model with a simple structure and high prediction accuracy can be obtained through evolution without it being necessary to know the structure and parameters of the model in advance, thereby reducing the difficulty of establishing the prediction model and avoiding the preset model structure based on the regression method. Then, the subjectivity of parameters is determined using a statistical method [15]. At present, the GEP method has been

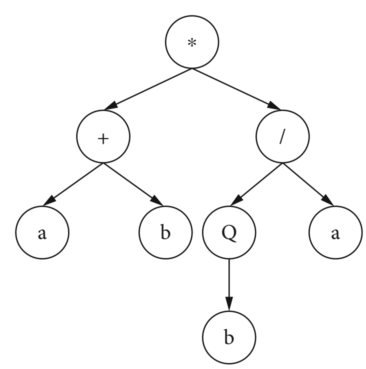

Figure 2: Expression tree corresponding to Equation (2).

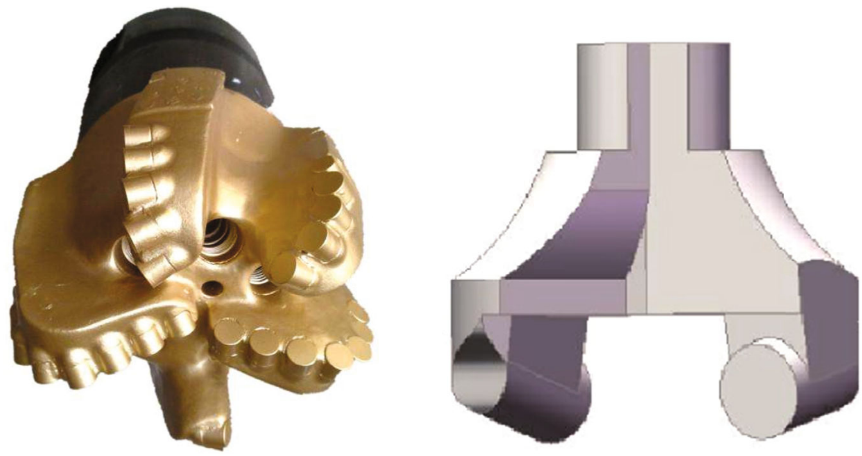

Figure 3: Simplified model of PDC bit with double cutting teeth.

successfully applied in many disciplines and fields [16–18]. It has not been reported that the GEP machine learning method has been used to predict bit wear. To predict the bit wear accurately under different working conditions, realizing the purpose of efficient drilling and prolonging the service life of the bit, it is necessary to study the GEP machine learning modeling method and its prediction effectiveness.

2. Equal-Probability Gene Expression Programming Algorithm (EP-GEP)

GEP combines the advantages of GAs and GP. In the form of expression, it inherits the simple and fast characteristics of the fixed-length linear coding of the GA. In terms of gene expression (semantic expression), it inherits the flexible and changeable characteristics of the GP tree structure, and it solves complex problems with simple coding two to four orders of magnitude faster than the traditional machine learning evolutionary algorithm [15].

However, the traditional GEP method has some problems, such as nondirectional evolution and premature convergence in the process of knowledge mining, which can easily fall into the local optimum and reduce the efficiency and quality of the overall optimal solution. Therefore, it is necessary to mitigate these defects. The proposed EP-GEP method can improve the convergence efficiency and solution quality of the algorithm.

The flow of the EP-GEP optimization calculation is shown in Figure 1. First, a certain number of chromosome individuals are randomly generated to form the initial population. Second, the candidate set is established by selecting excellent individuals in the initial population. According to the bit wear analysis, the best fitness function of the individual in the group suitable for the problem expression is selected. The responsiveness of each individual in the group is assessed. Then, the individual is selected, mutated, inserted, and recombined, and other genetic operations are carried out to produce new offspring and form new groups. Then, they enter the next round of the optimization process. If local precocious convergence occurs, the algorithm enters the calculation process of equal-probability gene expression optimization (taking three equal probability individuals as an example in Figure 1), generating new offspring to form a new population, and they enter the next round of optimization calculation. Then, the above optimization calculation process is repeated until the iteration termination condition is satisfied.

2.1. Gene Structure. The target of EP-GEP is a chromosome (genome) composed of a single gene or multiple genes. The gene in EP-GEP is a simplification of the gene principle in biology. The gene in EP-GEP is composed of a head and tail. The head can be composed of a function symbol (F) and a terminal symbol (t), whereas the tail can only be composed of terminal symbol t. The chromosome (or individual) in EP-GEP is composed of one or more genes of equal length, and multiple genes are connected by a connection function. Each individual represents a candidate solution to the problem to be solved. Several of these chromosomes constitute the entire population.

