Petroleum Science 21 (2024) 621–640

Contents lists available at ScienceDirect

Petroleum Science

journal homepage: www.keaipublishing.com/en/journals/petroleum-science

Original Paper

Research on a TOPSIS energy efficiency evaluation system for crude oil gathering and transportation systems based on a GA-BP neural network

Xue-Qiang Zhang [a, b], Qing-Lin Cheng [a, *], Wei Sun [a], Yi Zhao [c], Zhi-Min Li [c]

[a] Key Lab of Ministry of Education for Enhancing the Oil and Gas Recovery Ratio, Northeast Petroleum University, Daqing, 163318, Heilongjiang, China
[b] China Petroleum Pipeline Material and Equipment Co., Ltd, Langfang, 065000, Hebei, China
[c] Research Institute of Petroleum Engineering and Technology, Sinopec Northwest Oilfield Company, Urumqi, 830011, Xinjiang, China

ARTICLE INFO

Article history:
Received 18 December 2022
Received in revised form
20 April 2023
Accepted 17 August 2023
Available online 19 August 2023

Edited by Jia-Jia Fei

Keywords:
Crude oil gathering and transportation system
GA-BP neural network
Energy efficiency evaluation
TOPSIS evaluation method
Energy saving and consumption reduction

ABSTRACT

As the main link of ground engineering, crude oil gathering and transportation systems require huge energy consumption and complex structures. It is necessary to establish an energy efficiency evaluation system for crude oil gathering and transportation systems and identify the energy efficiency gaps. In this paper, the energy efficiency evaluation system of the crude oil gathering and transportation system in an oilfield in western China is established. Combined with the big data analysis method, the GA-BP neural network is used to establish the energy efficiency index prediction model for crude oil gathering and transportation systems. The comprehensive energy consumption, gas consumption, power consumption, energy utilization rate, heat utilization rate, and power utilization rate of crude oil gathering and transportation systems are predicted. Considering the efficiency and unit consumption index of the crude oil gathering and transportation system, the energy efficiency evaluation system of the crude oil gathering and transportation system is established based on a game theory combined weighting method and TOPSIS evaluation method, and the subjective weight is determined by the triangular fuzzy analytic hierarchy process. The entropy weight method determines the objective weight, and the combined weight of game theory combines subjectivity with objectivity to comprehensively evaluate the comprehensive energy efficiency of crude oil gathering and transportation systems and their subsystems. Finally, the weak links in energy utilization are identified, and energy conservation and consumption reduction are improved. The above research provides technical support for the green, efficient and intelligent development of crude oil gathering and transportation systems.

1. Introduction

As oilfields gradually enter the late stage of exploitation, crude oil production decreases, and water content increases year by year. The contradiction between high energy consumption and low efficiency in oilfields is becoming increasingly obvious. It is necessary to reduce energy consumption and improve energy efficiency in oilfields. At present, the energy efficiency evaluation method is often used in oilfield businesses to improve the economic benefits of oilfield enterprises. As an important part of gathering and processing, it is necessary to establish the overall energy efficiency evaluation system of crude oil gathering and transportation systems, identify the weak links of energy consumption, and to improve the energy savings of crude oil gathering and transportation systems to achieve high production levels and high efficiency in the oilfield industry.

In recent years, many scholars have studied the energy efficiency evaluation of crude oil gathering and transportation systems and produced some notable achievements. Among them, Tang et al. (2021) comprehensively considered the basic evaluation indices of heating furnaces and pump units, established an energy efficiency evaluation system of multilevel crude oil gathering and transportation systems, analyzed the change law of energy efficiency in different seasons, and determined the weak links of energy utilization. Based on the analytic thought of analytic hierarchy process,

* Corresponding author.
E-mail address: chengqinglin7212@163.com (Q.-L. Cheng).

https://doi.org/10.1016/j.petsci.2023.08.020

Yao et al. (2021) identified the weak links in the energy used in the transfer station system based on the heat and power consumption of the transfer station, and gave suggestions for improvement. Zang et al. (2020) built an index system for energy efficiency of oilfield heating furnaces based on heating furnace indexes such as thermal efficiency, air-fuel ratio, load rate and smoke emission ratio. They used entropy weight method to determine the weight of each index, calculated the comprehensive influence factor of the index, analyzed the operation of heating furnaces, and proposed targeted improvement measures. Cao et al. (2020) established a set of energy efficiency index system for key energy use levels of oilfield enterprise systems. Taking Tarim Oilfield as an example, they proposed a weighted comprehensive evaluation method of energy efficiency based on matrix operation. Li (2020) analyzed the main energy consumption of the combined station and found that the high energy consumption was due to the large oil and gas processing capacity, high oil and gas content and complex oil and gas properties. In view of the above reasons, the energy consumption system of the joint station is optimized by improving oil and gas treatment technology and introducing big data information control. Yao (2020) divided the gathering and transportation system into two stages according to the technological process and production operation status of the gathering and transportation system in the first area of oil recovery operation, selected evaluation methods and evaluation indexes for the gathering and transportation stations and pipelines respectively, and finally evaluated the oil loss of the gathering and transportation system. Kou (2021) used GRU algorithm to establish a machine learn-based prediction model of pump station energy consumption and flow, and verified that the accuracy of the model was high enough to achieve the prediction of pump station energy consumption and flow in oilfield production. Paitoon et al. (2020) pointed out that artificial intelligence can improve people's cognition and more effectively reach the best level within a certain period of time. Reasonable use of artificial intelligence is of great benefit to the oil industry. Anirbid et al. (2021) conducted a comprehensive survey on the research status of machine learning and artificial intelligence to solve problems in the oil and gas industry. Research shows that rational use of intelligent systems can reduce risks and maintenance costs. Using this emerging technology can accelerate the development and progress of the oil and gas industry.

At present, the research on the energy efficiency evaluation system of crude oil gathering and transportation system only adopts subjective or objective evaluation methods to identify the weak links of energy consumption in the existing operation status, which neither comprehensively considers the two factors of efficiency and unit consumption, nor can it carry out energy efficiency risk warning. Therefore, it is necessary to combine artificial intelligence with energy efficiency evaluation of crude oil gathering and transportation system to establish a digital energy efficiency evaluation system of crude oil gathering and transportation system. In this paper, the GA-BP neural network model is used to predict the basic energy efficiency index. On this basis, the triangular fuzzy analytic hierarchy process is used to determine the subjective weight, the entropy weight method is used to determine the objective weight, and the game theory combination weighting combines the subjective and objective. TOPSIS evaluation method is used to comprehensively evaluate the comprehensive energy efficiency of crude oil gathering and transportation system. The energy efficiency evaluation system can not only speed up the collection, calculation and analysis of data, but also can predict the weak links of energy use, and ultimately achieve the purpose of saving energy and reducing costs. The relevant research results can provide a theoretical basis for promoting the development of digital crude oil gathering and transportation system.

2. Energy efficiency prediction of a crude oil gathering and transportation system based on a GA-BP neural network

At present, oilfields are in the stage of rapid development. Under the background of the current energy revolution and energy transformation, accelerating the digital transformation of the oil and gas industry and realizing the intellectualization of the oil and gas industry are the current development trends. Therefore, it is necessary to combine digital technologies such as big data and artificial intelligence (Papadopoulos et al., 2022) with energy efficiency evaluations of crude oil gathering and transportation systems and use GA-BP neural networks to predict the energy efficiency of crude oil gathering and transportation systems, which can provide a theoretical basis for the development of intelligent crude oil gathering and transportation systems.

2.1. Basic principle of the GA-BP neural network

In essence, the improved BP neural network model of the genetic algorithm searches the solution space (Wang C. et al., 2022) of target information widely by the genetic algorithm, locates the better BP neural network form searched by the genetic algorithm, and then obtains the optimal result of the prediction problem by training. The evolutionary process of the BP neural network improved by the genetic algorithm is shown in Fig. 1.

The steps (Yuan et al., 2021; Wang Y. et al., 2022; Wu et al., 2020; Li et al., 2020) of the GA-BP neural network are as follows.

(1) Definition of variables at each level

First, define the variables of the input layer, output layer, and hidden layer, and the respective number of nodes, where the connection weights between each layer are ω_{ij} and ω_{jk} respectively: initialize them and set the learning rate and neuron transfer function, BP. The neural network model is shown in Fig. 2.

(2) The GA encodes the initial value and calculates fitness

Import the initial training sample, calculate the sampling error and bring it into the fitness formula to obtain the connection weight of the fitness. In the genetic algorithm, individual fitness is used to evaluate the pros and cons of each individual to determine the size of its genetic chance.

(3) Perform selection, crossover, mutation operations

Selection refers to the direct inheritance of superior individuals to the next generation or the generation of new individuals through pairing and crossover, which are then inherited by the next generation. Crossover refers to the operation of replacing and recombining part of the structure of the two parent individuals to generate a new individual. Mutation is the change in gene values at certain loci of individual strings in the population, generally 0 to 1 or 1 to 0. After the population $P(t)$ is selected, crossed, and mutated, the next generation population $P(t+1)$ is obtained.

(4) Obtain optimal weights and thresholds of the BP neural network

Two thresholds can be set: one is that if the evolutionary algebra has reached the maximum, the individual with the maximum fitness obtained in the evolution process is used as the optimal solution output, and the calculation is terminated; the other is to set an error if, for a certain population in the population, the error of each individual has reached the requirement: in this case, the

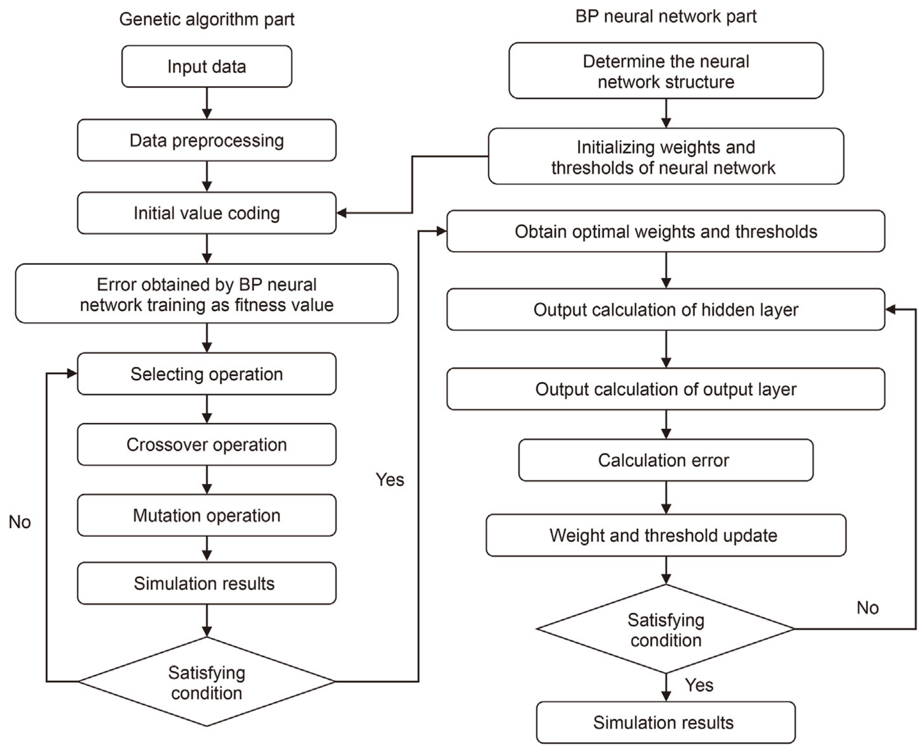

Fig. 1. Flow chart of the GA-BP genetic algorithm.

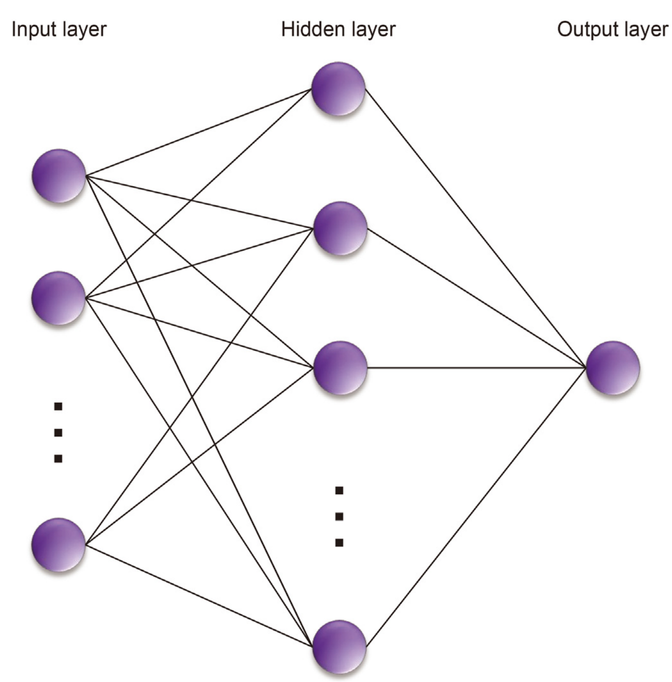

Fig. 2. BP neural network model diagram.

individual with the best fitness is output as the optimal approximate solution, and the calculation is terminated.

