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Prediction method of reciprocating compressor inlet pressure and shaft power based on GA - BP neural network

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Abstract. Aiming at the problems of inlet pressure and shaft power prediction in the optimization operation of natural gas compressor unit, a method of inlet pressure and shaft power prediction based on GA-BP neural network is proposed. The method by testing inlet pressure, the output flow rate and the output pressure are used to predict the inlet pressure and the shaft power of the compressor. The compressor operating condition is adjusted according to the inlet pressure, and the compressor operation station is adjusted according to the shaft power to achieve the energy saving and reduce consumption. The experiments show that the method can predict the inlet pressure, and the error is less than 2.75%. By predicting the shaft power and adjusting the operation combination, the energy saving is about 10%.

Key words. GA-BP neural network, reciprocating compressor, pressure prediction, shaft power prediction.

1. Introduction

In the process of transporting the natural gas, compressor unit has large energy consumption. It is shown that the energy consumption of the compressor unit is about between 3% to 5% of the total energy of the pipeline. Therefore, it is necessary to optimize the operation of the compressor unit. Experts pointed out that through

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strict fine-tuning and optimization approach, the energy consumption can reduce about 20% [1].

The Place Type place University of Place Name Regina and Sask Energy/TransGas Company used a fuzzy programming model to calculate the compressor's dynamic response[2]. Suming Wu and Mercado et al. solved the fuel cost problem of natural gas pipeline compressor station under steady state condition, and gave the optimization scheme of natural gas pipeline network[3]. Chebouba et al. used the ant colony algorithm to optimize the gas transmission line with compressor [4]. Mohamadi Baghmolaei et al. studied several optimization methods with the objective function as the lowest energy consumption of gas transmission line compressor. The optimization results shown that artificial neural network (ANN) has the best optimization effect [5]. Advantica Stone Company and Simone Company, the United States TETCO gas pipeline companies have conducted a non-steady-state optimization of the gas pipeline network under the operation, and made some progress in the model and algorithm [6–8]. It can be seen that breakthroughs have been made in the study of the optimization of gas transmission line operation.

Reciprocating natural gas compressors are the core equipment of the gas transmission line. The mathematical model includes equality constraint and inequality constraint. The mathematical model of the compressor is used to predict the inlet pressure and the shaft power, which is important for the optimization of the gas transmission line.

Based on the objective of minimizing the energy consumption of the reciprocating compressor station and ensuring the gas pressure and the gas capacity of the gas transmission line, the neural network calculation method is used to predict the inlet pressure and the shaft power of the compressor unit and optimize the compressor operating condition, a reasonable allocation of the compressor combination of the operation to achieve the purpose of energy saving and reducing consumption.

2. Gas transmission line compressor operating model

As the compressor station contains the number of compressors and models are not the same, to a single compressor as a unit, this paper compressor energy consumption optimization analysis.

According to the compressor theory, the reciprocating compressor shaft power can be expressed as:

$$N_z = \frac{N_i}{\eta_m} = k_1 P_{cin} Q_{cin} \left[\left(\frac{P_{out}}{P_{cin}} \right)^{k_2} - 1 \right] / \eta_m \tag{1}$$

where, N_z, N_i are the compressor shaft power and indicating power (kW), P_{cin}, P_{out} are the compressor inlet pressure and exhaust pressure (P_a), Q_{cin} is the inspiratory capacity of the compressor (m^3/s), η_m is the compressor mechanical efficiency; k_1, k_2 are coefficients relating to the nature of the compressor.

As can be seen from the above equation, the compressor shaft power, intake and exhaust pressure, intake air flow, exhaust flow, speed, etc. are closely related.

Compressor intake volume should be within a certain range:

$$\begin{cases} Q_{cin\min} \leq Q_{cin} \leq Q_{cin\max} \\ Q_{out\min} \leq Q_{out} \leq Q_{out\max} \end{cases} \tag{2}$$

where,$Q_{cin}, Q_{cin\min}, Q_{cin\max}$are the inspiratory capacity of the compressor, the minimum inspiratory capacity, the maximum inspiratory capacity (m^3/s),$Q_{out}, Q_{out\min}, Q_{out\max}$are the compressor exhaust flow, the minimum exhaust flow, the maximum exhaust flow.

