ARTICLE IN PRESS

Petroleum Science xxx (xxxx) xxx

Contents lists available at ScienceDirect

Petroleum Science

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

Original Paper

Research on low carbon emission optimization operation technology of natural gas pipeline under multi-energy structure

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ARTICLE INFO

Article history:
Received 28 December 2021
Received in revised form
22 September 2022
Accepted 22 September 2022
Available online xxx

Edited by Xiu-Qiu Peng

Keywords:
Natural gas
Pipeline optimization
NHPSO-JTVAC algorithm
Carbon emission
New energy

ABSTRACT

In order to reduce the carbon emissions of natural gas pipelines, based on the background of different energy structures, this paper proposes a general low carbon and low consumption operation model of natural gas pipelines, which is used to fine calculate the carbon emissions and energy consumption of natural gas pipeline. In this paper, an improved particle swarm optimization (NHPSO-JTVAC) algorithm is used to solve the model and the optimal scheduling scheme is given. Taking a parallel pipeline located in western China as an example, the case is analyzed. The results show that after optimization, under the existing energy types, the pipeline system can reduce 31.14% of carbon emissions, and after introducing part of new energy, the pipeline system can reduce 34.02% of carbon emissions, but the energy consumption has increased.

1. Introduction

1.1. Research background

The “Paris Agreement” stipulates that efforts should be made to control the global average temperature rise within 1.5 °C compared with the pre-industrial period (Morgan and Patomaki, 2021). According to the 2018 report of the Intergovernmental Panel on Climate Change (IPCC), achieving this goal would require carbon neutrality by around 2050. Therefore, since 2018, many countries have made carbon neutrality commitments, and most countries set a target for 2050. According to Energy and Climate Intelligent Unit data (Energy), 34 countries and regions have explicitly proposed carbon neutralization targets, as shown in Table 1.

It can be seen from Table 1 that carbon emission has attracted the attention of countries all over the world, but most countries have not reached the goal of a carbon peak, which requires joint efforts in various fields.

In recent years, as low-carbon energy, the demand for natural gas has gradually increased worldwide (Petkovic et al., 2021; Gunton et al., 2021; Daneshzand et al., 2018). According to the prediction of Zheng et al. (2021), from 2024 to 2030, China's average total natural gas demand will rise from 315.378 billion m^3 to 436.327 billion m^3. With the increasing demand for natural gas, the pipeline system will consume more energy, and the emission of CO_2 is closely related to energy consumption (Yuan et al., 2019). It was found that China's energy supply chain and its production processes account for 43.8% of total CO_2 emissions (National Development and Reform Commission, 2016b). Therefore, reducing CO_2 emissions during natural gas transportation is very important for China's entire energy supply chain to achieve the goal of “carbon peaking and carbon neutralization” as soon as possible.

1.2. Literature review

At present, the research on low-carbon emissions of natural gas pipeline systems mostly focuses on pipeline leakage (Boothroyd et al., 2018; Dianita et al., 2018; Balcombe et al., 2018). In this article, we consider the carbon emissions of natural gas pipelines

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https://doi.org/10.1016/j.petsci.2022.09.025
1995-8226/

Please cite this article as: E.-B. Liu, Y. Peng, S.-B. Peng *et al.*, Research on low carbon emission optimization operation technology of natural gas pipeline under multi-energy structure, Petroleum Science, https://doi.org/10.1016/j.petsci.2022.09.025

Nomenclature

Symbols(Optimization model)

a	A coefficient of +1 for inflow and −1 for outflow
c_p	Specific heat capacity of gas at constant pressure, J/(kg·K)
C	Energy consumption
D	Pipeline outside diameter, m
g	Acceleration of gravity, 9.8 m^2/s
H	The energy head of a compressor, kJ/kg
k_v	Compressor variability index
k_t	Temperature rise coefficient
K	The total heat transfer coefficient of the pipeline, W/m^2·K
l	Number of compressors started
L	Length of the pipeline, m
M	Gas mass flow, kg/s
M_1	The absolute volume of inflow and outflow component k, m^3
M_2	Flow exchanged between nodes and the outside world, m^3
M_w	The molecular weight of natural gas, kg/mol
N	Compressor power, kW
P	Pipeline pressure, Pa