(5) Calculation of hidden layer output

According to the input vector, connection weight, and hidden layer threshold, the hidden layer output layer H is calculated as follows:

$$H_j = f\left[\sum_{i=1}^{n}(\omega_{ij} - a_j)\right];\ \ j = 1, 2, \cdots, s \tag{1}$$

The transfer function is as follows:

$$f(x) = \frac{1}{1 + \mathrm{e}^{-x}} \tag{2}$$

(6) Output calculation of the output layer

According to the hidden layer output, calculate the predicted output O:

$$O_k = \sum_{j}^{1} H_j\omega_{jk} - b_k; k = 1, 2, \cdots, m \tag{3}$$

(7) Training error calculation

Calculate the grid prediction error e based on the network predicted output O and expected Y:

$$e^k = Y_k - O_k; k = 1, 2, \cdots, m \tag{4}$$

(8) Weight, threshold update

Adjust the connection weights according to the backpropagation error:

$$\omega_{ij} = \omega_{ij} + \eta H_j(1 - H_j)x(i)\sum_{k=1}^{m}\omega_{jk}e \tag{5}$$

$$\omega_{jk} = \omega_{jk} + \eta H_j e_k, j = 1, 2, \cdots, s; k = 1, 2, \cdots, m \tag{6}$$

Adjust the node threshold p,t according to the backpropagation error e:

$$p_j = p_j + \eta H_j(1 - H_j)x(i)\sum_{k=1}^{m}\omega_{jk}e_k, j = 1, 2, \cdots, s \tag{7}$$

$$t_k = t_k + e^k; k = 1, 2, \cdots, m \tag{8}$$

(9) Judge whether the training is completed according to the error.

When the error no longer decreases, the training ends. If the error signal still decreases, continue to update the weights and thresholds.

2.2. Energy efficiency prediction of a crude oil gathering and transportation system based on a GA-BP neural network

There are three plants in the crude oil gathering and transportation system predicted by the GA-BP neural network. Among them, the X1 plant has 99 wells, 12 transfer stations, and 1 combined station, and the X2 plant has 135 wells, 14 transfer stations, and 1 combined station. the X3 plant has 80 wells, 11 transfer stations, and 1 union station. The overall process of the crude oil gathering and transportation system is as follows: the oil well-produced liquid is heated by the wellhead heating furnace and then transported to the metering station. The metering station mainly measures the incoming liquid. The liquid is separated, pressurized, heated, and transported to the outside. Transfer stations are built within some of the blocks, taking into account the functions of the metering station and the transfer station. The liquid processed by the transfer station is transported to the combined station, and its main function is oil-water separation. After dehydration, it enters the crude oil stabilization tower for stabilization and desulfurization, and the processed qualified crude oil is transported to the oil depot under pressure. A schematic diagram of the crude oil gathering and transportation system of an oilfield in western China is shown in Fig. 3.

2.2.1. GA-BP neural network design

(1) Number of network layers. A BP network can contain one or more hidden layers. Through the analysis, it can be determined that the network of a single hidden layer can achieve any nonlinear mapping by appropriately increasing the number of neuron nodes; usually, a single hidden layer can meet the needs, so a single hidden layer BP neural network is selected.

(2) Enter the number of layer nodes. When predicting the unit consumption and efficiency of the crude oil gathering and transportation system, the dimension of the input vector is determined by the relevant operating parameters of the crude oil gathering and transportation system and its subsystems, and then the number of nodes in the input layer is determined.

(3) The number of hidden layer nodes. The number of hidden layer nodes has a great influence on the training effect of the BP neural network. At present, there is no ideal analytical formula to determine a reasonable number of hidden layer nodes. The commonly used empirical formula for the number of hidden layer nodes is estimated as follows:

① $\sum_{i=0}^{n} C_M^i > k$, where k is the number of samples, M is the number of neurons in the hidden layer, and n is the number of neurons in the input layer. If $i > M$, specify $C_M^i = 0$.

② $M = \sqrt{n+m} + a$, where m and n are the number of neurons in the output layer and input layer, respectively, and a is a constant between [0, 10].

③ $R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i')^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$, where n is the number of neurons in the input layer.

Based on the above formula, we calculate the number of hidden layer neurons, compare the prediction performance of different hidden layer neuron nodes, and select the neuron hidden layer node number with the best performance.

(4) The number of neurons in the output layer. The number of neurons in the output layer is determined according to the characteristics of the crude oil gathering and transportation system and is predicted by a single index. Therefore, the number of neurons in the hidden layer is 1. The power consumption of collection and transmission, the comprehensive energy consumption of collection and transmission of unit liquid volume, the utilization rate of energy, the utilization rate of heat energy, and the utilization rate of electric energy are forecasted.

(5) The choice of the transfer function and training method. Generally, the hidden layer uses the sigmoid function, while the output layer uses a linear function, and the training method selects the gradient descent method.

(6) The training method selects the standard gradient descent method.

(7) GA-BP neural network training parameter settings. When predicting the efficiency and unit consumption of the crude oil gathering and transportation system, there are a total of 509 sets of data, and 60 sets of data are selected as the test set. The population size was 20, the number of evolutionary iterations was 50, and the crossover probability and

Fig. 3. Schematic diagram of the crude oil gathering and transportation system in an oilfield in western China.

mutation probability were 0.2 and 0.1, respectively. After the above parameters are determined, the training data are normalized and input into the network for learning. If the network successfully converges, the neural network prediction model can be obtained.

2.2.2. *Efficiency prediction of the crude oil gathering and transportation system*

When evaluating the energy efficiency of the crude oil gathering and transportation system, it is necessary to collect the daily data of the oil gathering wellhead system, the transfer station system, and the combined station system and then perform the calculation after sorting. Energy efficiency predictions are carried out to effectively promote the intelligent development of crude oil gathering and transportation systems. The efficiency index of the crude oil gathering and transportation system is mainly related to the three subsystem parameters of the transfer station, the union station, and the oil gathering wellhead. Based on this, the BP neural network structure is determined. The neural network structure diagram of the efficiency prediction model is shown in Fig. 4.

When predicting the efficiency of crude oil gathering and transportation systems, the test algorithm is used for the hidden layer nodes. The curve coincidence degree is better when the number of hidden layer nodes of the energy utilization BP neural network is 17~19, and the prediction effect is the best when the number of hidden layer nodes is 18. Similarly, it is concluded that when the numbers of hidden layer nodes of the heat utilization rate and power utilization rate are 20 and 24, respectively, the real value best coincides with the predicted curve. The efficiency prediction results of the crude oil gathering and transportation system are shown in Fig. 5.

Fig. 5 shows the prediction results of the GA-BP neural network and BP neural network for energy utilization, thermal energy utilization, and electric energy utilization of the crude oil gathering and transportation system. By comparing the prediction results of the BP and GA-BP neural networks, it is found that the predicted values of energy utilization, heat energy utilization, and electric energy utilization of the GA-BP neural network model have a high coincidence degree with the actual values, and the curve coincidence degree is significantly higher than that of the BP neural network model.

2.2.3. *Unit consumption prediction of crude oil gathering and transportation system*

When predicting the unit consumption of crude oil gathering and transportation systems, the main indices include the comprehensive energy consumption of unit liquid gathering and transportation, the gas consumption of unit liquid gathering and transportation, and the comprehensive energy consumption of unit liquid gathering and transportation. The structure diagram of the neural network for predicting the unit consumption of crude oil gathering and transportation systems is shown in Fig. 6.

When predicting the comprehensive energy consumption of the crude oil gathering and transportation system per unit of liquid volume, the input layer mainly includes the power consumption, gas consumption, and treatment liquid volume of the crude oil gathering and transportation system; when predicting the gas consumption and power consumption of unit liquid collection, the input layer of the BP neural network is the same as the input layer of heat and power utilization. Through the trial calculation of the number of hidden layer nodes of each neural network, the curve coincidence degree and the prediction accuracy are higher when the number of hidden layer nodes of comprehensive energy consumption, gas consumption, and power consumption per unit of liquid gathering and transportation are 12, 9 and 10, respectively. The unit consumption prediction results of the crude oil gathering and transportation system are shown in Fig. 7.

Fig. 7 shows the prediction results of the GA-BP neural network and BP neural network for unit consumption of crude oil gathering and transportation systems. The predicted values of comprehensive energy consumption per unit liquid volume, gas consumption per unit liquid volume, and power consumption per unit liquid volume of the GA-BP neural network model are highly coincident with the actual values, and the curve coincidence degree is significantly higher than that of the BP neural network model. Through the above prediction model, the efficiency and unit consumption of the three subsystems of the transfer station, the combined station, and the oil gathering wellhead can be predicted. The GA-BP neural network solves the problem of a large amount of data and long calculation time in the energy efficiency evaluation of crude oil gathering and transportation systems, which is beneficial to improving the calculation speed of unit consumption and efficiency of crude oil gathering and transportation systems.

2.3. *Evaluation of the energy efficiency prediction model for the crude oil gathering and transportation system*

When predicting the energy efficiency of crude oil gathering and transportation systems, it is necessary to evaluate the model and analyse the influences of error on each index. The prediction data errors of crude oil gathering and transportation system efficiency and unit consumption of the GA-BP and BP neural networks are shown in Fig. 8.

Fig. 8 shows that the data error predicted by the GA-BP neural network model in the energy efficiency prediction of the crude oil gathering and transportation system fluctuates above and below the 0 reference line, and the fluctuation amplitude is significantly smaller than the error curve predicted by the BP neural network model. The GA-BP neural network error is less than that of the BP neural network.

To further determine the energy efficiency prediction accuracy (Hu et al., 2022) of crude oil gathering and transportation systems, the determination coefficient R^2 is used to evaluate the fitting accuracy of the prediction model of crude oil gathering and transportation system efficiency and unit consumption. As shown in Eq. (9), the R^2 value is between 0 and 1; the closer to 1, the higher the prediction accuracy. Take energy efficiency prediction as an example to illustrate R^2. When R^2 is between 0.85 and 0.95, the energy efficiency level of oilfield enterprises can be roughly estimated in general engineering. When R^2 is greater than 0.95, it can be used in the actual project prediction with small error, which can guide the actual production of the oilfield, conduct research and analysis, and play an early warning role in energy saving and consumption reduction projects.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - y_i')^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2} \tag{9}$$

In the formula, n is the number of samples; y is the actual value of the model; y_i' is the model predictive value; and $\overline{y}$ is the average of the actual values.

The fitting accuracy of the unit consumption and efficiency prediction model of the crude oil gathering and transportation system is obtained by Eq. (9), as shown in Table 1.

The fitting accuracy calculation shows that the determination coefficient of the GA-BP neural network prediction model is higher than that of the BP neural network model. The determination

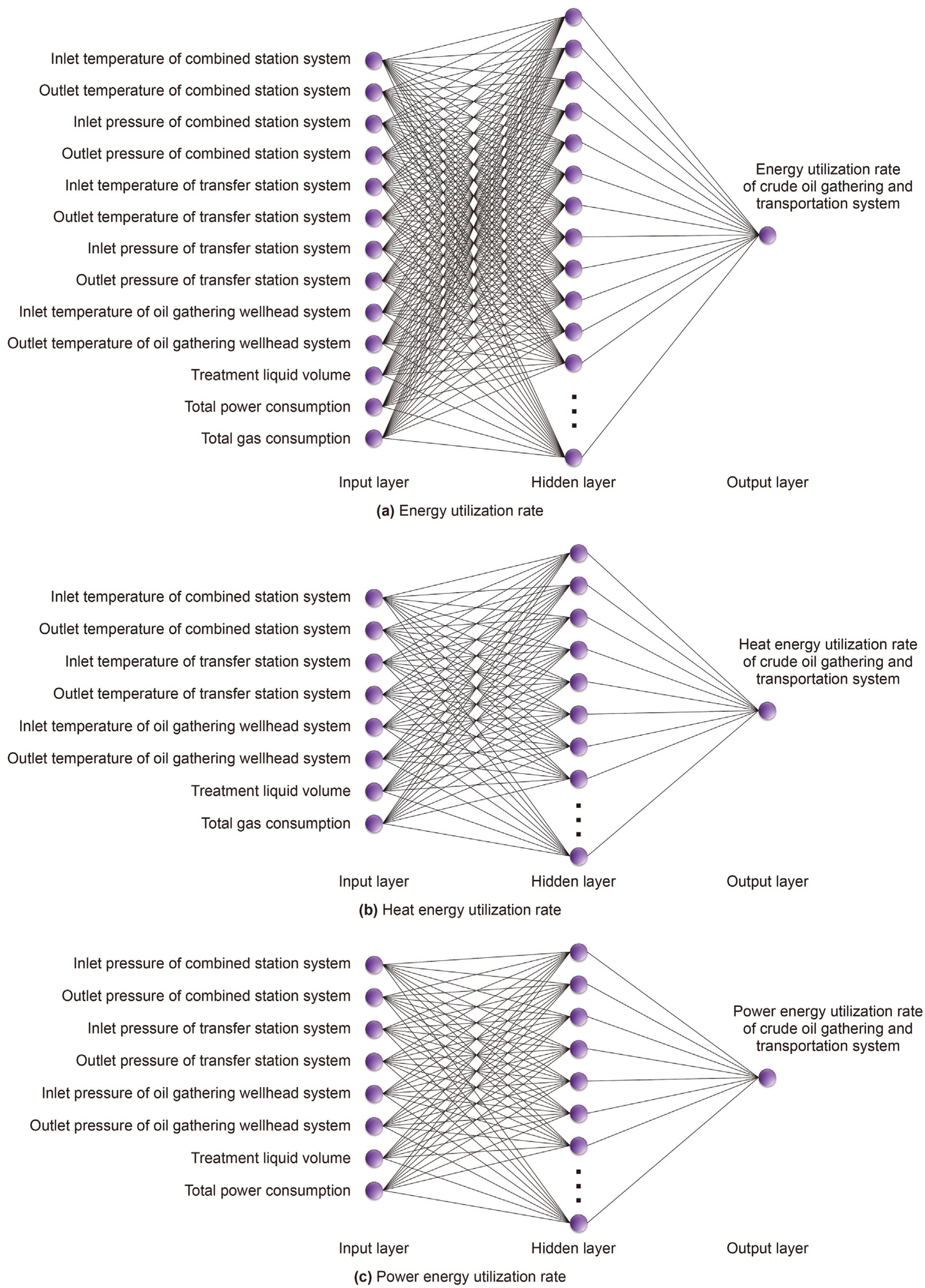

Fig. 4. Diagram of the neural network model for efficiency prediction of crude oil gathering and transportation systems.