In order to ensure the safety of gas transmission, gas inlet pressure and exhaust pressure limit is as follows:

$$\begin{cases} P_{cin\min} \leq P_{cin} \leq P_{cin\max} \\ P_{out\min} \leq P_{out} \leq P_{out\max} \end{cases} \tag{3}$$

Where,$P_{cin}, P_{cin\min}, P_{cin\max}$are the compressor inlet pressure, minimum inlet pressure, maximum inlet pressure(P_a),$P_{out}, P_{out\min}, P_{out\max}$are the compressor exhaust pressure, the minimum exhaust pressure, maximum exhaust pressure.

Taking into account the actual working conditions of the compressor, the compressor shaft power and speed limits are as follows:

$$R = 1 \tag{4}$$

Where,$N_i, N_{i\min}, N_{i\max}$are the compressor shaft power, minimum shaft power, the maximum shaft power (kW),$n_m, n_{m\min}, n_{m\max}$are the compressor speed, minimum speed, maximum speed $(r/\min)$.

Under the condition of guaranteeing the downstream gas pressure and the gas volume, the power consumption of the compressor unit is the lowest. It can be seen from Equation 1 that the compressor suction pressure and shaft power are closely related with suction volume, compressor speed, exhaust pressure, exhaust flow, and gas temperature (suction temperature and exhaust temperature).

3. Compressor pressure and shaft power estimation model based on the GA-BP neural network

3.1. BP neural network

BP (Back Propagation) is a multi-layer feed forward neural network trained by the error back propagation algorithm, and is one of the most widely used neural network models. BP network can learn and store a large number of inputs - outputs model mapping, without revealing the mathematical relationship between the description of the mathematical equation. The rule of learning is to use the steepest descent method to adjust the weights and thresholds of the network through back propagation so as to minimize the sum of squares of errors of the network. The typical structure of multilayer feed forward network is shown in Figure 1.

In Figure 1, there are $m$neurons in the input layer,p neurons in the hidden layer, n

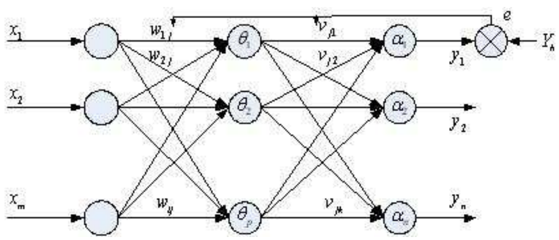

Fig. 1. Typical structure of neural network

neurons in the output layer, $w_{ij}(i = 1, 2, \cdots, m; j = 1, 2, \cdots, p)$are the weights of the input layer to the hidden layer, $v_{jk}(j = 1, 2, \cdots, p; k = 1, 2, \cdots, n)$are the hidden layer to the output layer weights, $\theta_j(j = 1, 2, \cdots, p)$are hidden layer threshold, $\alpha_k(k = 1, 2, \cdots, n)$are the output layer threshold, $(x_1, x_2, \cdots, x_m)$are the network input vector, $(y_1, y_2, \cdots, y_n)$are the network output vector, $Y_h$is the desired output, and e is the error.

In the BP neural network, and then use the BP algorithm to train weights. As the BP neural network algorithm uses the standard gradient descent algorithm, there are easy to fall into the local extreme values, the data "over-fitting" and other shortcomings. So, in order to improve the BP neural network algorithm, this paper uses genetic algorithm (GA) to optimize the BP neural network.

3.2. Genetic algorithm

Genetic algorithm (GA) is a multi-point search global optimization algorithm based on the principle of biological evolution, so it can avoid local optimization. Genetic algorithm uses heuristic principle, according to a certain fitness function, deals with individuals in the population, retains the high fitness of individual genetic operations (selection, crossover, mutation), and searches for the optimal solution. The process of genetic algorithm to optimize the BP neural network is composed of population initialization, fitness function, selection, and crossover and mutation operation. The process of optimization is shown in Figure 2.