The relationship between tail length t and head length h is

$$t = h \times (n - 1) + 1, \tag{1}$$

where n represents the maximum number of variables required by the function character (for example, open-ended operation, $n = 1$; multiplication or addition operation, $n = 2$).

For example, the expression tree corresponding to Equation (2) is shown in Figure 2.

$$(a + b) * \left(\frac{b^{1/2}}{a}\right). \tag{2}$$

The parsing rule of the expression tree is from top to bottom and from left to right, until the node is the terminator. The gene after the termination point is the noncoding

Table 1: Attribute parameters of polycrystalline diamond and conglomerate.

Parameter name	Polycrystalline diamond	Conglomerate
Density ($kg \cdot m^{-3}$)	3520	2540
Elastic modulus (MPa)	8.9×10^5	5.4×10^4
Poisson's ratio	0.07	0.27
Thermal conductivity ($J \cdot m^{-1} \cdot s^{-1} \cdot °C^{-1}$)	543.0	3.5
Specific heat capacity ($J \cdot kg^{-1} \cdot °C^{-1}$)	790.0	800.0
Coefficient of thermal expansion (10^{-6}°C)	2.5	52.0
Compressive strength (MPa)	270.0	67.6
Wear coefficient	3×10^{-7}	3×10^{-7}

region of the chromosome, so it is no longer in operation. Here, the function character set is $\{*, +, /, Q\}$ (Q is the square-root operation), and the terminator set is $\{a, b\}$. If the head length h of the gene is 6, then, according to Equation (1), the tail length t is 7, and the total length of the gene is 13 [20].

2.2. Genetic Operator. EP-GEP creates an initial population in the algorithm, and each chromosome in the population represents a solution to the problem. Then, a series of genetic operations are carried out to generate new high-fitness offspring individuals to obtain better solutions. The basic genetic operators of EP-GEP include selection, mutation, inversion, insertion, root insertion, gene transformation, single point recombination, two-point recombination, and gene recombination [19].

2.3. Fitness Function. To obtain the best solution, it is necessary to evaluate the environmental adaptability of the newly generated chromosomes. Similar to other machine learning evolutionary algorithms, EP-GEP uses the fitness function value (i.e., fitness) to evaluate the quality of chromosomes. Sometimes, the fitness function can be defined according to the solution of the problem. The commonly used fitness functions in the symbolic regression are the complex correlation coefficient method, relative hits, absolute hits, mean square error (MSE), root MSE (RMSE), absolute mean difference, relative variance, relative root mean square error, and relative absolute value difference.

In this study, the RMSE was obtained using the fitness function expressed in the following equation.

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{j=1}^{m}\left(y_j - \hat{y}_j\right)}. \tag{3}$$

2.4. Finite-Element Simulation Model

2.4.1. Simplified Model of Cutting Teeth. Among the main parameters affecting the rock-breaking efficiency of the PDC bit, the back dip angle mainly represents the cutting ability of the cutting teeth for the formation. The role of the side angle is to produce a pushing force on the cuttings to discharge them, and the circumferential angle determines

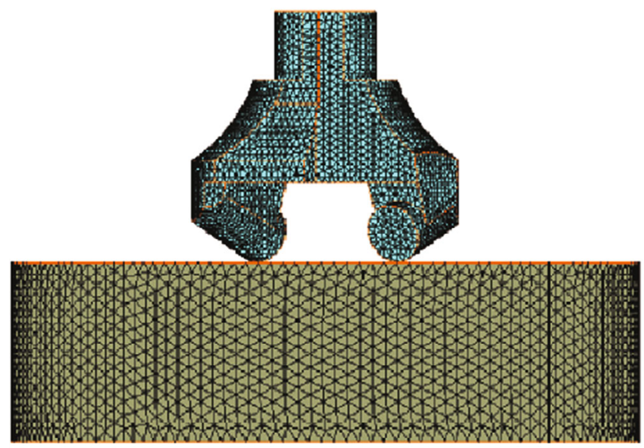

Figure 4: Mesh generation of finite-element model for rock breaking of PDC bit with double cutting teeth.