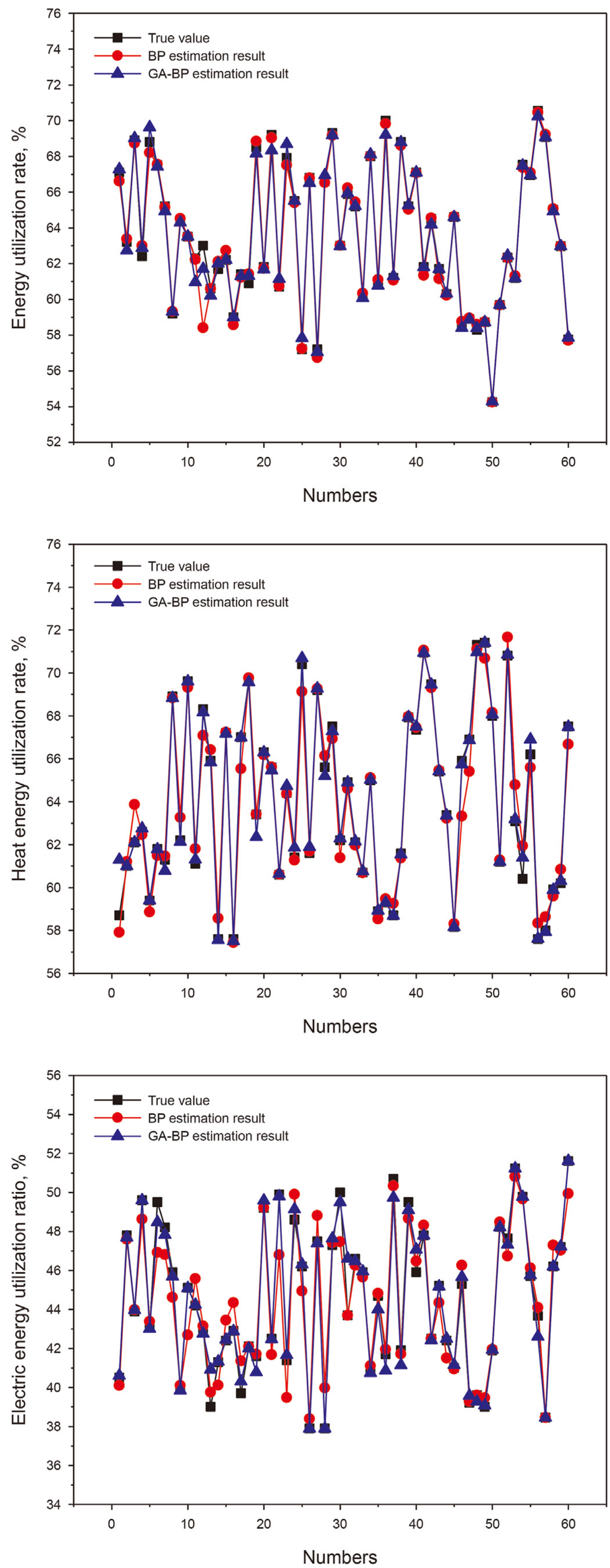

Fig. 5. Comparison of efficiency prediction results of the crude oil gathering and transportation system.

coefficients of energy utilization, heat energy utilization, and electric energy utilization in the GA-BP neural network efficiency model are 0.9906, 0.9895, and 0.9746, respectively. The determination coefficients of comprehensive energy consumption, gas consumption, and power consumption in unit liquid gathering and transportation in the GA-BP neural network efficiency model are 0.9822, 0.9694, and 0.9923, respectively. The GA-BP neural network model can effectively improve the prediction accuracy of the BP neural network model. Among them, the prediction results of electric consumption and energy utilization rate per unit of liquid collection are the best, the determination coefficients are greater than 0.9, and the prediction accuracy is high.

The GA-BP neural network model can not only reduce the workload of energy efficiency evaluation and calculation of crude oil gathering and transportation systems but also predict the future energy efficiency through parameters. This in-depth analysis and mining of large amounts of data of crude oil gathering and transportation systems are conducive to improving the development of digital oilfields, improving the energy efficiency calculation efficiency of crude oil gathering and transportation systems, and providing certain theoretical support for energy conservation and consumption reduction of crude oil gathering and transportation systems in oilfields.

3. Establishment of an energy efficiency evaluation system model for a crude oil gathering and transportation system

The energy structure of the crude oil gathering and transportation system is complex, and the energy consumption is enormous, involving multiple transfer stations, combined stations, and gathering wellheads. It is necessary to consider many factors of each subsystem. Therefore, before the energy efficiency evaluation, it is necessary to determine the index weight of each subsystem and evaluate the energy efficiency of the crude oil gathering and transportation system. At present, the calculation methods of index weight (Li P. et al., 2021; Raghav et al., 2022; Zhou et al., 2021; He et al., 2022) are mainly divided into the subjective weight method, objective weight method, and combined weight method.

3.1. Evaluation index weight calculation method of crude oil gathering and transportation system

At present, the subjective weighting method mainly poses the disadvantages of subjective randomness and uncertainty, and the objective weighting method has the disadvantages of different samples producing different results. Therefore, the combination weighting method is adopted, and the subjective weighting method is combined with the objective weighting method. Based on game theory, the optimal combination weight is determined. The subjective weighting method is based on the triangular fuzzy analytic hierarchy process and combines triangular fuzzy theory with the analytic hierarchy process. The objective weighting method uses the entropy weight method. Finally, game theory combination weighting is carried out, and the TOPSIS method is used to evaluate the energy efficiency after weighting.

3.1.1. Determining subjective weight based on the triangular fuzzy analytic hierarchy process

The analytic hierarchy process (AHP) (Vinodh, 2020) refers to a complex multiobjective decision problem as a system, and the target is decomposed into multiple objectives or criteria. Triangular fuzzy number theory (Li H. et al., 2021) can enable a more comprehensive evaluation of the target and compensate for the defects of the analytic hierarchy process. This absolute 1–9 scale method is rarely used in practical production, so the constructed

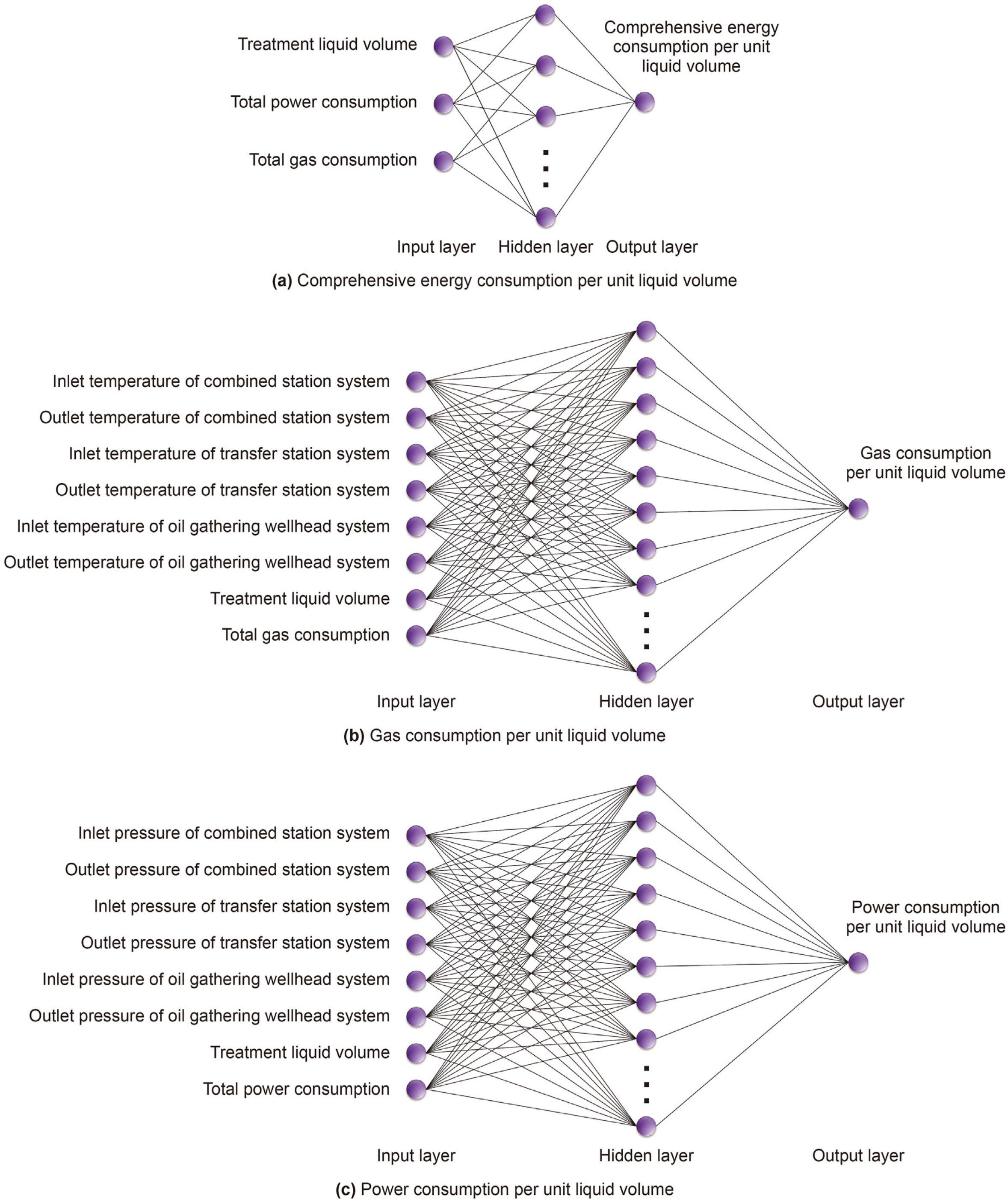

Fig. 6. Neural network model for efficiency prediction of crude oil gathering and transportation system.

evaluation matrix cannot accurately reflect the complexity and fuzziness of human cognition of objective things. Therefore, the triangular fuzzy theory is combined with the analytic hierarchy process to improve its scale method and evaluation matrix. The subjective weight determined by the triangular fuzzy analytic hierarchy process is as follows.

(1) Building a Hierarchical Structure Model

According to the evaluation objectives, the evaluation objectives are listed at the highest level, the criteria are listed in the middle level, and the implementation methods of each criterion are listed at the lowest level.

(2) Triangular fuzzy number and judgement matrix

The triangular fuzzy number is defined as if a=(a_l,a_m,a_u), where $0 < a_l < a_m < a_u$, and a is called a triangular fuzzy number. The membership function is as follows:

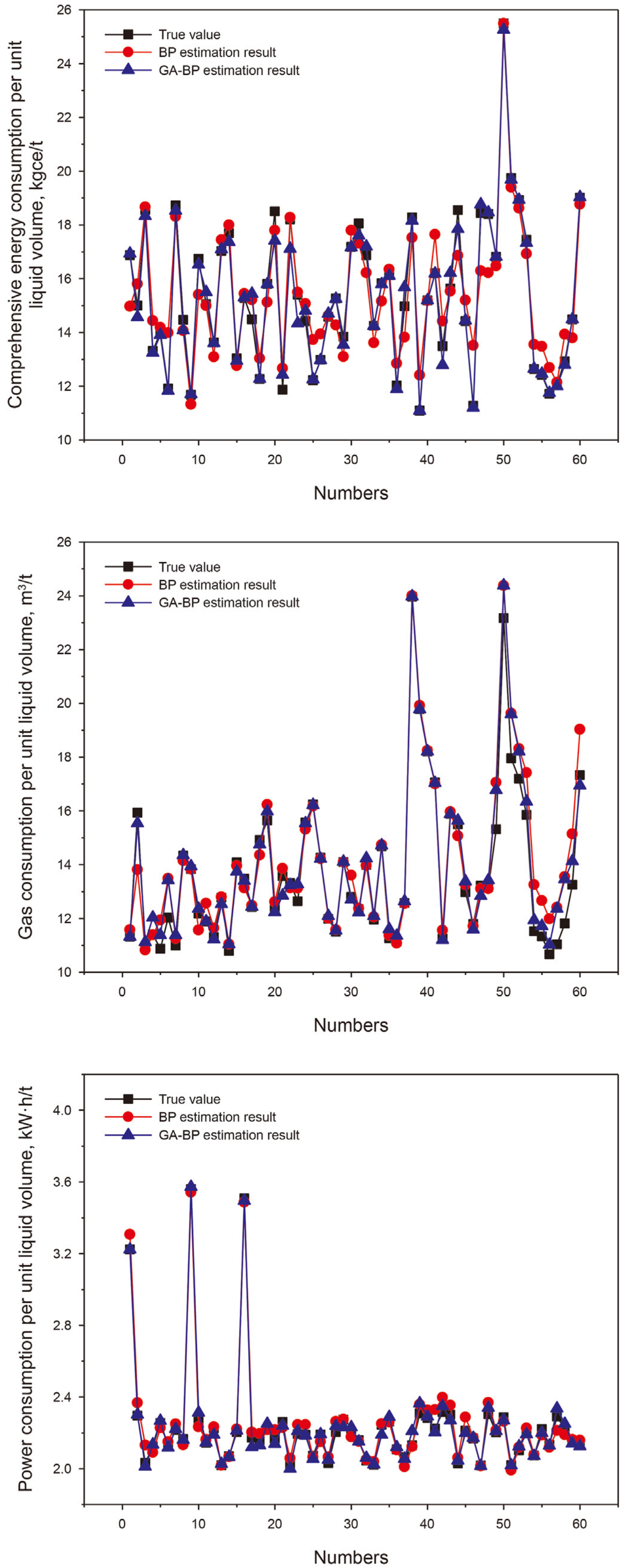

Fig. 7. Comparison of efficiency prediction results of crude oil gathering and transportation system.

$$a(x)=\begin{cases}0 & x<a_l\\ \dfrac{x-a_l}{a_m-a_l} & a_l<x<a_m\\ \dfrac{au-x}{a_u-a_m} & a_m<x<a_u\\ 0 & x>a_u\end{cases} \tag{10}$$

In the evaluation scheme, a_l is the most conservative estimate and the lower bound of the triangular fuzzy number, a_m is the most likely value, and a_u is the most optimistic evaluation value, and the upper bound of the triangular fuzzy number. The index system was used to construct the judgement matrix, combined with expert advice and based on the 0.1–0.9 scale method, as shown in Table 2.