Subscripts(Optimization model)

e	Electricity
$e1$	Wind electricity
$e2$	Solar electricity
g	Natural gas
i	Number of the pipeline
$_{in}$	Compressor inlet
j	Number of gas compressor
k	Number of the electric compressor
l	Number of the compressor using Solar electricity

Symbols(Optimization algorithm)

b_1, b_2	Learning factor
$Iter$	Iteration steps
P	The optimal position of particles

Subscripts(Optimization algorithm)

g	Global value
i	The particle number
$_q$	Pipeline throughput, 10^4 Nm^3/d
r	Compressor speed, r/min
R	Gas constant, 8.314 kJ/(kmol·K)
Re	Reynolds number
S	Switch status of intermediate valve
ΔS	The height difference between the beginning and end of the pipeline, m
t	Compressor running time, h
T_0	Ambient temperature, K
T	Temperature, K
T_{cp}	The average temperature of the pipeline, K
Z	The natural gas compression factor
η	Compressor efficiency
γ	Absolute equivalent roughness of pipeline wall, mm
ε	Carbon emission coefficient
λ	The coefficient of friction
ζ	The gas consumption rate of gas turbine, Nm^3/kWh
m	Pipeline node
min	The minimum value
max	The maximum value
n	pipeline component
$_{out}$	Compressor outlet
$_Q$	Starting point of pipeline
w	Number of the compressor using wind electricity
Z	Pipeline end point
v	Particle velocity
w	A standard normal random number
x	The current position of the particle
j	Particle dimension

from another perspective: the self-consuming energy of the natural gas transportation pipeline. In fact, according to the estimation of Howarth et al. (2011), the total fugitive emissions of natural gas during transportation, storage, and distribution account for 1.4–3.6% of the total transmission. However, according to the study of Tabkhi et al. (2010), the self-consuming gas of the natural gas pipeline transport can reach 3%–5% of the total amount of transport gas throughout the system. According to the research of Liu et al. (2019a), the actual gas consumption of the second west-east gas transmission line for one month can reach 9292.30 × 10^4 Nm^3 and the actual power consumption is 3212.54 × 10^4 kWh. Golik et al. (2018) compared the power parameters of a motor (SDG2-12500-2 R UHL3.1) and a gas turbine (GTU MS5002E), which can reach 12.5 MW and 32 MW respectively. Therefore, the energy consumption of compressors is also the main carbon emission source of natural gas pipeline systems (Lyon, 2016). However, there are few studies on how to reduce the carbon emission of self-energy consumption of natural gas pipeline systems. Through literature research, there are two main reasons:

(1) When the system consumes only one energy, energy consumption and carbon emissions are linearly related.

Table 1
Carbon neutrality targets proposed by various countries.

Nature of Commitment	Committed time	Country/Region	Quantity
_	Achieved	Suriname, Bhutan	2
Legal document	2045	Germany, Sweden	2
	2050	United Kingdom, France, Denmark, New Zealand, Hungary	5
Proposed legislation	2050	European Union, Canada, South Korea, Spain, Chile, Fiji	6
Policy documents	2035	Finland	1
	2040	Austria, Iceland	2
	2050	United States, Japan, South Africa, Brazil, Switzerland, Norway, Ireland, Portugal, Panama, Costa Rica, Slovenia, Andorra, Vatican City, Marshall Islands	14
	2060	China, Kazakhstan	2

Each energy has a unique carbon emission factor. Kashani and Molaei (2014) took the minimum carbon emission as one of the optimization goals, and they found that the emissions of carbon dioxide and the best-operating costs were linear. But in their research cases, the compressor type is only the gas compressor. Arya and Honwad (2018) proposed a multi-objective ant colony optimization algorithm to reduce the energy consumption of the compressor and increase the pipeline throughput. This study mainly calculates the fuel consumption of the turbine. Yang et al. (2020) also combined the golden section algorithm and dynamic programming algorithm to reduce the energy consumption of gas compressor units in an annular pipeline.