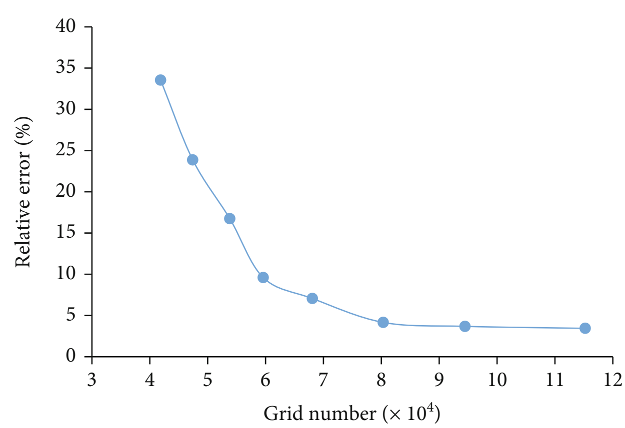

Figure 5: Influence of grid number on simulation accuracy.

the distribution of the cutting teeth. The finite-element software used was MSC Marc. When finite-element software is used to model and simulate the all the PDC bit cutting teeth, there are two problems. First, the model is more complex. Because there are many factors affecting the rock breaking by a bit, it is difficult to highlight the role of the back dip angle of the cutting teeth of the bit in rock breaking. Second,

Table 2: Experimental parameters of EP-GEP.

Parameter	Value	Parameter	Value
Population size	78	Length of head	9
Gene number	6	Mutation rate	0.00138
Recombination rate	0.00277	One-point recombination rate	0.00277
Two-point recombination rate	0.00277	Transposition rate	0.00277
Root insertion sequence transposition rate	0.00546	Insertion sequence transposition rate	0.00546
Link function fitness function	*	Fitness function	RMSE

calculation is difficult, leading to the nonconvergence phenomenon, which affects the stability and reliability of the simulation results. Based on previous research and the above two considerations, the entire cutting tooth model is simplified to a double cutting tooth model (see Figure 3). The basic parameters of the simplified model are as follows: the side angle is 25°, the diameter of the composite chip is 13.4 mm, and the maximum diameter of the bit is 60 mm [21].

2.4.2. Material Parameters and Basic Assumptions

(1) Material Parameters. The material property parameters of the conglomerate and PCD are shown in Table 1.

(2) Basic Assumptions. The classical Archard wear model was used to simulate the wear of the PDC bit [22]. Because the maximum diameter of the PDC bit with double cutting teeth is 60 mm, to reduce the influence of rock side loading on rock breaking, according to Saint Venant's principle [23], a cylindrical rock sample with a diameter of 180 mm and a height of 40 mm was used to simulate the actual formation rock. In addition, the formation rock was assumed to be isotropic, and the influence of the drilling fluid on the cutting tooth wear was ignored. The failure criterion of the rock was the linear Mohr–Coulomb criterion. The confining pressure was loaded on the side of the rock in the form of stress, and thermal/structural analysis was selected for the analysis task.

2.4.3. Grid Size and Accuracy Control. A 10-node tetrahedral mesh was adopted, and the mesh was refined. The mesh division of the finite-element model for the rock breaking of the PDC bit with double cutting teeth is shown in Figure 4. When the rock sample is broken and deformed, mesh redivision technology is used to solve the subsequent simulation problems.

When the PDC bit crown top ($r = 100$ mm) had an off-cutting tooth loading pressure of 1.5×10^3 N and rotating speed of 120 r/min, the wear volume of the PDC bit was 19.70 mm^3 when the composite was scrapped. The errors in the simulation results under different grid numbers were compared according to the results of the physical simulation experiment. It was found that, when the mesh number was greater than 8.00×10^4, the wear of the cutting teeth tended to be stable. Considering the calculation accuracy and simulation time, the mesh size was 1.6 mm, the mesh number was 9.44×10^4, and the cutting tooth wear was 18.98 mm^3. Compared with the experimental data in a previous report [5], the relative error was 3.67% (Figure 5).

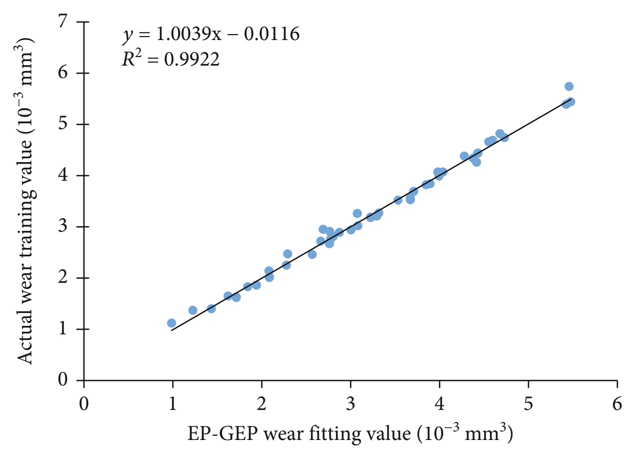

Figure 6: Comparison between wear amount of training dataset and EP-GEP fitting value.