(3) Calculation of index weight

The judgement matrix $\boldsymbol{A}=(a_{ij})_{n\times n}$ was given by experts, where $a_{ij}=(a_{lij},a_{mij},a_{uij})$ represents the relative importance of i to j and n represents the number of weight indicators to be determined. The weighted vector $w=(w_1,w_2,\ldots,w_n)^T$ of the triangular fuzzy number complementary judgement matrix $\boldsymbol{A}$ is calculated and normalized. The calculation process is as follows:

$$\begin{aligned} w_i&=\frac{\sum_{j=1}^{n}a_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n}a_{ij}}=\frac{\sum_{j=1}^{n}\left(a_{lij},a_{mij},a_{uij}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(a_{lij},a_{mij},a_{uij}\right)}\\ &=\left(\frac{\sum_{j=1}^{n}a_{lij}}{\sum_{i=1}^{n}\sum_{j=1}^{n}a_{uij}},\frac{\sum_{j=1}^{n}a_{mij}}{\sum_{i=1}^{n}\sum_{j=1}^{n}a_{mij}},\frac{\sum_{j=1}^{n}a_{uij}}{\sum_{i=1}^{n}\sum_{j=1}^{n}a_{lij}}\right),i\in N \end{aligned} \tag{11}$$

After determining the triangular fuzzy weight vector, it is necessary to defuzzify it. Let $M_1=(l_1,m_1,u_1)$ and $M_2=(l_2,m_2,u_2)$ be triangular fuzzy numbers. The triangular function of the possible degree of $M_1>M_2$ is defined as:

$$\begin{aligned} p(M_1>M_2)&=\lambda\max\left\{1-\max\left(\frac{m_2-l_1}{m_1-l_1+m_2-l_2},0\right),0\right\}\\ &+(1-\lambda)\max\left\{1-\max\left(\frac{u_2-m_1}{u_1-m_1+u_2-m_2},0\right),0\right\} \end{aligned} \tag{12}$$

where $\lambda\in[0,1]$, and its value depends on the decision risk attitude: $\lambda\in[0,1]$ for a risky decision, $\lambda=0.5$ for a risk-neutral decision, and $\lambda<0.5$ for a risk-averse decision. According to the above formula, the possibility degree matrix $\boldsymbol{P}=\left(p_{ij}\right)_{n\times n}$ can be established. The matrix provides the possible degree of information of each index compared with each other. Next, the triangular fuzzy number is sorted to obtain the possibility degree matrix and to determine the index weight formula:

$$\omega_i=\frac{1}{n}\left(\sum_{j=1}^{n}p_{ij}+1-\frac{n}{2}\right),i\in N \tag{13}$$

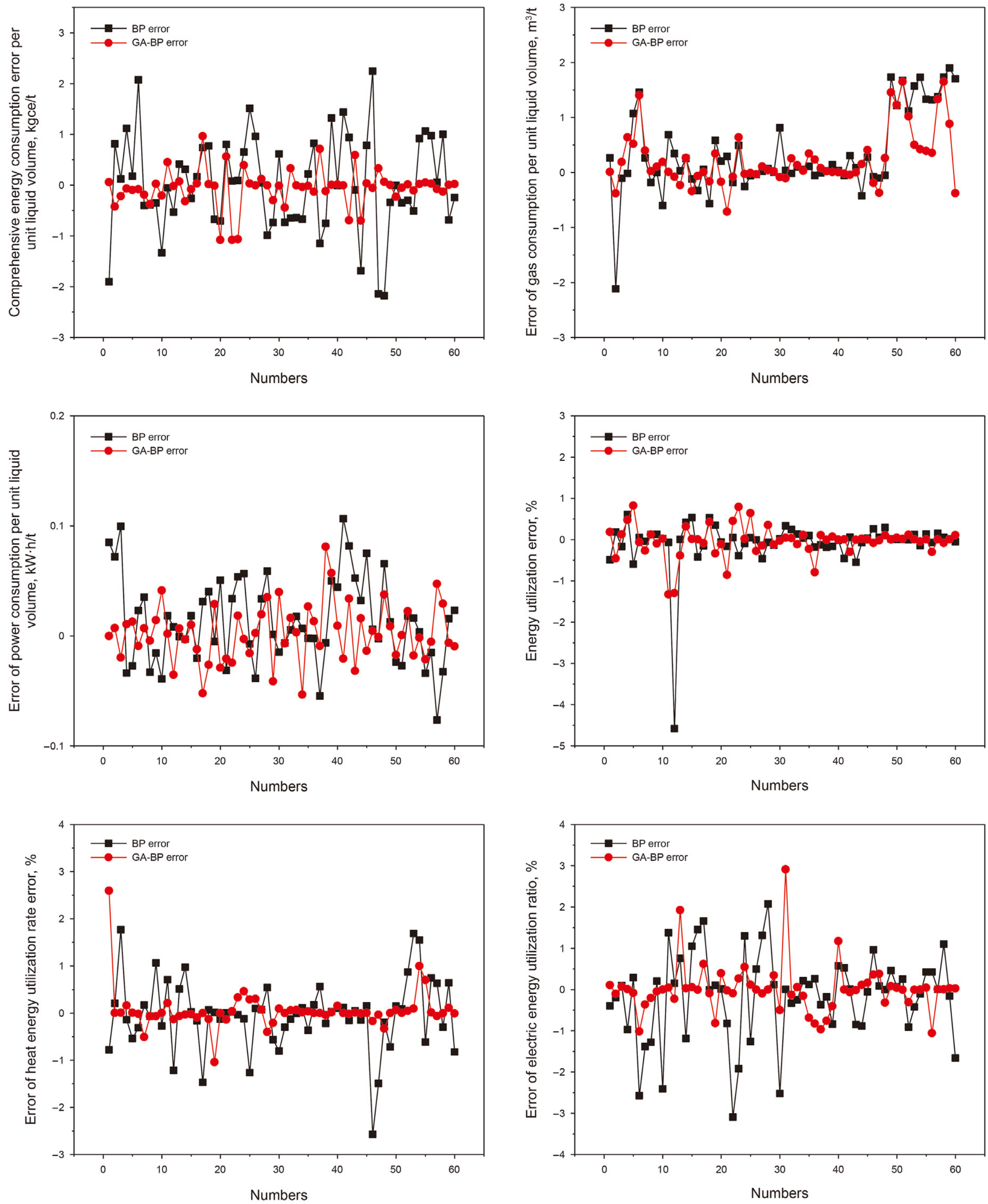

Fig. 8. Energy efficiency prediction error results of the crude oil gathering and transportation system.

Table 1
Fitting accuracy of the energy efficiency prediction model for crude oil gathering and transportation systems.

Energy efficiency prediction of crude oil gathering and transportation system	Comprehensive energy consumption per unit liquid volume	Gas consumption per unit liquid volume	Power consumption per unit liquid volume	Energy utilization rate	Heat energy utilization rate	Electric energy utilization rate
GA-BP determination coefficient R^2	0.9822	0.9694	0.9923	0.9906	0.9895	0.9746
BP determination coefficient R^2	0.9570	0.9620	0.9892	0.9723	0.9838	0.9611

Table 2
0.1–0.9 scale method.

Scale	The comparative importance of two factors	Scale	The comparative importance of two factors
0.1	The latter is more important than the other extreme	0.6	The former is slightly more important than the other
0.2	The latter is more important than the other	0.7	The former is more important than the other
0.3	The latter is more important than the other	0.8	The former is more important than the other
0.4	The latter is slightly more important than the other	0.9	The former is more important than the other
0.5	Equal importance	–	

3.1.2. Determination of the objective weight of the evaluation index by the entropy weight method

The entropy weight method is an objective weighting method (Wang, et al., 2021). In the specific use process, according to the dispersion degree of data of each index, the entropy weight of each index is calculated by using the information entropy, and then the entropy weight is corrected according to each index to obtain a more objective index weight. The specific calculation steps are as follows.

(1) Constructing the Index Matrix

Whether there is a negative number in the input matrix is determined. Assuming that there are n objects to be evaluated, the positive matrix composed of m evaluation indices is as follows:

$$\boldsymbol{X} = \begin{bmatrix} x_{11}, x_{12}, \cdots, x_{1m} \\ x_{21}, x_{22}, \cdots, x_{2m} \\ \vdots \vdots \ddots \vdots \\ x_{n1}, x_{n2}, \cdots, x_{nm} \end{bmatrix} \tag{14}$$

Let $\boldsymbol{Z}$ be a standardized matrix and z_{ij} be the element in Z:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum\limits_{i=1}^{n} x_{ij}^2}} \tag{15}$$

If there is a negative number in the $\boldsymbol{Z}$ matrix, the standardized formula is:

$$z_{ij} = \frac{x_{ij} - \min\{x_{1j}, x_{2j}, \cdots x_{nj}\}}{\max\{x_{1j}, x_{2j}, \cdots x_{nj}\} - \min\{x_{1j}, x_{2j}, \cdots x_{nj}\}} \tag{16}$$

(2) Calculation of relative entropy

Calculate the probability matrix $\boldsymbol{P}$, where each element p_{ij} in $\boldsymbol{P}$ is calculated as follows:

$$p_{ij} = \frac{z_{ij}}{\sum\limits_{i=1}^{n} z_{ij}} \tag{17}$$

Ensure that the sum of each column is 1: that is, the sum of probabilities corresponding to each index is 1.

(3) Determination of the weight of each evaluation index by the entropy weight method

The entropy of each evaluation index is calculated by the entropy formula of the entropy weight method, and the entropy weight of each evaluation index is further calculated. For the jth index, the calculation formula of the information entropy is as follows.

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln\left(p_{ij}\right), j = (1, 2, \cdots, m) \tag{18}$$

Definition of information utility value:

$$d_j = 1 - e_j \tag{19}$$

By normalizing the information utility value, we can obtain the entropy weight of each index:

$$\omega_j = \frac{d_j}{\sum\limits_{j=1}^{m} d_j}, (j = 1, 2, 3, \cdots, m) \tag{20}$$

3.1.3. Combination weighting method based on game theory

To accurately evaluate the energy efficiency of crude oil gathering and transportation systems, it is necessary to ensure the accuracy of the weighting. However, subjective weighting methods such as the analytic hierarchy process (AHP) only rely on subjective expert opinions, which include certain instability. Objective weighting methods such as the entropy weight method pose high requirements for data quality in the index system. Therefore, the combination weighting method of game theory is introduced to determine the weight of the energy efficiency evaluation system of crude oil gathering and transportation systems. The combination weighting method based on game theory first determines the basic weight of the triangular fuzzy analytic hierarchy process and entropy weight method. The triangular fuzzy analytic hierarchy process relies on the quantitative analysis method. The entropy weight method makes full use of the objective weight of sample data, and the two methods can complement each other. On this basis, the combination weighting model of game theory is used to minimize the deviation between the weights obtained by the two methods, find the optimal combination and determine the optimal combination weight.

Based on the combination weighting method (Zhu et al., 2021) of game theory and game theory, this method assumes that a weighting method is used to calculate the weight of an evaluation index. Through the calculation of the weight, q basic weight vector sets can be obtained, namely, $\omega_k = (\omega_{k1}, \omega_{k2}, \cdots, \omega_{km})$, $k = 1, 2, \cdots, q$. Through the combination weighting method based on game theory, the weights obtained by the analytic hierarchy process and entropy weight method are integrated, and the weight vector set $\omega_i = (\omega_1, \omega_2, \cdots, \omega_i)$, $i = 1, 2, \cdots, n$, is obtained. Then, the arbitrary linear combination of n basic weight vectors is:

$$\omega = \sum_{i=1}^{n} \varepsilon_i \omega_i^T, \varepsilon_i > 0 \tag{21}$$

The linear combination is optimized to minimize the difference between ω and ω_i. The objective function of the optimal weight vector is as follows:

$$\min\left\| \sum_{i=1}^{n} \varepsilon_i \omega_i^T - \omega_i^T \right\|_2, i = 1, 2, \cdots, n \tag{22}$$

According to the matrix differential properties, the linear equations of the first derivative condition after the optimization are as follows:

$$\begin{bmatrix} \omega_1\omega_1^T & \omega_1\omega_2^T & \cdots & \omega_1\omega_i^T \\ \omega_2\omega_1^T & \omega_2\omega_2^T & \cdots & \omega_2\omega_i^T \\ \vdots & \vdots & & \vdots \\ \omega_j\omega_1^T & \omega_j\omega_2^T & \cdots & \omega_j\omega_1^T \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_i \end{bmatrix} = \begin{bmatrix} \omega_1\omega_1^T \\ \omega_2\omega_2^T \\ \vdots \\ \omega_j\omega_j^T \end{bmatrix} \tag{23}$$

The linear combination ε_i is obtained through the above equation, and the optimal linear combination is obtained by normalizing ε_i:

$$\varepsilon_i^* = \frac{|\varepsilon_i|}{\sum_{i=1}^{n} |\varepsilon_i|} \tag{24}$$

Finally, the optimal combination weight based on the triangular fuzzy analytic hierarchy process and entropy weight method is obtained:

$$\omega_{ij}^* = \sum_{i=1}^{n} \varepsilon_i^* \omega_i^T, \varepsilon_i > 0 \tag{25}$$

3.2. TOPSIS evaluation model

TOPSIS is an approximate ideal solution ranking method, which is often referred to as the distance method of superior and inferior solutions. The TOPSIS (Tian et al., 2021; Wang et al., 2021; Li J. et al., 2021; Cheng et al., 2020) method is a commonly used comprehensive evaluation method. The results can accurately reflect the gap between the evaluation schemes and obtain the energy efficiency evaluation results.