It can be seen from the above documents that the power equipment of the natural gas transmission system in many studies is mainly a gas compressor, and natural gas is consumed. Therefore, as long as the energy consumption is minimum, the carbon emission of the system can be minimized. However, in recent years, some scholars have considered more types of energy consumption. For example, Liu et al. (2014, 2019c, 2019b) considered both the gas compressor and electric drive compressor in the steady-state optimization of China's west to east gas transmission pipeline. After that, they considered the power consumption of the air cooler in the pipeline system (Liu et al., 2019a), and studied the power and gas consumption of the system. Zhao et al. (2021) proposed an optimal operating model for the compressor. In their research, there are both gas compressors and electric compressors in the same compressor station. During operation, the two types of compressors can be switched to realize the flexibility of energy consumption. In these cases, pipeline energy consumption and carbon emission cannot be regarded as a simple linear relationship.

(2) The scale of the pipeline is small, and the carbon emission generated by self-energy consumption is small

In many studies, due to the small scale of pipelines and the small number of compressors, the carbon emission itself is small. Wang et al. (2018) developed a MILP model of the natural gas transmission network. In their four optimization cases, the number of compressors is no more than two. Su et al. (2019) proposed an optimization model aiming at minimum supply risk and minimum energy cost. They considered the uncertainty of pipeline supply conditions and customer demand and obtained good results. However, in their research case, the pipeline system has only two compressor stations, and the pipeline length is 10 km.

At present, in the natural gas pipeline transmission system, the compressor is not only the gas compressor. In some areas with low power costs, the electric drive may have more advantages than the gas drive (Liu et al., 2019b; Deng, 2016). Because the carbon emission coefficient of electric energy is different from that of natural gas, the carbon emission, and single energy consumption will no longer change linearly, and the combination of different energy sources will make the optimization process more complex. In addition, the new energy power has a smaller carbon emission coefficient (Zhai et al., 2020; Salman et al., 2019; Li and Wang, 2019; Tong et al., 2020). If the new energy power is considered in the natural gas long-distance transmission pipeline, the carbon emission of the whole system will be further reduced.

1.3. Article contribution

In order to deal with the problem of large carbon emissions from existing natural gas pipelines, this paper aims to develop a general low-carbon operation model for natural gas pipelines. We take a parallel pipeline in Western China as a research case, and the length of the pipeline reaches 2500 km. As shown in Fig. 1, each pipeline has 14 compressor stations, and there are both electric compressors and gas compressors.

The main contributions of this article are as follows:

(1) The optimization model of multi-energy minimum carbon emissions of the natural gas pipeline is established to realize the calculation of the minimum carbon emissions of the pipeline system.
(2) Different energy consumption under the minimum carbon emission target can be determined to give the corresponding energy structure of pipeline system.
(3) When the pipeline system consumes different energy, the relationship between energy consumption and carbon emission can be determined.

The main structure of the article is as follows: In the second part, the basic calculation model of the natural gas pipeline is established, the relationship between energy consumption and carbon emission is analyzed, and the optimization model and optimization algorithm are given. In the third part, the actual operation case is introduced and the optimization model is verified; In the fourth part, the carbon emission and energy consumption of different schemes are analyzed, and the relationship between carbon emission and energy consumption under different energy structures is given. The conclusion of this paper is given in the fifth part.