2.5. PDC Bit Wear Dataset

2.5.1. Single-Factor Wear Dataset. The finite-element numerical simulation method was used to fix three of the four variables of the bit cutting teeth, such as the back angle, temperature, linear velocity, and bit pressure, to simulate the change law of bit wear when the other variable changes. For example, when the inclination angle, temperature, and linear speed of the cutting teeth are fixed, different bit pressures are set, and the wear amount of the bit is determined by simulation. This can be expressed as

$$y = \{\alpha, T, v, x\}, \tag{4}$$

where y is the bit wear, α is the back angle of the cutting teeth, T is the temperature, v is the linear speed, and x is the weight on the bit.

Equation (4) can be further expressed as the following vector form:

$$(\alpha, T, v, x, y). \tag{5}$$

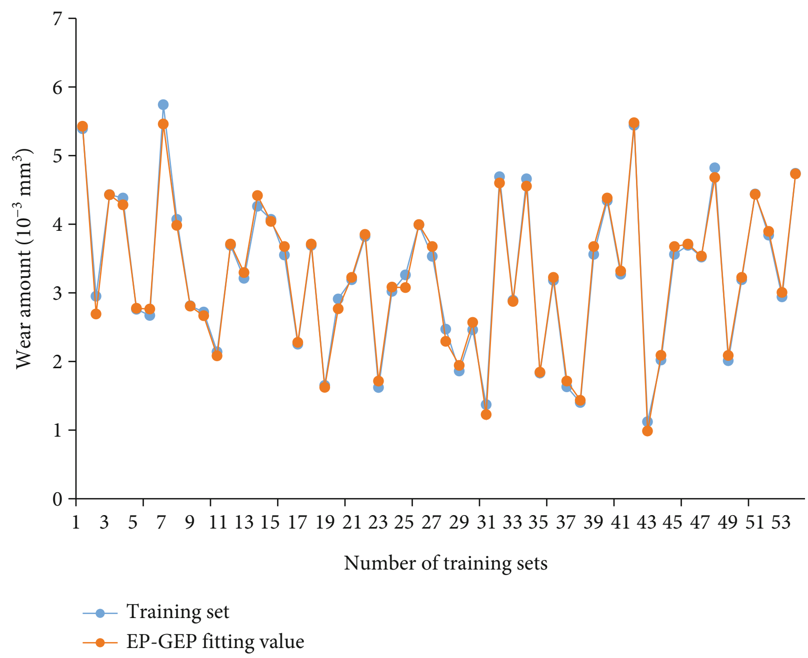

FIGURE 7: Comparison of training set wear and EP-GEP fitting value.

The effects of other single variables on bit wear can be studied similarly.

The dataset in the form of Equation (5) and the previous experimental data were combined into a single-factor wear dataset, which was a part of the machine learning training set.

2.5.2. Multifactor Wear Dataset. The finite-element numerical simulation method was used to fix one of the four variables of the bit cutting teeth (the back angle, temperature, linear velocity, and bit pressure) to simulate the change law of bit wear when the other three variables change. For example, when the back angle of the cutting teeth was fixed as a variable, different temperatures, linear velocities, and bit pressures were set to determine the wear amount of the bit through simulation. This can be expressed as

$$y = \{\alpha, x_1, x_2, x_3\}, \tag{6}$$

where y is the bit wear, α is the back angle of the cutting teeth, x_1 is the temperature, x_2 is the linear speed, and x_3 is the weight on the bit.

Equation (6) can be further expressed in the following vector form:

$$(\alpha, x_1, x_2, x_3, y). \tag{7}$$

The influences of other variables on the bit wear can be studied similarly.

The dataset of Equation (7) and that of single-factor wear were combined to establish a complete machine learning training set.

3. Results and Analysis

3.1. EP-GEP Time Series Model Training. Fifty-four groups of data from 80 groups were used for the EP-GEP time series training. The experimental parameters are shown in Table 2. The remaining 26 sets of data were used for validation.

After training, the R^2 value of the model was 0.9922, as shown in Figures 6 and 7.

The expression tree structure of individual genes is shown in parts (1)–(6) in Figure 8.

3.2. EP-GEP Model Validation. The model was compared with the validation dataset to verify the prediction ability of the EP-GEP model. A comparison between the wear amount of the validation set and the EP-GEP prediction value is shown in Figure 9, and the relative error comparison results are shown in Figure 10.