(1) Matrix forwardization

In the TOPSIS method, all indicators are unified forward. The formula for converting very small indicators to very large indicators is *max-x*. If all elements are positive, then $1/x$ can also be used.

(2) Standardization of the positive matrix

The purpose of standardization is to eliminate the influence of different dimensions. The positive matrix consisting of n objects to be evaluated and m evaluation indices is obtained.

(3) Score calculation and normalization

Define the maximum:

$$Z^+ = (\max\{z_{11}, z_{21}, \cdots z_{n1}\}, \max\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, \max\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) \tag{26}$$

Define the minimum:

$$Z^- = (\min\{z_{11}, z_{21}, \cdots z_{n1}\}, \min\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, \min\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) \tag{27}$$

Define the distance between the ith (i = 1, 2, …, n) evaluation object and the maximum:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \omega_j \left(Z_j^+ - z_{ij}\right)^2} \tag{28}$$

Define the distance between the ith (i = 1, 2, …, n) evaluation object and the minimum:

$$D_i^- = \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^- - z_{ij}\right)^2} \tag{29}$$

(4) Calculation of relative closeness

The relative closeness of each evaluation object is calculated as follows:

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{30}$$

3.3. Example analysis of the energy efficiency evaluation system for the crude oil gathering and transportation system

3.3.1. Evaluation index weight calculation

According to the energy efficiency data of the crude oil gathering and transportation system and its subsystems predicted by the GA-BP neural network, the combination weighting method based on game theory is used to calculate the index weight of the row. According to the wellhead-transfer station-combined station gathering and transportation process in crude oil gathering and transportation systems, the energy consumption structure is complex, and the energy consumption is large. Therefore, it is necessary to establish a scientific, complete, and detailed energy efficiency evaluation system for crude oil gathering and transportation systems. This system first analyses the overall crude oil gathering and transportation system and then analyses the energy efficiency of the combined station, the transfer station, and the gathering well mouth system. The energy efficiency evaluation system for crude oil gathering and transportation systems and three subsystems is shown in Fig. 9.

(1) Subjective empowerment method

The G-M layer reveals the influence degree of the unit consumption and efficiency of each subsystem in the crude oil gathering and transportation system. According to expert opinions, the triangular fuzzy matrix of the G-M layer is obtained, as shown in Table 3.

According to the constructed triangular fuzzy weight vector, the triangular fuzzy weight vector of the G-M and C-D layers is obtained. The triangular fuzzy weight vector of G-M is:

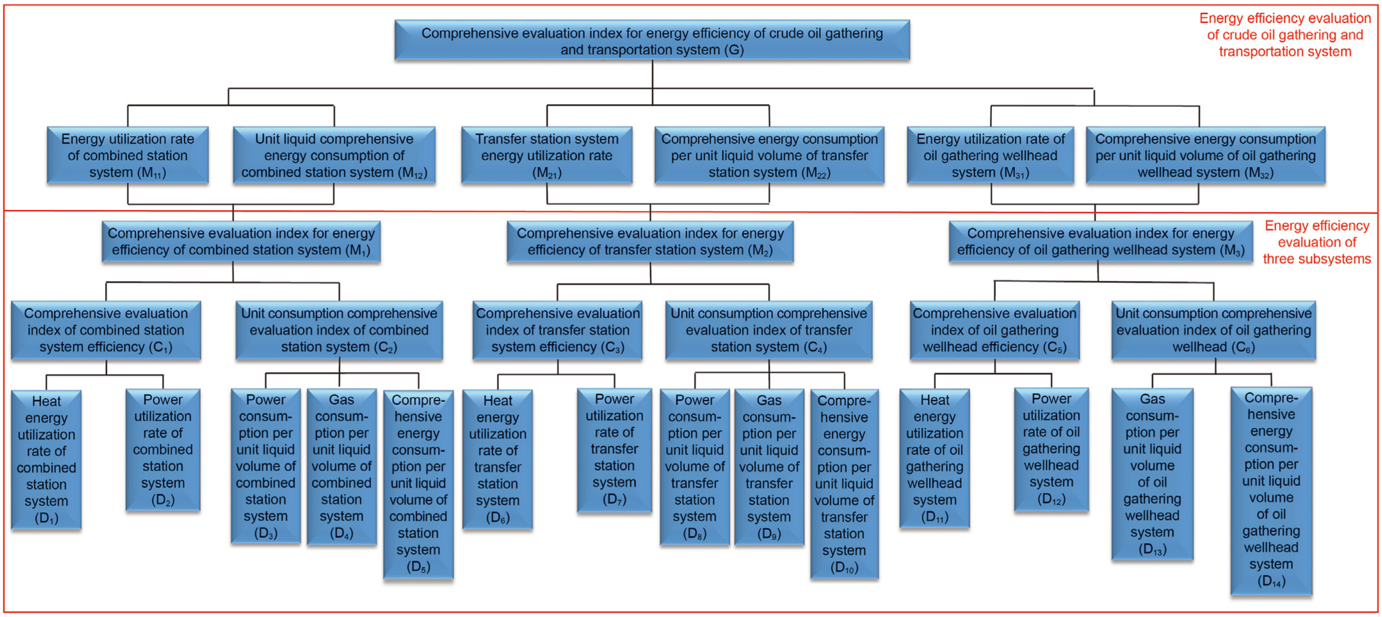

Fig. 9. Energy efficiency evaluation system of the crude oil gathering and transportation system and subsystems.

Table 3
G-M triangular fuzzy matrix.

G-M	M_{11}	M_{12}	M_{21}	M_{22}	M_{31}	M_{32}
$\boldsymbol{M}_{11}$	0.5,0.5,0.5	0.3,0.3,0.5	0.6,0.6,0.8	0.5,0.5,0.6	0.3,0.3,0.4	0.6,0.6,0.7
$\boldsymbol{M}_{12}$	0.6,0.6,0.6	0.5,0.5,0.5	0.7,0.7,0.7	0.6,0.7,0.7	0.7,0.8,0.8	0.6,0.7,0.7
$\boldsymbol{M}_{21}$	0.3,0.4,0.5	0.3,0.3,0.4	0.5,0.5,0.5	0.4,0.4,0.5	0.5,0.5,0.6	0.5,0.5,0.5
$\boldsymbol{M}_{22}$	0.6,0.6,0.7	0.2,0.3,0.3	0.6,0.6,0.8	0.5,0.5,0.5	0.4,0.5,0.5	0.3,0.3,0.4
$\boldsymbol{M}_{31}$	0.5,0.6,0.6	0.1,0.3,0.3	0.4,0.5,0.5	0.3,0.4,0.4	0.5,0.5,0.5	0.4,0.5,0.6
$\boldsymbol{M}_{32}$	0.5,0.5,0.5	0.3,0.4,0.4	0.6,0.7,0.8	0.4,0.5,0.6	0.3,0.4,0.4	0.5,0.5,0.5

$$
\begin{aligned}
w_{\mathrm{G-M,}} = {} & \left(w_{M_{11}}, w_{M_{12}}, w_{M_{21}}, w_{M_{22}}, w_{M_{31}}, w_{M_{32}}\right)^T = ((0.141, 0.156, 0.213), (0.187, 0.222, 0.244), (0.126, 0.144, 0.183), \\
& (0.131, 0.156, 0.195), (0.111, 0.156, 0.177), (0.111, 0.156, 0.177))^T;
\end{aligned}
$$

The triangular fuzzy numbers are compared with each other. The possibility degree between G-M and C-D is determined by a risk-neutral decision, and the possibility degree matrix is established. The G-M possibility matrix is:

$$
\boldsymbol{P}_{\mathrm{G-M}} = \begin{bmatrix} 0.500 & 0 & 0.811 & 0.613 & 0.745 & 0.745 \\ 1 & 0.500 & 1 & 1 & 1 & 1 \\ 0.189 & 0 & 0.500 & 0.330 & 0.495 & 0.495 \\ 0.387 & 0 & 0.670 & 0.500 & 0.649 & 0.649 \\ 0.255 & 0 & 0.505 & 0.351 & 0.500 & 0.500 \\ 0.255 & 0 & 0.505 & 0.351 & 0.500 & 0.500 \end{bmatrix}
$$

The index weight based on the triangular fuzzy analytic hierarchy process is finally obtained through the possibility degree matrix. The subjective index weight of the G-M layer is $\omega_{\mathrm{G-M,}} = \left(\omega_{M_{11}}, \omega_{M_{12}}, \omega_{M_{21}}, \omega_{M_{22}}, \omega_{M_{31}}, \omega_{M_{32}}\right)^T = (0.236, 0.583, 0.002, 0.142, 0.019, 0.019)^T$;

The subjective index weights of each subsystem are as follows:

The C_1-D subjective index weight is $\omega_{C_1-\mathrm{D}} = \left(\omega_{D_1}, \omega_{D_2}\right)^T = (0.75, 0.25)^T$;

The C_2-D subjective index weight is $\omega_{C_2-\mathrm{D}} = \left(\omega_{D_3}, \omega_{D_4}, \omega_{D_5}\right)^T = (0.123, 0.210, 0.667)^T$;

The C_3-D subjective index weight is $\omega_{C_3-\mathrm{D}} = \left(\omega_{D_6}, \omega_{D_7}\right)^T = (0.75, 0.25)^T$;

The C_4-D subjective index weight is $\omega_{C_4-\mathrm{D}} = \left(\omega_{D_8}, \omega_{D_9}, \omega_{D_{10}}\right)^T = (0.127, 0.220, 0.653)^T$;

The C_5-D subjective index weight is $\omega_{C_5-\mathrm{D}} = \left(\omega_{D_{11}}, \omega_{D_{12}}\right)^T = (1, 0)^T$.

The C_6-D subjective index weight is $\omega_{C_6-\mathrm{D}} = \left(\omega_{D_{13}}, \omega_{D_{14}}\right)^T = (0.413, 0.587)^T$;

(2) Objective empowerment method

The entropy weight method offers strong objectivity and adaptability. Therefore, the entropy weight method is used to determine the objective weight of the energy efficiency evaluation system, calculate the information entropy, obtain the information utility value, and ultimately obtain the entropy weight. The objective index weights of the crude oil gathering and transportation system and each subsystem are obtained by the entropy weight method:

The G-M objective index weight is

$$
\begin{aligned}
\omega'_{\mathrm{G-M,}} & = \left(\omega'_{M_{11}}, \omega'_{M_{12}}, \omega'_{M_{21}}, \omega'_{M_{22}}, \omega'_{M_{31}}, \omega'_{M_{32}}\right)^T \\
& = (0.0064, 0.8486, 0.0341, 0.0847, 0.0062, 0.0199)^T
\end{aligned}
$$

The objective index weight of C_1-D is $\omega'_{C_1-D} = \left(\omega'_{D_1}, \omega'_{D_2}\right)^T = (0.507, 0.493)^T$;

The objective index weight of C_2-D is $\omega'_{C_2-D} = \left(\omega'_{D_3}, \omega'_{D_4}, \omega'_{D_5}\right)^T = (0.367, 0.319, 0.315)^T$;

The objective index weight of C_3-D is $\omega'_{C_3-D} = \left(\omega'_{D_6}, \omega'_{D_7}\right)^T = (0.512, 0.488)^T$;

The objective index weight of C_4-D is $\omega'_{C_4-D} = \left(\omega'_{D_8}, \omega'_{D_9}, \omega'_{D_{10}}\right)^T = (0.059, 0.492, 0.449)^T$;

The objective index weight of C_5-D is $\omega'_{C_5-D} = \left(\omega'_{D_{11}}, \omega'_{D_{12}}\right)^T = (1, 0)^T$.

The objective index weight of C_6-D is $\omega'_{C_6-D} = \left(\omega'_{D_{13}}, \omega'_{D_{14}}\right)^T = (0.5, 0.5)^T$;

(3) Combined weighting method based on game theory

According to the subjective weight calculated by the triangular fuzzy analytic hierarchy process and the objective weight calculated by the entropy weight method, the G-M layer weight combination model is obtained as follows:

$$\begin{bmatrix} 0.417 & 0.509 \\ 0.509 & 0.729 \end{bmatrix} \begin{bmatrix} \varepsilon_{1,C_1-D} \\ \varepsilon_{2,C_1-D} \end{bmatrix} = \begin{bmatrix} 0.417 \\ 0.729 \end{bmatrix}$$

According to the above weight combination model, the optimal combination coefficient is obtained and normalized. The calculation results of the G-M layer are shown in Table 4.

Finally, the combination weighting result of game theory is obtained by the combination weighting formula, and the combination weighting result of the G-M layer is $\omega^*_{G-M} = \left(\omega^*_{M_{11}}, \omega^*_{M_{12}}, \omega^*_{M_{21}}, \omega^*_{M_{22}}, \omega^*_{M_{31}}, \omega^*_{M_{32}}\right)^T = (0.103, 0.736, 0.020, 0.109, 0.011, 0.019)^T$.

Similarly, the combination weighting results of each subsystem are as follows:

The C_1-D layer combination weighting result is $\omega^*_{C_1-D} = \left(\omega^*_{D_1}, \omega_{D_2}\right)^T = (0.636, 0.364)^T$.

The C_2-D layer combination weighting result is $\omega^*_{C_2-D} = \left(\omega^*_{D_3}, \omega^*_{D_4}, \omega^*_{D_5}\right)^T = (0.228, 0.257, 0.515)^T$.

The C_3-D layer combination weighting result is $\omega^*_{C_3-D} = \left(\omega^*_{D_6}, \omega^*_{D_7}\right)^T = (0.639, 0.361)^T$.

The C_4-D layer combination weighting result is $\omega^*_{C_4-D} = \left(\omega^*_{D_8}, \omega^*_{D_9}, \omega^*_{D_{10}}\right)^T = (0.094, 0.352, 0.554)^T$.