2. Model and method

2.1. Calculation model of natural gas pipeline

2.1.1. Pipeline calculation

The end temperature of the gas transmission pipeline is calculated by the Sukhov formula (Li and Huang, 2016; Liu et al., 2020).

$$
\begin{aligned}
T_Z &= T_0 + (T_Q - T_0)e^{-aL} \\
a &= \frac{K\pi D}{Mc_p}
\end{aligned} \tag{1}
$$

The calculation formula of terminal pressure of gas transmission pipeline is as follows(Li and Huang, 2016):

$$
\begin{aligned}
P_Z &= \sqrt{P_Q^2(1-\delta\Delta S) - bM^2L\left(1-\frac{\delta\Delta S}{2}\right)} \\
\delta &= \frac{2g}{ZRT_{cp}}, b = \frac{16\lambda ZRT_{cp}}{\pi^2 D^5}
\end{aligned} \tag{2}
$$

For a long-distance gas transmission pipeline, the flow state in the pipeline is basically in the resistance square area. In this paper, Colebrook white formula is used to calculate the friction coefficient. This method has the advantages of high precision, such as Eq. (3) (Kody and Xiang, 2018; Yu et al., 2020).

$$
\frac{1}{\sqrt{\lambda}} = -2.01 \cdot \lg\left(\frac{\gamma}{3.71d} + \frac{2.51}{\mathrm{Re}\sqrt{\lambda}}\right) \tag{3}
$$

2.1.2. Compressor calculation

The compressor is the power equipment in the natural gas pipeline system, and its outlet pressure calculation formula is as follows (Kody and Xiang, 2018):

$$
P_{out} = P_{in}\left(\frac{HM_w}{ZRT_{in}}\frac{k_v-1}{k_v}+1\right)^{\frac{k_v}{k_v-1}} \tag{4}
$$

The calculation formula of compressor outlet temperature is as follows (Liu et al., 2014):

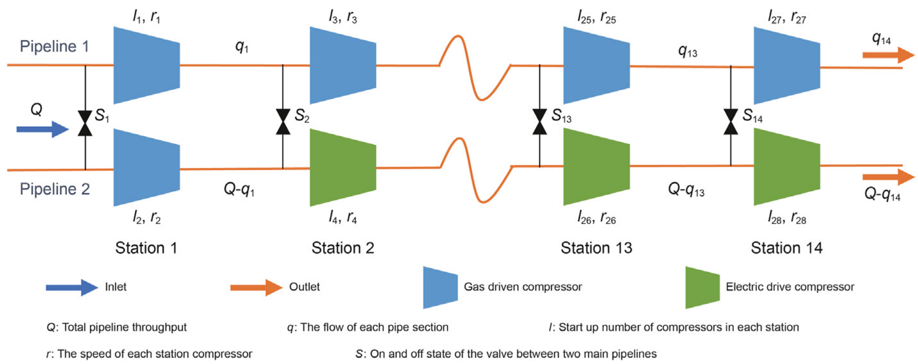


Fig. 1. Schematic diagram of parallel pipeline.

$$T_{out} = T_{in}\left(1 + \frac{1}{k_t}\left(\left(\frac{P_{out}}{P_{in}}\right)^{\frac{k_v-1}{k_v}} - 1\right)\right) \tag{5}$$

The power calculation formula of the compressor is as follows (Liu et al., 2014):

$$N = \frac{MH}{\eta} \tag{6}$$

2.2. Optimization model

2.2.1. Analysis of the relationship between energy consumption and carbon emissions

The pipeline studied in this paper is located in northwest China, where the grid emission factor is 0.6671 kg CO_2/kWh (Liang, 2018), and the emission factor of natural gas is 2.1622 kg CO_2/m^3. Meanwhile, the gas-to-standard coal coefficient is 1.33 kgce/m^3, and the electric-to-standard coal coefficient is 0.1229 kgce/kWh. Based on the above data, this paper calculates the natural gas and electric energy required to produce 1 ton of standard coal and 1 ton of CO_2, as shown in Table 2.

It can be seen from Table 2 that when the same energy (such as benchmark 1) is produced, electricity has more carbon emissions. Therefore, to reduce carbon emissions, it is necessary to reduce the use of electricity. With emissions of the same CO_2 (such as benchmark 2), natural gas produces more energy, so when the energy required by the system is constant, the amount of natural gas needs to be increased. It can be seen that whether to reduce carbon emissions or energy consumption, it is necessary to increase the consumption of natural gas and reduce electricity consumption.