As shown in Figure 9, the validation set is basically consistent with the EP-GEP prediction results, and the gap is small. Figure 10 reveals that the relative error between the prediction results of the EP-GEP model and the verification set is small, with a maximum relative error of 9.49%, a minimum of 0.13%, and an average of 3.64%. This shows that the model established by the EP-GEP method can accurately fit the bit wear.

3.3. EP-GEP Model Prediction. To highlight the generality of the model, an irregular real number was selected for the value of the influencing factors. All parameters were covered according to the Latin hypercube experimental design method. In Table 3, the predicted value of the EP-GEP model and the results of finite-element simulation are compared. The maximum relative error is −7.01%, the minimum

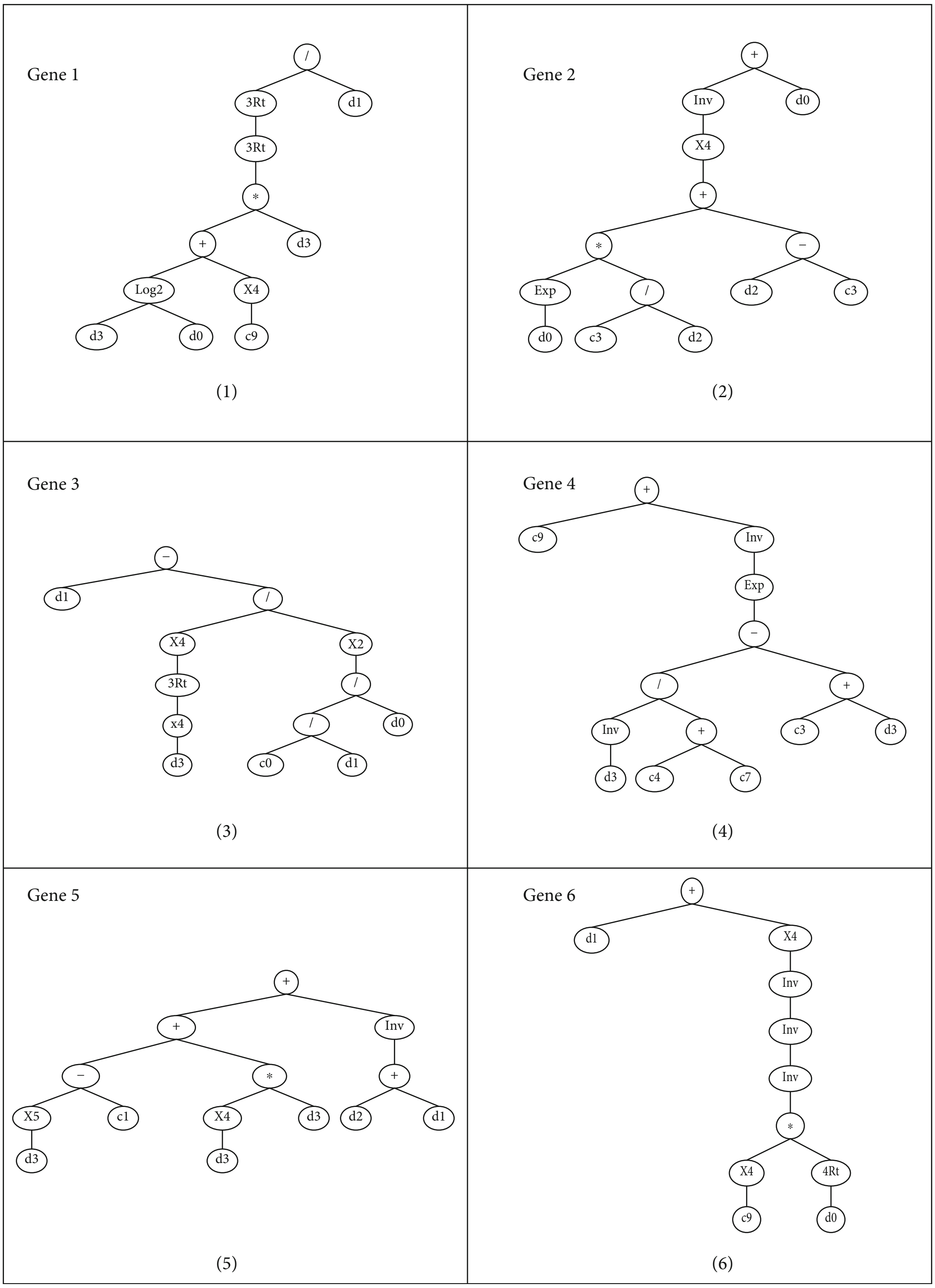

Figure 8: Expression trees of genes 1–6.

error is −0.47%, and the average relative error is −0.99%. From the perspective of prediction accuracy, the model can meet the demand of PDC bit wear prediction research.