The C_5-D layer combination weighting result is $\omega^*_{C_5-D} = \left(\omega^*_{D_{11}}, \omega^*_{D_{12}}\right)^T = (1, 0)^T$.

The C_6-D layer combination weighting result is $\omega^*_{C_6-D} = \left(\omega^*_{D_{13}}, \omega^*_{D_{14}}\right)^T = (0.456, 0.544)^T$.

Table 4
Optimal combination coefficient of the G-M layer.

G-M	Optimal combination coefficient	Normalization
$\varepsilon_{1,G-M}$	0.7726	0.4229
$\varepsilon_{2,G-M}$	1.0544	0.5771

According to the wellhead energy consumption of the target oilfield, only the wellhead heating furnace energy consumption equipment is available in the wellhead system, and there is no power consumption equipment. Therefore, the weight of D_{12} is 0, and the weight of D_{11} is 1.

3.3.2. *Energy efficiency evaluation system of the crude oil gathering and transportation system*

According to the established energy efficiency system of the crude oil gathering and transportation system, TOPSIS analysis is carried out on each subsystem to determine the closeness between the energy efficiency of each system and the ideal degree. The closer the closeness is to 1, the more energy efficient the system is. In the evaluation index, the power consumption, gas consumption, and comprehensive energy consumption per unit of liquid collection of each system are very small indicators, which must be converted into very large indicators by the $1/x$ operation, and then the standardization matrix of the whole system and each subsystem and the positive and negative ideal scheme are obtained. The standardization matrix of the G-M layer and the positive and negative ideal schemes are shown in Table 5.

According to the positive and negative ideal schemes, the Euclidean distance between each evaluation object and the optimal worst vector is determined, and the relative closeness of each target is calculated. The relative closeness reflects the closeness between the evaluation index and the ideal state. The closer the relative closeness is to 1, the higher the energy efficiency level is. When the relative sticking progress is greater than 0.9, it is at the level of high efficiency and energy saving; when the relative sticking progress is between 0.8 and 0.9, it is at a normal level; when the relative sticking progress is less than 0.8, it is at the level of high energy consumption and low efficiency. The closer to 0, the greater the energy consumption and the lower the efficiency. The calculation results of G-M are shown in Fig. 10.

This method comprehensively considers the energy consumption and energy efficiency of the joint station, transfer station and oil gathering wellhead system, and obtains the monthly and annual relative closeness of the crude oil gathering and transportation system. According to the results, the relative closeness of July, August and September is above 0.9, among which S8 > S7 > S9. The energy consumption level is the best at this stage, which is closer to the ideal state. The energy efficiency structure of the gathering and transportation system from July to September can guide the actual production and achieve the level of energy saving and consumption reduction. The relative closeness degree from January to April and December is relatively low, which is lower than 0.4, among which S1 > S12 > S4 > S3 > S2, and the lowest in February is 0.0707. The unit consumption and efficiency of the above months are different from the ideal state, and the energy efficiency level is poor. The results show that the gathering system needs to optimize the winter warm energy structure and improve the energy efficiency level.

The TOPSIS evaluation of the combined station, transfer station, and system is carried out, and relative closeness of C_1-D and C_2-D in the combined station system are calculated as shown in Fig. 11.

C_1-D is the energy efficiency evaluation of the combined station system. Considering the thermal energy utilization rate and electric energy utilization rate of the combined station system, the relative closeness degree of the combined station system is obtained. The maximum relative closeness degree of the combined station system in September is 0.9399, and the efficiency is the closest to the ideal situation. The relative closeness degree in June, August and October is between 0.7 and 0.8. The electric energy utilization rate and thermal energy utilization rate are relatively high, and the efficiency level is good. The relative closeness degree in January to

Table 5
G-M standardized matrix.

Number	G-M					
	Energy utilization rate of combined station	Comprehensive energy consumption of combined station	Transfer station energy utilization rate	Comprehensive energy consumption of transfer station	Energy utilization rate of oil gathering wellhead	Comprehensive energy consumption of oil gathering wellhead
1	0.0847	0.0674	0.0772	0.0899	0.0805	0.0854
2	0.0809	0.0396	0.0730	0.0810	0.0806	0.0869
3	0.0840	0.0549	0.0798	0.0777	0.0822	0.0819
4	0.0855	0.0582	0.0850	0.0785	0.0838	0.0906
5	0.0884	0.0696	0.0820	0.0775	0.0831	0.0894
6	0.0844	0.1061	0.0898	0.0872	0.0846	0.0821
7	0.0832	0.1106	0.0869	0.0938	0.0859	0.0838
8	0.0853	0.1130	0.0921	0.0976	0.0886	0.0829
9	0.0795	0.1087	0.0912	0.0967	0.0864	0.0828
10	0.0836	0.1053	0.0852	0.0803	0.0827	0.0810
11	0.0795	0.1016	0.0817	0.0721	0.0811	0.0732
12	0.0810	0.0649	0.0759	0.0677	0.0804	0.0799
13	0.0833	0.0819	0.0827	0.0826	0.0837	0.0826
Z+	0.0884	0.1130	0.0921	0.0976	0.0886	0.0906
Z-	0.0795	0.0396	0.0730	0.0677	0.0804	0.0732

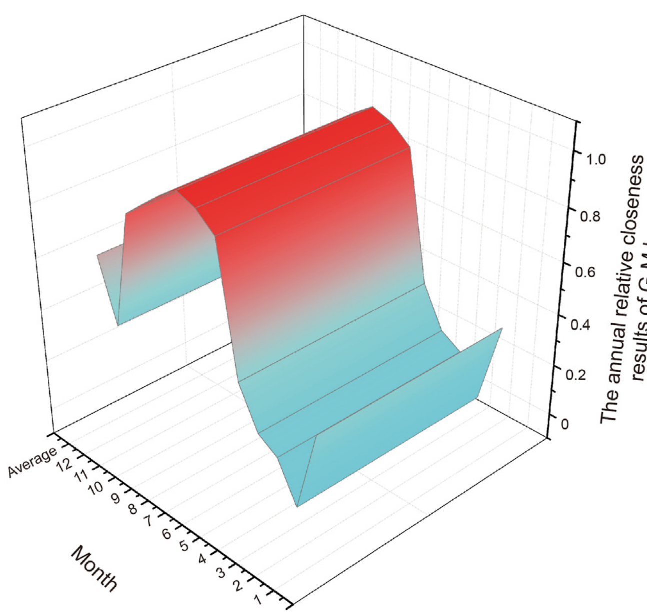

Fig. 10. Annual relative similarity of the G-M layer.

March and December is relatively low, between 0 and 0.3. The relative closeness degree in February is the lowest, which is 0.0247. C_2-D is the energy efficiency evaluation of the unit consumption of the combined station system. Through the comprehensive analysis of gas consumption, power consumption and comprehensive energy consumption, the monthly and annual relative closeness degree of the combined station system is obtained. The relative closeness degree from July to September is greater than 0.9, and the relative closeness degree in June and October is 0.8906 and 0.8971, respectively. The relative closeness degree from June to October is ranked as S8 > S7 > S9 > S10 > S6. The energy consumption of the combined station system in August is the closest to the ideal state. The relative closeness degree from January to April is small, less than 0.4, and the energy consumption is large. In summary, the winter and spring energy efficiency structure can be adjusted according to the energy efficiency structure of the combined station system in August and September to improve the efficiency of the combined station system and reduce the energy consumption of the combined station system. The calculation results of C_3-D and C_4-D in the transfer station system are shown in Fig. 12.

The C_3-D layer comprehensively considers the thermal energy utilization rate and electric energy utilization rate of the transfer station, and obtains the relative closeness of the efficiency of the transfer station system. The trend of energy efficiency evaluation of the transfer station is similar to that of the combined station system. The maximum relative closeness of the transfer station system in September is 0.9398, which is the closest to the ideal situation. The relative closeness of June, August and October is between 0.7 and 0.8, and the utilization of thermal energy and electric energy is better. The relative closeness of January to March and December is low, and the relative closeness of February is 0.0247, which is the lowest, and the efficiency is poor. The C_4-D layer comprehensively considers the gas consumption, power consumption and comprehensive energy consumption of the transfer station system to calculate the relative closeness. The relative closeness in August and September is greater than 0.9, which is close to the ideal energy consumption state. The relative closeness in February, March and November is small, less than 0.4, and the lowest in December is 0.0170. The energy consumption level is poor and the unit consumption is large. It is necessary to use the energy efficiency structure in August and September to guide the actual production of the transfer station system and improve the energy consumption level.

The calculation results of C_5-D and C_6-D in the wellhead system are shown in Fig. 13.

Because the oil gathering wellhead system only has heating furnace heat consumption equipment and no power consumption equipment, the wellhead system is mainly based on heat energy utilization rate. The relative closeness of the oil gathering wellhead system in C_5-D layer in August is the largest, which is the closest to the ideal situation. The relative closeness of January, February, November and December is between 0.7 and 0.8, the heat energy utilization rate is relatively high, and the energy use effect is better. The relative closeness of January, March and December is lower, less than 0.4, and the energy use effect is the worst. C_6-D is the unit consumption evaluation of the oil gathering wellhead system. The relative closeness of the oil gathering wellhead system in each month and annual average is calculated. The relative closeness in April and May is greater than 0.9, which is close to the ideal energy consumption state. The relative closeness in February, March, November and December is small, less than 0.4, the energy efficiency result is poor, and the energy consumption is large. The energy efficiency structure in April, May and August can be used to

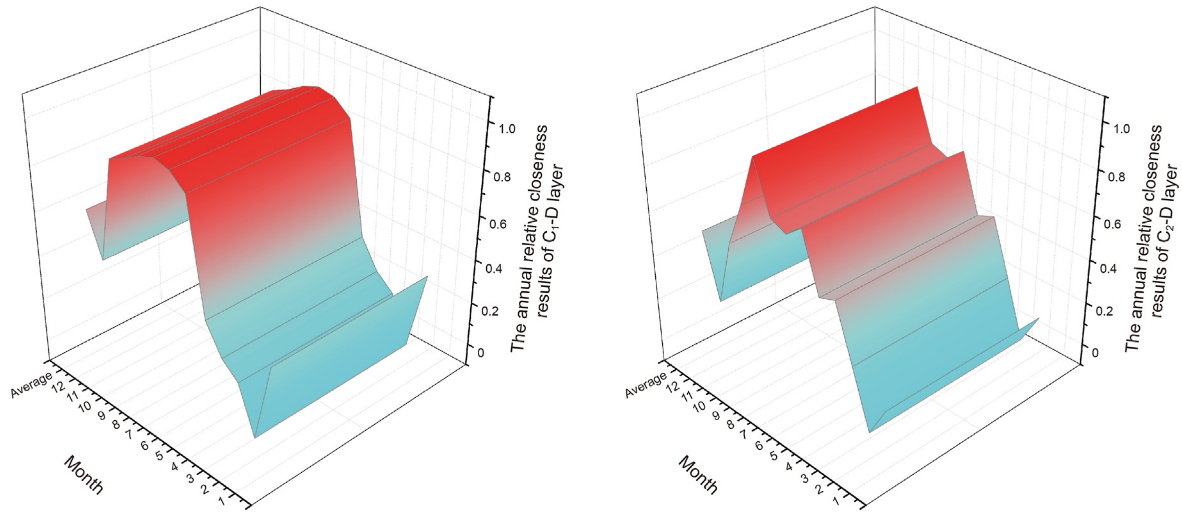

Fig. 11. Annual relative similarity results of the C_1-D and C_2-D layers.

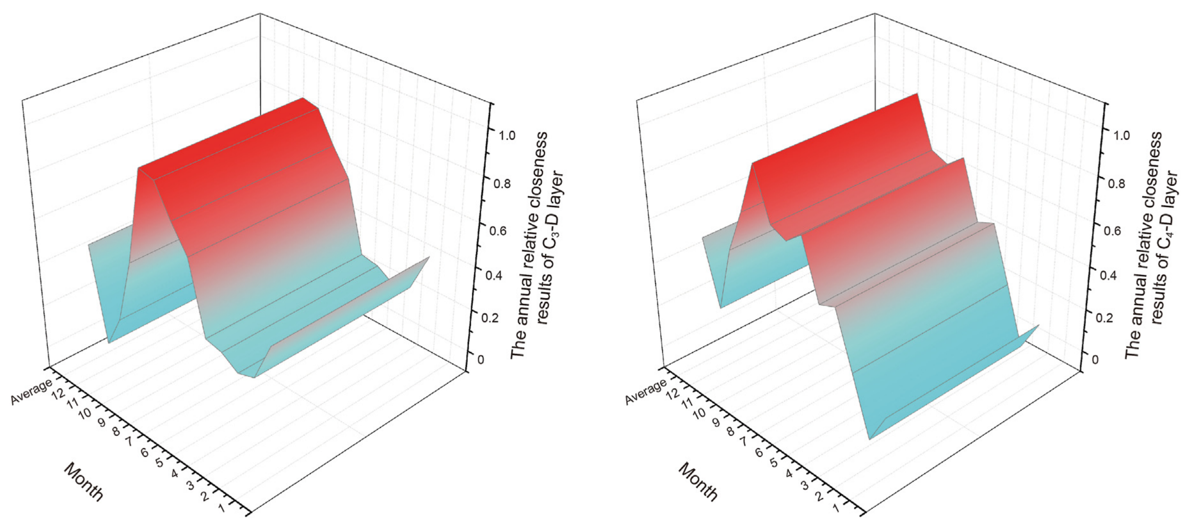

Fig. 12. Calculation results of the relative similarity of the C_3-D and C_4-D layers.