The simulated pipeline passes through the Xinjiang and Gansu provinces of China. Under the guidance of policies, this region is vigorously developing wind power and photovoltaic energy. We have obtained the carbon emission coefficients of wind power and photovoltaic power from the China Life Cycle Basic Database (CLCD) and Ecoinvent database (Liu et al., 2010; Hou et al., 2012), which are 0.0112 kg CO_2/kWh and 0.0704 kg CO_2/kWh, respectively. The fixed energy consumption and carbon emission of wind power and photoelectric are shown in Table 3.

It can be seen from Table 3 that when wind power and photovoltaics generate the same energy consumption (Benchmark 3), the CO_2 emissions are less than the CO_2 emissions of natural gas. When wind power and photovoltaics emit the same CO_2 (Benchmark 4), the energy produced is much greater than that of natural gas.

2.2.2. Objective function

Taking the minimum carbon emission during the operation of the parallel pipeline system as the objective function, this paper establishes two objective functions based on the existing energy structure and the introduction of new energy. The optimization model is based on the following assumptions: ① The flow state of gas in the pipeline is steady flow; ② The flow is equally divided between parallel compressors (In the same station, the compressor has the same performance.).

Objective 1: the system consumes natural gas and electric energy.

$$\min C_1 = \min \sum_{i=1}^{i=N_i}\sum_{j=1}^{j=N_j} \varepsilon_g C_{gi}^{j} + \sum_{i=1}^{i=N_i}\sum_{k=1}^{k=N_k} \varepsilon_e C_{ei}^{k} \tag{7}$$

Objective 2: the system consumes natural gas, electric energy, and new energy power. In China, due to the instability of wind power and photoelectric, its effective power generation time accounts for only about 1/5 of the whole year.

$$\min C_2 = \min \sum_{i=1}^{i=N_i}\sum_{j=1}^{j=N_j} \varepsilon_g C_{gi}^{j} + \frac{1}{5}\left(\sum_{i=1}^{i=N_i}\sum_{w=1}^{w=N_w} \varepsilon_{e1} C_{ei}^{w} + \sum_{i=1}^{i=N_i}\sum_{l=1}^{l=N_l} \varepsilon_{e2} C_{ei}^{l}\right) + \frac{4}{5}\left(\sum_{i=1}^{i=N_i}\sum_{k=1}^{k=N_k} \varepsilon_e C_{ei}^{k}\right) \tag{8}$$

In Eq. (7) and Eq. (8), the calculation formula of C_g is as follows:

Table 2
Comparison table of fixed energy consumption and fixed carbon emission.

Category	Natural gas		Electric energy	
Benchmark 1	Consumption, m^3	Carbon emissions, kg CO_2	Consumption, kW·h	Carbon emissions, kg CO_2
1 tce	751.88	1625.71	8136.70	5427.99
Benchmark 2	Consumption, m^3	Standard coal, tce	Consumption, kW·h	Standard coal, tce
1 tCO_2	426.49	0.615	1499.03	0.184

Table 3
Wind power and photoelectric consumption under fixed energy consumption and carbon emission.

Category	Wind energy		Photovoltaic energy	
Benchmark 3	Consumption, kWh	Carbon emissions, kg CO_2	Consumption, kWh	Carbon emissions, kg CO_2
1 tce	8136.70	91.13	8136.70	572.82
Benchmark 4	Consumption, kWh	Standard coal, tce	Consumption, kWh	Standard coal, tce
1 tCO_2	89285.71	10.97	14204.55	1.75

$$C_g = \frac{N_g t_g}{\eta_g}\zeta \tag{9}$$

In Eq. (7) and Eq. (8), the calculation formula of C_e is as follows:

$$C_e = \frac{N_e t_e}{\eta_e} \tag{10}$$

2.2.3. Decision variables

In the objective function, carbon emission is directly related to the gas and power consumption of the compressor, and the variables affecting the compressor energy consumption in the model are decision variables, as shown below:

$$X = (q, l, r, S) \tag{11}$$

2.2.4. Constraints

(1) Compressor speed constraint

$$r_{\min} \le r \le r_{\max} \tag{12}$$

(2) Pipeline pressure constraints

$$P_{\min} \le P \le P_{\max} \tag{13}$$

(3) Flow constraint

$$\sum_{n \in C_m, m=1}^{N_m} a_{mn} M_{1mn} + \sum_{m=1}^{N_m} M_{2m} - \sum_{j=1}^{N_j} C_{g_j} = 0 \tag{14}$$