3.4. Sensitivity Research Based on Deng's Gray Relational Analysis. The sensitivity of each influencing factor to the wear amount in Table 3 was analyzed by Deng's correlation degree method and the gray correlation theory [24, 25].

If X_i is a system factor and its observation data at the k-th moment is $x_i(k)$, then the behavior sequence of the factor X_i is $X_i = (x_i(1), x_i(2)\cdots\cdots x_i(n))$. Here, X_0 is the reference sequence, and X_1 is the comparison sequence.

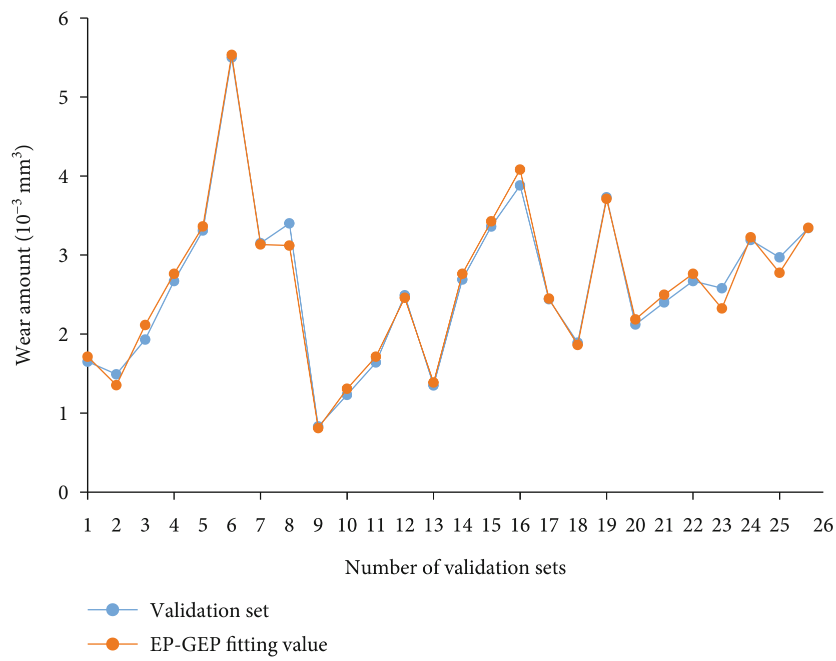

FIGURE 9: Comparison of wear amount of verification set and EP-GEP prediction value.

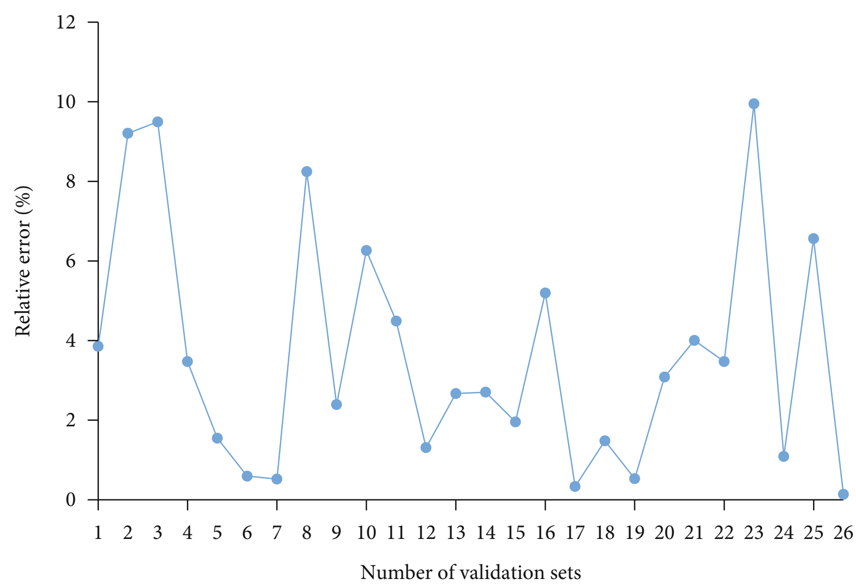

FIGURE 10: Comparison of relative error between verification set and EP-GEP.