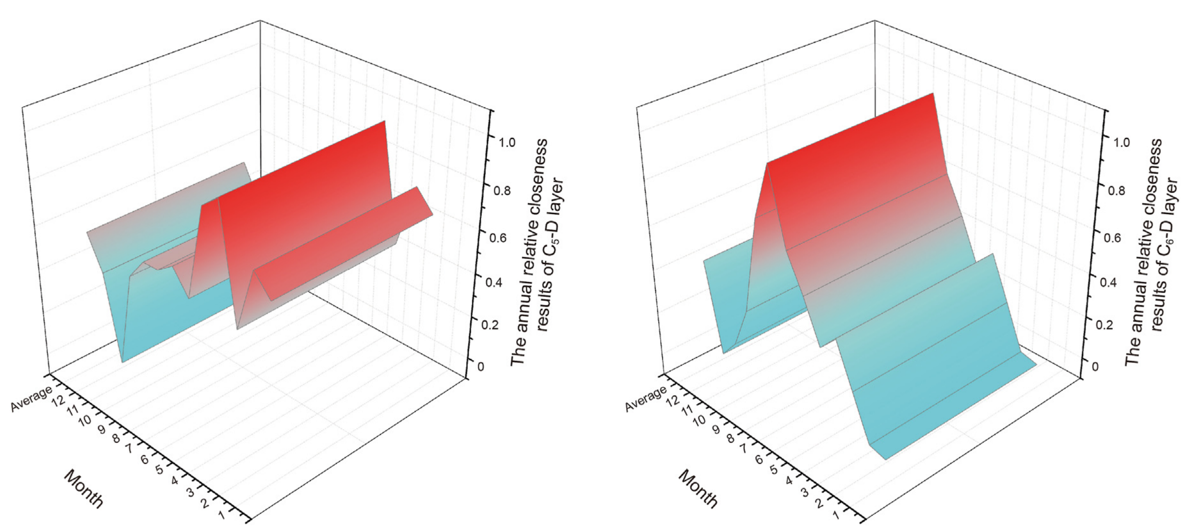

Fig. 13. Calculation results of the relative similarity of the C_5-D and C_6-D layers.

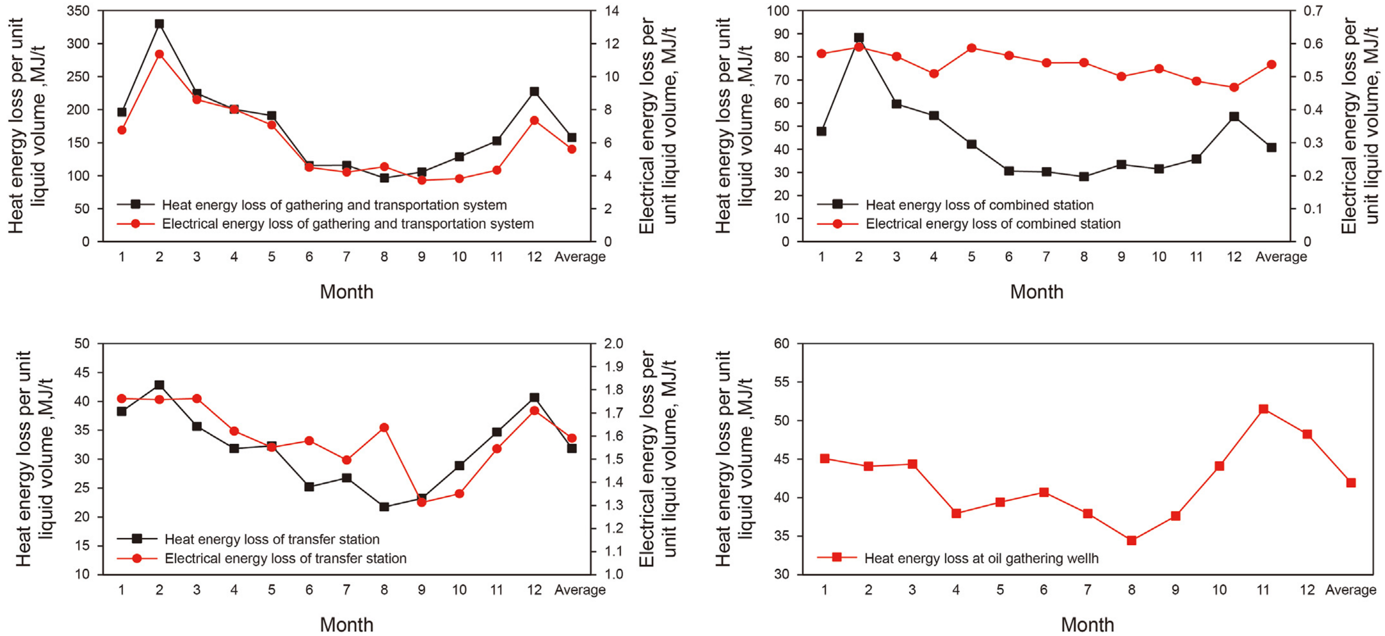

Fig. 14. Results of energy loss per unit volume of crude oil gathering and transportation system.

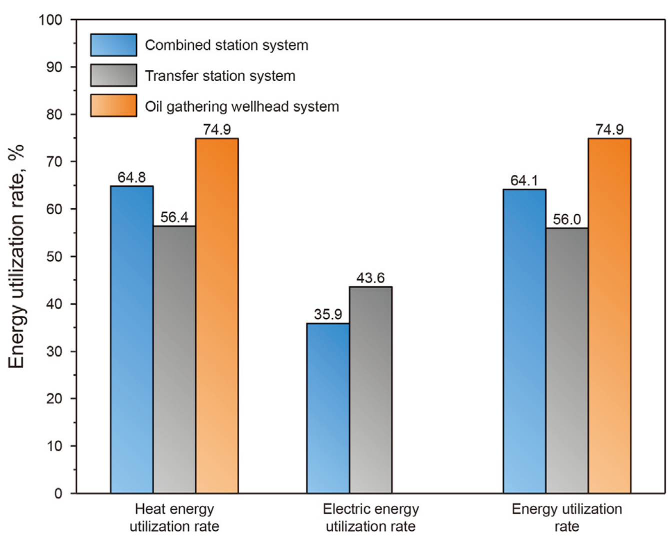

Fig. 15. Efficiency comparison chart of the three subsystems.

guide the actual production of the wellhead system and reduce the actual energy consumption of the wellhead system.

4. Identification of weak energy links in the crude oil gathering and transportation system

According to the energy efficiency evaluation results of the crude oil gathering and transportation system, it is necessary to identify the weak links of energy use and put forward improvement measures for the weak links to provide technical support for energy conservation and consumption reduction of crude oil gathering and transportation systems.

4.1. *Weak energy consumption analysis of the crude oil gathering and transportation system*

Through the energy efficiency evaluation system of the crude oil gathering and transportation system, it is concluded that the heat energy utilization rate of the crude oil gathering and transportation system is low in January, February, November and December, the energy utilization rate is low from January to March, and the energy consumption is weak. To further analyse the energy consumption of the crude oil gathering and transportation system in different months, the unit liquid energy loss of each crude oil gathering and transportation system and each subsystem are calculated, as shown in Fig. 14.

The thermal energy utilization of crude oil gathering and transportation system is poor in January, February and December. The main reason is that the ambient temperature is low and the heat loss is large at this time, and the heat loss per unit liquid volume of the transfer station, the joint station and the oil gathering well mouth subsystem is large in winter. Therefore, in winter, the heat energy consumption of crude oil gathering and transportation system is high and the efficiency is low. The electric energy loss per unit liquid volume of crude oil gathering and transportation system is higher from January to March. The main reason is that the amount of liquid treated is less from January to March, and the annual change trend of electric energy utilization rate of transfer station and joint station is relatively stable. According to the trend chart of electric energy loss per unit liquid volume of transfer station and joint station, the power consumption is not greatly reduced, which leads to the increase of electric energy loss per unit liquid volume of crude oil gathering and transportation system, and the energy consumption of electric energy is poor. By calculating the energy loss per unit liquid volume of crude oil gathering and transportation system, the specific amount of energy loss is determined, which is helpful to identify the weakest link of energy consumption and make priority improvement.

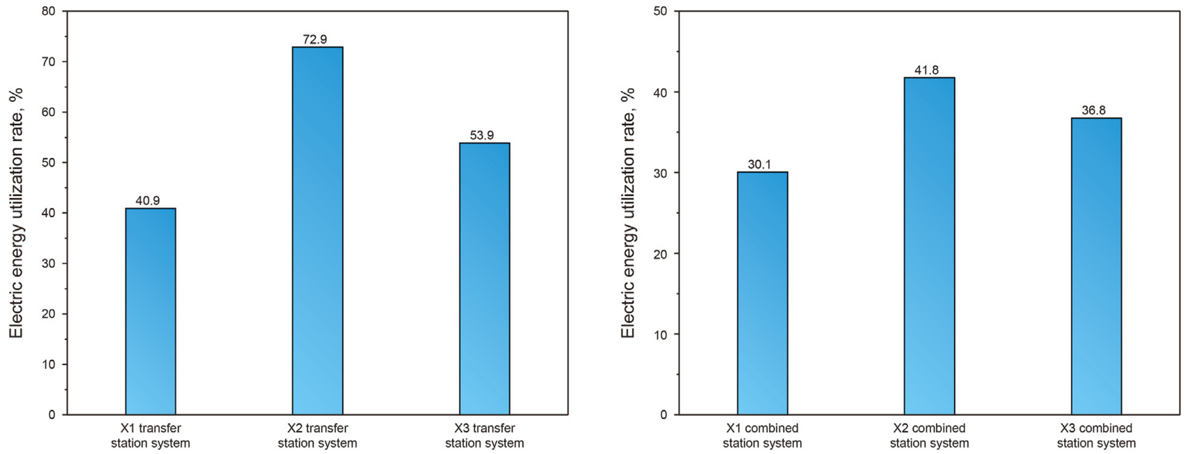

Fig. 16. Identification of weak links.

4.2. Identification of energy weak links in crude oil gathering and transportation system

To analyse the utilization rates of thermal energy and electric energy of the combined station, oil gathering wellhead, relay system, and subsystems more clearly in the crude oil gathering and transportation system, the efficiency of each subsystem is shown in Fig. 15.

By comparing the energy utilization rate of the three subsystems, the highest energy utilization rate of the oil gathering wellhead system is 74.9%, and the lowest energy utilization rate of the transfer station system is 56.0%. Through the analysis of the thermal energy utilization rate and power utilization rate of the docking transfer station system and the joint station system, the lowest thermal energy utilization rate of the transfer station system is 56.4%, and the lowest power utilization rate of the joint station system is 35.9%. For the gathering and transportation system, it is necessary to carry out normal oil and gas operation. Therefore, the heat energy of the transfer station system and the electric energy of the combined station system are selected for energy saving improvement through efficiency comparison, which can not only ensure normal oil and gas operation, but also reduce energy consumption.

Through the above diagram (see Fig. 16), it can be seen that the thermal energy utilization rate of the transfer station of X1 plant and the energy utilization rate of the joint station of X1 plant are the lowest, 40.9% and 30.1% respectively, and the energy consumption is the weakest. The weakest station in the transfer station system of X1 plant is A7 transfer station, and the thermal energy utilization rate is 22.2%. Therefore, on the premise of ensuring production, priority should be given to the energy saving improvement of the combined station of X1 plant and the heat energy of A7 transfer station.

4.3. Energy conservation improvement measures for crude oil gathering and transportation system

According to the weak link identification of energy consumption in the crude oil gathering and transportation system, the energy-saving transformation is mainly carried out for the A7 station and X1 combined station. The heat energy of the A7 station is relatively weak, and the energy of combined station X1 is relatively weak. Therefore, it is necessary to improve the efficiency of the pump and heating furnace in the transfer station and the combined station to reduce the energy consumption of the gathering and transportation system.

4.3.1. Measures to improve the efficiency of a heating furnace

Aiming at the weak link of heating furnace energy consumption in the A7 transfer station, the most economical and practical method is selected to improve the efficiency of the heating furnace. According to the test report data, the exhaust gas temperature of the A7 transfer station is 276.4 °C, which is greater than 220 °C. Therefore, the thermal efficiency of the heating furnace is low, and the energy consumption is large. The specific improvement measures for the above problems (Wang, 2021; Li Q. et al., 2021) are as follows.

(1) For the burner, first, it is necessary to regularly check whether the gas pressure is stable and whether it meets the pressure requirements of the burner. Additionally, blockage of the fire hole must be checked. When the conditions are available, the air volume and gas volume for a specific period are measured to determine whether the setting of the air-fuel ratio meets the requirements. Combined with different production conditions, resetting is carried out to achieve the best operation state.
(2) To prevent the fouling and clogging of flue gas ash in the flue gas system of the heating furnace, it is necessary to regularly check the operation status of the heating furnace, blow ash away in time, remove flue gas fouling, and keep the heating surface clean to fully absorb the flue gas heat, improve the heat transfer effect, reduce the exhaust gas temperature, and improve the service life and operational efficiency of the heating furnace.
(3) Resetting the control parameters of the heating furnace so that the heating furnace can maintain stable operation and improve combustion efficiency.
(4) Clean up the burner inlet and install a filter to prevent impurities in the burner from affecting the air volume.

4.3.2. Pump efficiency measures

For the weak link of energy consumption of the X1 combined station pump, through the test data of the X1 combined station pump, it can be found that the service life of the pump is long, the long-term operation of the pump leads to serious scaling corrosion of the pump parts and pipelines, and impeller corrosion will cause an increase in the gap between the mouth ring, the cavity, and the sand hole. The following measures can be implemented to improve

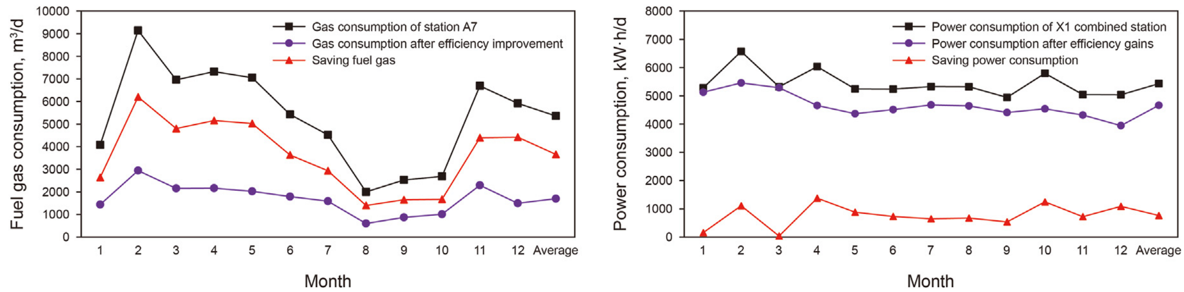

Fig. 17. A7 station and X1 combined station fuel gas and power consumption savings.

the efficiency of the pump (Zhao et al., 2021).