3.3. Estimation model

From the equations (**??**)1) to (**??**)4), we can see that the compressor pressure and shaft power have close relationships with suction volume, compressor speed, exhaust pressure, exhaust flow, and gas temperature (suction temperature and exhaust temperature). Therefore, this paper selects inlet air temperature, exhaust pressure, and exhaust gas flow as BP neural network input, suction pressure and shaft power as the output of BP neural network. The pressure and shaft power estimation model is shown in Figure 3.

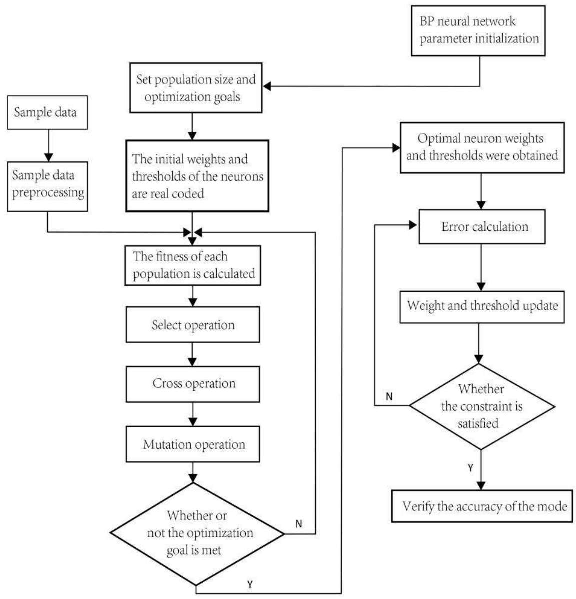

Fig. 2. the flow chart of genetic algorithm optimization BP neural network algorithm

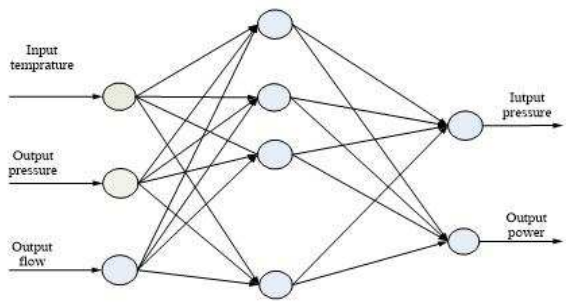

Fig. 3. Estimation model of compressor inlet pressure and shaft power

4. Experiments

4.1. Prediction error indicators

The mean absolute percent error (MAPE) and root mean square error (RMSE) are selected as the index of the reciprocating compressor suction pressure and shaft power to predict error indicators, the specific reference formula is:

$$MAPE = \left| \frac{P_{pin} - P_{cin}}{P_{cin}} \right| \times 100\% \tag{5}$$

Where, P_{pin} is the predicted suction pressure; P_{cin} is the actual suction pressure.

4.2. Application experiment

In the West-East Gas Pipeline system, a 6RDSA-1 type reciprocating natural gas compressor unit has been used.

In this paper, a large number of on-site testing experiments were carried out. The data of the test part are shown in Table 1, the temperature data are 0 , 4 , 8 , ..., 20 . The inspiratory pressure data is 1.5, 1.8, 2.1,. . . ,4.5MPaG. Suction pressure data are 4.8 5, 5.0, 5.2, ..., 6.0MPaG, and the 2046 groups of orthogonal experimental data are collected.