If $\gamma(x_0(k), x_i(k))$ is the real number, then the calculation formula of Deng's correlation degree is as follows:

$$\gamma(x_0(k), x_i(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|}, \tag{8}$$

$$\gamma(X_0, X_i) = \frac{1}{n}\sum_{k=1}^{n} \gamma(x_0(k), x_i(k)). \tag{9}$$

Equation (9) is the average value of $\gamma(x_0(k), x_i(k))$ when the four axioms of the gray relation are satisfied [25]. When $\gamma(X_0, X_i)$ is the gray relational degree of X_1 to X_0, $\gamma(x_0(k), x_i(k))$ is the gray correlation coefficient of X_1 to X_0.

The results show that Dun's correlation degrees of the cutter inclination angle α, temperature T, linear velocity V, and bit pressure P on wear are 0.7032, 0.7208, 0.7159, and 0.7138, respectively. According to Deng's correlation degree, the temperature has the greatest influence on the bit wear during rock breaking, followed by the rake angle of the

Table 3: Comparison of relative error between EP-GEP model predicted value and finite-element simulation result.

Serial number	α (°)	T (°C)	V (m·s^{-1})	P (N)	EP-GEP (V/mm^3)	Relative error with the simulated value of finite-element method (%)
1	12	120	0.07	1580	1.722	−2.433
2	12	220	0.13	1870	2.601	−3.302
3	12	340	0.23	2060	4.343	1.592
4	12	430	0.27	2265	5.730	−2.873
5	12	550	0.29	2775	8.023	2.368
6	17	120	0.13	2060	2.599	2.757
7	17	220	0.23	2265	3.741	3.885
8	17	340	0.27	2775	5.156	−6.776
9	17	430	0.29	1580	5.855	2.073
10	17	550	0.07	1870	2.907	3.174
11	22	120	0.23	2775	4.155	3.243
12	22	220	0.27	1580	3.712	−2.722
13	22	340	0.29	1870	4.979	−6.980
14	22	430	0.07	2060	2.515	−7.010
15	22	550	0.13	2265	4.263	−0.585
16	27	120	0.27	1870	2.826	0.626
17	27	220	0.29	2060	3.650	−6.791
18	27	340	0.07	2265	2.226	−5.063
19	27	430	0.13	2775	3.390	−2.726
20	27	550	0.23	1580	5.346	6.506
21	33	120	0.29	2265	2.138	−5.392
22	33	220	0.07	2775	1.776	4.279
23	33	340	0.13	1580	1.810	−0.501
24	33	430	0.23	1870	3.220	−1.587
25	33	550	0.27	2060	4.639	−0.468

cutting teeth, linear velocity, and bit pressure [21]. Therefore, when the PDC bit is drilling in hard formations, such as gravel, reducing the local high temperature generated by bit cutting and maintaining the high-bit-pressure and low-rotation-speed mode can reduce bit wear and prolong service life to a certain extent.

4. Conclusions

(1) Through the verification of the experimental results and the sensitivity analysis of the mesh number and on the basis of verifying the accuracy of the numerical simulation model, finite-element prediction results of wear under different cutting tooth caster angle, temperature, linear velocity, and bit pressure were introduced into a machine learning training dataset

(2) The EP-GEP machine learning method was used to carry out modeling and prediction research. Through a comparative analysis of the model effectiveness and prediction ability, it was proven that the EP-GEP model has good prediction accuracy

(3) The results of EP-GEP wear prediction and gray correlation sensitivity analysis show that, after the actual PDC bit cuts the formation to produce a local high temperature, taking appropriate cooling measures, appropriately increasing the bit pressure, and reducing the rotating speed can effectively reduce the bit wear and prolong the service life

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, or publication of this article.

Acknowledgments

This study was supported by the Scientific Research Development Plan of Shandong Province (j18ka205), the Scientific Research Start-Up Fund for Introducing High-Level Talents from the Shengli College of China University of Petroleum (Beijing) (kq2019-005), and the Key R&D Program of Dongying City in Shandong Province (2018kjcx).

References

[1] L. Zongyu, Z. Fei, and L. Ming, "Key drilling technology for glutenite tight oil horizontal wells in Mahu oilfield, Xinjiang," *Petroleum Drilling Technology*, vol. 47, no. 2, pp. 9–14, 2019.

[2] L. Li, Z. Lubin, and Z. Lingzhan, "Drilling and completion technology for efficient development of Mahu low permeability reservoir," *Xinjiang Petroleum Science and Technology*, vol. 27, no. 2, pp. 1–6, 2017.

[3] C. A. Cheatham and D. A. Loeb, "Effects of field wear on PDC bit performance," in *SPE/IADC Drilling Conference*, Louisiana, USA, 1985.