(1) Replacing or repairing wear-resistant rings and impellers, checking shaft seals and other parts, cleaning, checking, and changing impellers to solve problems such as excessive wear of shell and impeller wear-resistant rings, leakage of other parts, blockage, and wear and corrosion of pump impellers; for the problems of friction between the impeller and wear ring, impeller, and shell and bearing damage, it is necessary to repair or replace the bearing.
(2) Bearing heat is mainly caused by insufficient bearing clearance, bearing wear or loose fit, which can be resolved by readjustment of bearing clearance, repair or replacement of bearings, and retightening of fasteners.
(3) If the gap is too large, leakage is significant, return fluid is excessive, and the internal power consumption is large, which leads to failure to meet the required flow. For resolution of these issues, the head, ring, and sleeve can be replaced.
(4) When wear of the balance ring is serious, the balance ring can be replaced directly.

4.3.3. *Energy conservation and efficiency improvement of the crude oil gathering and transportation system*

According to the energy-saving evaluation of the heating furnace and pump in GB/T31453-2015, “Specification for Energy-saving Monitoring of Oilfield Production System” (GB/T 31453–2015.), after the energy-saving improvement of the heating furnace and pump in the A7 transfer station and X1 combined station, the utilization rate of heat energy in the A7 station and the utilization rate of electric energy in the X1 combined station are increased to 70% and 34% of the energy-saving evaluation value, respectively. The fuel gas and power consumption are saved as shown in Fig. 17.

Through the energy-saving improvement of the A7 station and X1 combined station, the average annual gas conservation amount achieved for the A7 station is 3660 m^3/d, and the gas conservation amounts are greater in February, March, April, November, and December. Among them, the gas conservation amount in February is as high as 6201 m^3/d, and the gas conservation amounts are less from August to October. With values between 2000 and 3000 m^3/d, the average annual power consumption of the X1 combined station is 768 kW·h/d, and the power consumption is higher in February, April, October, and December: 1,111, 1,377, 1,250 and 1,091 kW·h/d, respectively. After transformation, the utilization rate of electric energy increases, and the power consumption decreases. Through conserving fuel gas and reducing power consumption to improve the economic benefits of crude oil gathering and transportation systems, the annual cost savings of fuel gas and power consumption are approximately $610,000.

5. Conclusion

(1) The BP neural network and GA-BP neural network are used to predict the efficiency and unit consumption index of crude oil gathering and transportation systems. The results show that the GA-BP neural network model can effectively improve the prediction accuracy of the BP neural network model. The determination coefficients of energy utilization, heat utilization, and power utilization in the efficiency model of the GA-BP neural network are 0.9906, 0.9895, and 0.9746, respectively. The determination coefficients of comprehensive energy consumption, gas consumption, and power consumption in the unit consumption model are 0.9822, 0.9694, and 0.9923, respectively. The GA-BP neural network model can not only reduce the workload of energy efficiency evaluation and calculation of crude oil gathering and transportation systems, but also predict future energy efficiency through parameters, providing certain theoretical support for energy conservation and consumption reduction of crude oil gathering and transportation systems in oilfields.
(2) The TOPSIS method based on the combined weighting of game theory is used to establish the energy efficiency evaluation system of the crude oil gathering and transportation system. The triangular fuzzy analytic hierarchy process is used to determine the subjective weight, and the entropy weight method is used to determine the objective weight. The combination weighting of game theory combines the subjective and objective weighting to comprehensively evaluate the comprehensive energy efficiency of the crude oil gathering and transportation system and its subsystems. By calculating the relative closeness of the crude oil gathering and transportation system, the relative closeness values in July, August and September are found to be above 0.9, and the energy consumption level for this period is the best. The relative closeness between January and April and December is relatively low, at less than 0.4, and the lowest value is 0.0707 in February. The unit consumption and efficiency in the above months are much different from those in the ideal state, and the energy efficiency level is poor.
(3) According to the identification of weak links in the energy consumption of crude oil gathering and transportation systems, the energy-saving transformation is mainly carried out for the A7 station and X1 combined station. Among them, the thermal energy of station A7 is relatively weak, and the electrical energy of combined station X1 is weak. After the energy-saving improvement of the A7 station and X1 combined station, the annual gas consumption of the A7 station is 3660 m^3/d, and the annual electricity consumption of the X1 combined station is 768 kW h/d. The annual fuel gas and electricity consumption cost savings is approximately

$610,000, which effectively improves the energy efficiency of the crude oil gathering and transportation system.

(4) This paper applies the big data analysis method to the energy efficiency evaluation of gathering and transportation system. GA-BP TOPSIS evaluation method is used to establish a digital energy efficiency evaluation system, which can realize the functions of energy efficiency prediction, early warning research and judgment, energy saving and consumption reduction. This method can effectively guide the optimization and adjustment of energy efficiency structure of gathering and transportation system and promote the development of digital gathering and transportation system. The evaluation system can also be used for energy efficiency evaluation in related fields to provide theoretical support for energy conservation and consumption reduction in future oilfield enterprises.

Declaration of competing interest

No conflict of interest exits in the submission of this manuscript, and manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed.

Acknowledgements

This work was financially supported by the National Natural Science Foundation of China (52074089 and 52104064), Natural Science Foundation of Heilongjiang Province of China (LH2019E019).

References

Anirbid, S., Kriti, Y., Kamakshi, R., et al., 2021. Application of machine learning and artificial intelligence in oil and gas industry. Petroleum Research 6 (4), 379–391. https://doi.org/10.1016/j.ptlrs.2021.05.009.

Cao, Y., Song, M.H., Zhao, W.D., et al., 2020. Analysis on energy efficiency evaluation method of key energy system in oil and gas fields: taking the Tarim oilfield as an example. Chem. Eng. Oil Gas 49 (3), 106–114. https://doi.org/10.3969/j.issn.1007-3426.2020.03.018 (in Chinese).

Cheng, Q.L., Wang, R.H., Sun, W., et al., 2020. Study of the comprehensive evaluation of energy efficiency of an oilfield heating furnace based on combination weighting method. J. Therm. Sci. Eng. Appl. 13 (1), 1–33. https://doi.org/10.1115/1.4047169.

GB/T 31453-2015. Monitoring and Testing Code for Energy Conservation of Oilfield Production System (in Chinese).

He, C.G., Tan, X.L., Zhou, X.H., et al., 2022. Investment benefit evaluation of intelligent distribution network project based on game theory combination weighting. J. Electr. Power Sci. Technol. 37 (1), 161–167. https://doi.org/10.19781/j.issn.1673-9140.2022.01.019 (in Chinese).

Hu, Y.H., He, M., Zhou, C.J., et al., 2022. Study on vibration velocity prediction of millisecond delay blasting based on GA-BP neural network. China Min. Mag. 31 (2), 72–77. https://doi.org/10.12075/j.issn.1004-4051.2022.02.008 (in Chinese).

Kou, T.Y., 2021. Application research on energy saving of pump station based on machine learning algorithm. Qingdao Univ. https://doi.org/10.27262/d.cnki.gqdau.2021.002287 (in Chinese).

Li, P., Wang, R.H., Li, Z.M., 2021. Energy efficiency evaluation of oil field heating furnace based on entropy weight-grey correlation-TOPSIS method, 51 (1), 97–107 (in Chinese).

Li, H., Huang, J., Hu, Y., et al., 2021. A new TMY generation method based on the entropy-based TOPSIS theory for different climatic zones in China. Energy 231, 120723. https://doi.org/10.1016/j.energy.2021.120723 (in Chinese).

Li, J., Liu, J., Yang, Z.H., 2021. Design of safety early warning system for construction ships in plateau reservoir area based on triangular fuzzy analytic hierarchy process. J. Shanghai Marit. Univ. 42 (1), 94–99+106. https://doi.org/10.13340/j.jsmu.2021.01.016 (in Chinese).

Li, Q., Wang, Z., Lu, L., et al., 2021. Construction risk evaluation of poor geological channels based on cloud model-improved AHP–matter–element theory. Sustainability 13 (17), 9632. https://doi.org/10.3390/su13179632.

Li, Y.F., Ren, C., Zhao, H.W., Chen, G.P., 2020. Investigating long-term vehicle speed prediction based on GA-BP algorithms and the road-traffic environment. Science China (Information Sciences) 63 (9), 121–123. https://doi.org/10.1007/s11432-019-2792-9.

Li, Y.L., 2020. Energy consumption analysis and system optimization analysis of combined station. Chem. Manag. (19), 62–63 (in Chinese).

Paitoon, T., Christine, W.C., Fanhua, Z., et al., 2020. Recent progress and new developments of applications of artificial intelligence (AI), knowledge-based systems (KBS), and machine learning (ML) in the petroleum industry. Petroleum 6, 319–320. https://doi.org/10.1016/j.petlm.2020.08.001.

Papadopoulos, T., Sivarajah, U., Spanaki, K., et al., 2022. Editorial: artificial Intelligence (AI) and data sharing in manufacturing, production and operations management research. Int. J. Prod. Res. 60. https://doi.org/10.1080/00207543.2021.2010979.

Raghav, L.P., Kumar, R.S., Raju, D.K., et al., 2022. Analytic hierarchy process (AHP) – swarm intelligence based flexible demand response management of grid-connected microgrid. Appl. Energy 306, 118058. https://doi.org/10.1016/j.apenergy.2021.118058.

Tang, S., Pang, Y.P., Li, Z.M., et al., 2021. Study on multi level energy efficiency evaluation system of crude oil gathering and transportation system, 51 (21), 1–8 (in Chinese).

Tian, C.S., Chen, Y., 2021. China's provincial agricultural carbon emissions measurement and low carbonization level evaluation:Based on the application of derivative indicators and TOPSIS. J. Nat. Resour. 36 (2), 395–410. https://doi.org/10.31497/zrzyxb.20210210 (in Chinese).

Vinodh, S., 2020. Parametric optimization of fused deposition modelling process using Grey based Taguchi and TOPSIS methods for an automotive component. Rapid Prototyp. J. https://doi.org/10.1108/RPJ-10-2019-0269.

Wang, C., Li, G., Ali, I., et al., 2022. The efficiency prediction of the laser charging based on GA-BP. Energies 15. https://doi.org/10.3390/en15093143.

Wang, F.Q., Ma, S.Y., Zhao, H., et al., 2021. A fuzzy comprehensive evaluation of water cycle health in Beijing-Tianjin-Hebei region based on combined weights of AHP and entropy method. South-to-North Water Trans. Water Sci. Technol. 19 (1), 67–74. https://doi.org/10.13476/j.cnki.nsbdqk.2021.0006 (in Chinese).

Wang, R.H., 2021. Analysis of energy efficiency influencing factors and study on multi-index evaluation system of oilfield heating furnace. NE Pet. Univ. https://doi.org/10.26995/d.cnki.gdqsc.2021.000162 (in Chinese).

Wang, W., Qi, Y., Jia, B., et al., 2021. Dynamic prediction model of spontaneous combustion risk in goaf based on improved CRITIC-G2-TOPSIS method and its application. PLoS One 16 (10), e0257499. https://doi.org/10.1371/JOURNAL.PONE.0257499.

Wang, Y., Ju, Z.H., Tang, Z.H., 2022. GA-BP neural network based load prediction of combined cooling, Heating and Power Energy Supply System. J. Inst. Eng. Electr. Eng. Div. (7), 40–42+189. https://doi.org/10.19768/j.cnki.dgjs.2022.07.011 (in Chinese).

Wu, X., Niu, H., Li, X.J., et al., 2020. A study on the GA-BP neural network model for surface roughness of basswood-veneered medium-density fiberboard. Holzforschung 74 (10), 979–988. https://doi.org/10.1515/hf-2019-0248.

Yao, B., Zhang, X.Q., Li, Z.M., et al., 2021. Study on evaluation system of energy efficiency index for metering and transfer station system, 51 (24), 106–116 (in Chinese).

Yao, C.X., 2020. Study on energy consumption and oil loss evaluation technology of heavy oil gathering system. NE Pet. Univ. https://doi.org/10.26995/d.cnki.gdqsc.2020.000524 (in Chinese).

Yuan, S.L., Lu, H.M., Wang, P.P., et al., 2021. Boron removal from metallurgical grade silicon by slag refining based on GA-BP neural network. Rare Met. 40 (1), 237–242.

Zang, W., Yang, Z., Deng, X., et al., 2020. Construction of energy efficiency benchmarking system for oil field heating furnace. Oil Gas Storage Transp. 39 (9), 1047–1053. https://doi.org/10.6047/j.issn.1000-8241.2020.09.013 (in Chinese).

Zhao, D.Y., Zhang, J., Wang, S., et al., 2021. Study on energy consumption evaluation system of oil field gathering pump unit based on correlation coefficient index screening method, 51 (2), 137–144 (in Chinese).

Zhou, Q., Zhang, Q., Li, H., 2021. Analysis on the level of higher universities in different countries using entropy weight method and analytic hierarchy process. In: 2021 4th International Conference on Information Systems and Computer Aided Education, pp. 2722–2727. https://doi.org/10.1145/3482632.3487502.

Zhu, D., Wang, R., Duan, J., et al., 2021. Comprehensive weight method based on game theory for identify critical transmission lines in power system. Int. J. Electr. Power Energy Syst. 124, 106362. https://doi.org/10.1016/j.ijepes.2020.106362.