Table 1. the test data of 6RDSA-1 reciprocating natural gas compressor (inlet air temperature of 0

Serial number	Inlet temperature	Inlet pressure	Exhaust temperature	Exhaust pressure	Exhaust flow	Shaft power
		MPaG		MPaG	E4Nm^3/d	kW
1	0	1.5	102.4	4.85	104.78	1873.64
2	0	1.8	87.1	4.85	139.70	2075.00
3	0	2.1	74.7	4.85	175.78	2183.69
4	0	2.4	64.0	4.85	212.94	2216.24
5	0	2.7	54.8	4.85	251.15	2184.25
6	0	3	46.7	4.85	290.38	2105.57
7	0	3.3	39.5	4.85	330.70	1981.45
8	0	3.6	32.9	4.85	372.03	1812.69
9	0	3.9	26.8	4.85	414.43	1601.70
10	0	4.2	21.1	4.85	457.94	1349.14
11	0	4.5	15.8	4.85	502.65	1053.28

The 2046 groups of data can be divided into training data and testing data. The GA-BP neural network model is set up as shown in Figure 4.The test results are shown in Figure 5.

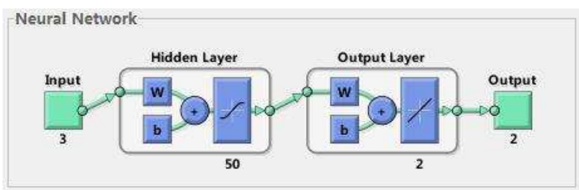

Fig. 4. The neural network model

4.3. Comparison of applications

Sample and predict the inlet pressure and the shaft power every 2 hours. The experimental result is shown in Table 2, and the maximum error is 2.59%.

Table 2. Comparison of model predictions with actual results (one-day operating data)

Serial number	Input parameters			Forecast result		Actual inlet pressure (MPG)	Error rate
	Inlet temperature	Exhaust pressure (MPG)	Daily flow of each compressor ($10^4 m^3$/day)	Inlet pressure (MPG)	Shaft power (KW)		
1	3.5	4.85	180.17	2.228	2163.66	2.23	0.09%
2	5.5	4.84	190.1	2.33	2166.38	2.28	2.2%
3	5	4.84	187.27	2.29	2168.88	2.28	0.04%
4	3.5	4.86	188.93	2.302	2173.17	2.26	1.77%
5	2.5	4.86	187.8	2.299	2183.93	2.26	1.72%
6	2.5	4.85	188.36	2.298	2177.66	2.24	2.59%

In order to further test the effectiveness of the model, this paper extracted a quarter of sampling data, The results of GA-BP model are shown in Table 3, and the maximum error is 2.75%, which satisfies the demand of field calculation.

Table 3. Comparison of model predictions with actual results

Date	Input parameters			Forecast result		Actual inlet pressure (MPG)	Error rate
	Inlet temperature	Exhaust pressure(MPG)	Daily flow of each compressor (10^4m^3/day)	Inlet pressure (MPG)	Shaft power (KW)		
March 19	5.5	4.83	186.39	2.28	2158.25	2.26	0.88%
March 20	4	4.83	189.39	2.3	2167.14	2.26	1.77%
March 21	3	4.82	189.6	2.31	2165	2.25	2.67%
March 22	3.5	4.8	187.89	2.29	2143.44	2.23	2.69%
March 23	3.5	4.84	185.41	2.28	2165.23	2.23	2.42%
March 25	3.5	4.82	186.91	2.28	2160.86	2.26	0.86%
March 26	4	4.74	215.41	2.52	2136.58	2.49	1.2%
March 27	6.5	4.67	275.99	2.99	2007.21	2.91	2.75%
March 29	6.5	4.75	276.46	2.99	2046.02	2.95	1.36%
March 31	9	4.71	280.01	3.02	2004.24	2.98	1.34%
April 2	5.5	4.47	358.44	3.58	1564.14	3.51	1.99%
April 3	6	4.52	365.38	3.63	1560.55	3.55	2.25%
April 5	8.5	4.6	368.95	3.67	1569.7	3.58	2.51%
April 6	10	4.68	349.40	3.55	1708.29	3.56	0.28%
April 9	10	4.63	348.33	3.55	1679.88	3.49	1.72%
May 1	15	4.71	233.43	2.69	2090.22	2.72	1.1%
May 2	12	4.63	235.49	2.69	2047.76	2.71	0.74%
May 3	13	4.69	235.08	2.68	2078.4	2.74	2.19%
May 4	15	4.59	240.96	2.73	2016.15	2.67	2.25%
May 5	14	4.89	241.77	2.78	2158.01	2.86	2.8%
May 8	13	4.87	243.48	2.78	2158.34	2.8	0.71%
May 12	10.5	4.91	249.37	2.81	2169.77	2.87	2.09%
May 13	10.5	4.86	241.5	2.74	2157.25	2.78	1.44%
May 15	11.5	4.9	237.68	2.73	2176.15	2.79	2.15%
May 16	13	4.85	240.6	2.74	2156.1	2.8	2.14%
May 17	13	4.63	239.57	2.71	2045.67	2.74	1.09%
May 18	13	4.83	233.22	2.69	2145.59	2.73	1.47%