[4] D. A. Glowka, "Implications of thermal wear phenomena for PDC bit design and operation," in *SPE Annual Technical Conference and Exhibition*, Nevada, USA, 1985.

[5] Z. Deyong, Y. Jun, and X. Cheng, "A modified determination method of rock's abrasiveness for well drilling using diamond bits," *Journal of China University of Petroleum*, vol. 40, no. 4, pp. 73–80, 2016.

[6] Z. H. Shaohe, X. Xiaohong, and F. Hhaijiang, "PDC abrasion rule affected by height of protrusion and linear velocity," *Journal of Central South University*, vol. 41, no. 6, pp. 2173–2177, 2010.

[7] I. H. Michaels, M. Mostofi, and T. Richard, "An experimental study of the wear of polycrystalline diamond compact bits," in *SPE 53rd U.S. Rock Mechanics/Geomechanics Symposium*, New York, USA, 2019.

[8] X. Xiaohong, *The study on the cutter's abrasion rule of PDC coring bit*, Central South University, Changsha, China, 2011.

[9] G. M. Gouda, M. Maestrami, and M. A. A. Saif, "A mathematical model to compute the PDC cutter wear value to terminate PDC bit run," in *SPE Middle East Oil and Gas Show and Conference*, Manama, Bahrain, 2011.

[10] D. Weber, T. F. Edgar, and L. W. Lake, "Improvements in capacitance-resistive modeling and optimization of large scale reservoirs," in *Paper presented at the SPE Western Regional Meeting*, San Jose, California, 2009.

[11] J. Li, Z. Lei, and S. Li, "Optimizing water flood performance to improve injector efficiency in fractured low-permeability reservoirs using streamline simulation," in *Paper presented at the SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition*, Dammam, Saudi Arabia, 2016.

[12] M. Khan, S. Alnuaim, and Z. Tariq, "Machine learning application for oil rate prediction in artificial gas lift wells," in *Paper presented at the SPE Middle East Oil and Gas Show and Conference*, Manama, Bahrain, 2019.

[13] C. Noshi, M. Eissa, and R. Abdalla, "An intelligent data driven approach for production prediction," in *Paper presented at the Offshore Technology Conference*, Houston, Texas, 2019.

[14] C. Ferreira, "Gene expression programming: a new adaptive algorithm for solving problems," *Complex Systems*, vol. 13, no. 2, pp. 87–129, 2001.

[15] Z. Kisi, "Comparative analysis of ozone level prediction models using gene expression programming and multiple linear regression," *Geofizika*, vol. 30, no. 30, pp. 43–74, 2013.

[16] C. Zhou, W. Xiao, and T. M. Tirpak, "Evolving accurate and compact classification rules with gene expression programming," *IEEE Transactions on Evolutionary Computation*, vol. 7, no. 6, pp. 519–531, 2003.

[17] N. D. Hoang and D. Tien Bui, "Spatial prediction of rainfall-induced shallow landslides using gene expression programming integrated with GIS: a case study in Vietnam," *Natural Hazards*, vol. 92, no. 3, pp. 1871–1887, 2018.

[18] J. Jedrzejowicz, P. Jedrzejowicz, and I. Wierzbowska, "Implementing gene expression programming in the parallel environment for big datasets' classification," *Vietnam Journal of Computer Science*, vol. 6, no. 2, pp. 163–175, 2019.

[19] L. Wang, M. Shao, G. Kou et al., "Time series analysis of production decline in carbonate reservoirs with machine learning," *Geofluids*, vol. 2021, 8 pages, 2021.

[20] C. Ferreira, *Gene Expression Programming: Mathematical Modeling by an Artificial Intelligence*, Springer, Berlin, 2006.

[21] H. Peng, G. Feng, Z. Liwei, W. Lili, and Y. Minghe, "Study on the wear law of PDC bits in conglomerate," *China Petroleum Machinery*, vol. 48, no. 7, pp. 1–6, 2020.

[22] J. F. Archard, "Contact and rubbing of flat surfaces," *Journal of Applied Physics*, vol. 24, no. 8, pp. 981–988, 1953.

[23] R. A. Toupin, "Saint-Venant's principle," *Archive for Rational Mechanics and Analysis*, vol. 18, no. 2, pp. 83–96, 1965.

[24] J. L. Deng, "Figure on difference information space in grey relational analysis source," *Journal of Grey Systems*, vol. 16, no. 2, pp. 121–139, 2004.

[25] J. L. Deng, *Course of Grey System Theory*, Huazhong University of Technology Press, 1990.