Using the predicted shaft power, then timely adjusting the number of compressor units when they put into the work, the results are shown in Table 4.

Table 4. The electricity consumption data of adjusting the compressor using the predicted shaft power

Month	Electricity consumption (kW/h)	Electricity cost (RMB)	Compressors operating number (number/day)	Treatment of natural gas 10^4m^3	Power consumption $°/10^4m^3$	A compressor power consumption °/number/day	Compressor inlet pressure (MPa)	Compressor outlet pressure (MPa)
January	10682661	4646153	172	31381	340	62108	2.2	4.73
February	11474826	4705152	180	29061	395	63749	2.13	4.76
March	10689498	4389940	160	28926	370	66809	2.31	4.81
April	7625520	3189218	87	21387	357	87650	3.02	4.73
May	6255026	2642194	94	22563	277	66543	2.83	4.84
June	6918247	2903154	94	23247	298	73598	3.01	4.83

In summary, by using the GA-BP neural network model, the inlet pressure can be predicted and the prediction error is less than 2.75%. After adopting this model, the number of the compressor is adjusted to save about 10% of the electricity.

5. Conclusion

(??)1)The method based on the GA-BP neural network to estimate the inlet pressure of the compressor is proposed, and it can estimate the inlet pressure more accurately than the traditional BP neural network and avoids the traditional BP algorithm which can easily fall into the local minimum and over-fitting problem.

(??)2)Taking the 6RDSA-1 type reciprocating natural gas compressor unit as an example, the GA-BP neural network modeling method is used to predict the inlet pressure , and the error is less than 2.75%. By predicting the shaft power, the electric energy saving is about 10% after adjusting the operation combination.

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References

[1] S. Wu: *Steady-State Simulation and Fuel Cost Minimization of Gas Pipeline Networks.* Ph. D. Dissertation Abstract and 24 pages, Dept. of Mathematics, U. of Houston, Houston, August(1998).

[2] C. K. Sun, V. Uraikul, C. W. Chan: *An integrated expert system/operations re-*

search apporach for the optimization of natural gas pipeline operations. Engineering applications of artificial intelligence *13* (2000), No. 4, 465-475.

[3] S. Wu, R. Z,Rios-Mercado, E. A. Boyd: *Model relaxations for the fuel cost minimization of steady-state gas pipeline networks*. Mathematical and computer modelling *31* (2000), No. 2, 197-220.

[4] A. Chebouba, F. Yalaoui, A. Smati: *Optimization of natural gas pipeline transportation using ant colony optimization*. Computers&operations research *36* (2009), No. 6, 1916-1923.

[5] M. MohamadiBaghmolaei, M. Mahmoudy, D. Jafari: *Assessing and optimization of pipeline system performance using intelligent systems.*Journal of natural gas science and engineering*18* (2014),64-76.

[6] S. Wright, M. Somani, C. Dii: *Compressor Station Optimization*. 30th Annual Meeting, PSIG (1998).

[7] H. H. Rachford: *Optimizing Pipeline Control in Transient Gas Flow*. 32nd Annual Meeting, PSIG(2000).

[8] C. Kelling: *A Pratical Approach to Transient Optimization for Gas Network*. 32nd Annual Meeting, PSIG (2000).

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