(4) Compressor power constraint

$$N_{\min} \le N \le N_{\max} \tag{15}$$

(5) Compressor outlet temperature constraint

$$T_{out} \le T_{out\ \max} \tag{16}$$

Through the above contents, the optimization model of the parallel pipeline can be established, and the modeling process is shown in Fig. 2:

Based on Fig. 2, the detailed modeling process is as follows:

① The decision variable $X = (q, l, r, S)$ is introduced and the initial compressor station inlet parameter is called.

② Judge whether the intermediate valve of the two pipes is open, determine the flow rate of each pipe, and then calculate the outlet pressure and outlet temperature of the compressor station based on Eq. (4) and Eq. (5);

③ Make the compressor outlet pressure P_{out} equal to the inlet pressure P_Q of the next pipe section, and the compressor outlet temperature T_{out} equal to the inlet temperature T_Q of the next pipe section;

④ Call the basic parameter module (environment data and pipeline data). Using Eq. (1) and Eq. (2), the terminal temperature T and terminal pressure P of the pipe section are calculated.

⑤ Make the end pressure P_Z of the upper pipe section equal to the inlet pressure P_{in} of the compressor station in the next section, and the end temperature T_Z equal to the inlet temperature T_{in} of the compressor station. Repeat steps ② to ⑤ until the pressure and temperature changes of each station in the system are calculated.

⑥ Setting constraints to calculate the gas consumption C_g of the gas compressor and the power consumption C_e of the electric compressor;

⑦ The carbon emission factors of natural gas, electric energy, and new energy are introduced to calculate the carbon emission of each energy;

⑧ The minimum carbon emission objective functions C_1 and C_2 (Eq. (7) and Eq. (8)) are established, and the optimization algorithm is used to solve them, so as to determine the low-carbon operation scheme of the pipeline system and give suggestions on energy structure adjustment.

2.3. Optimization algorithm

With the progress of mathematics and computer science, the kinds of optimization algorithms are increasing gradually. Among them, particle swarm optimization (PSO) is simple and easy to implement and needs to adjust fewer parameters, so many scholars have applied it. However, the particle swarm optimization algorithm also has some shortcomings, such as fast convergence speed and easy-to-find local optimal value. Through literature research, this paper finally determined four high-performance improved particle swarm optimization algorithms, which are PPSO (Ghasemi et al., 2019a), NHPSO-JTVAC (Ghasemi et al., 2019b), CPSO (Liu et al., 2005), and EDW-PSO (Meenakshi et al., 2021).

2.3.1. Algorithm selection

The model established in this paper has a large number of optimization variables and a large dimension. In order to select the method suitable for solving the model in this paper, four algorithms are used to solve the optimization model respectively. To make a fair comparison, the overall size and a minimum number of iterations were set to 50 and 300, respectively, for each test. Four improved particle swarm optimization algorithms were used to solve objective function 1 and objective function 2 for 30 times respectively, and the Best, Worst, Mean and standard deviation values (SD) of the results obtained by each algorithm were recorded after 30 independent experiments, as shown in Table 4.

As shown in Table 4, among the solution results of the four algorithms, NHPSO-JTVAC shows the best performance. PPSO algorithm also performs well when solving objective function 1, but when solving objective function 2, the result deviation is large. CPSO algorithm and EDW-PSO algorithm both show poor performance in the solving process of the two objectives. Therefore, this paper mainly uses the NHPSO-JTVAC algorithm to solve the model.

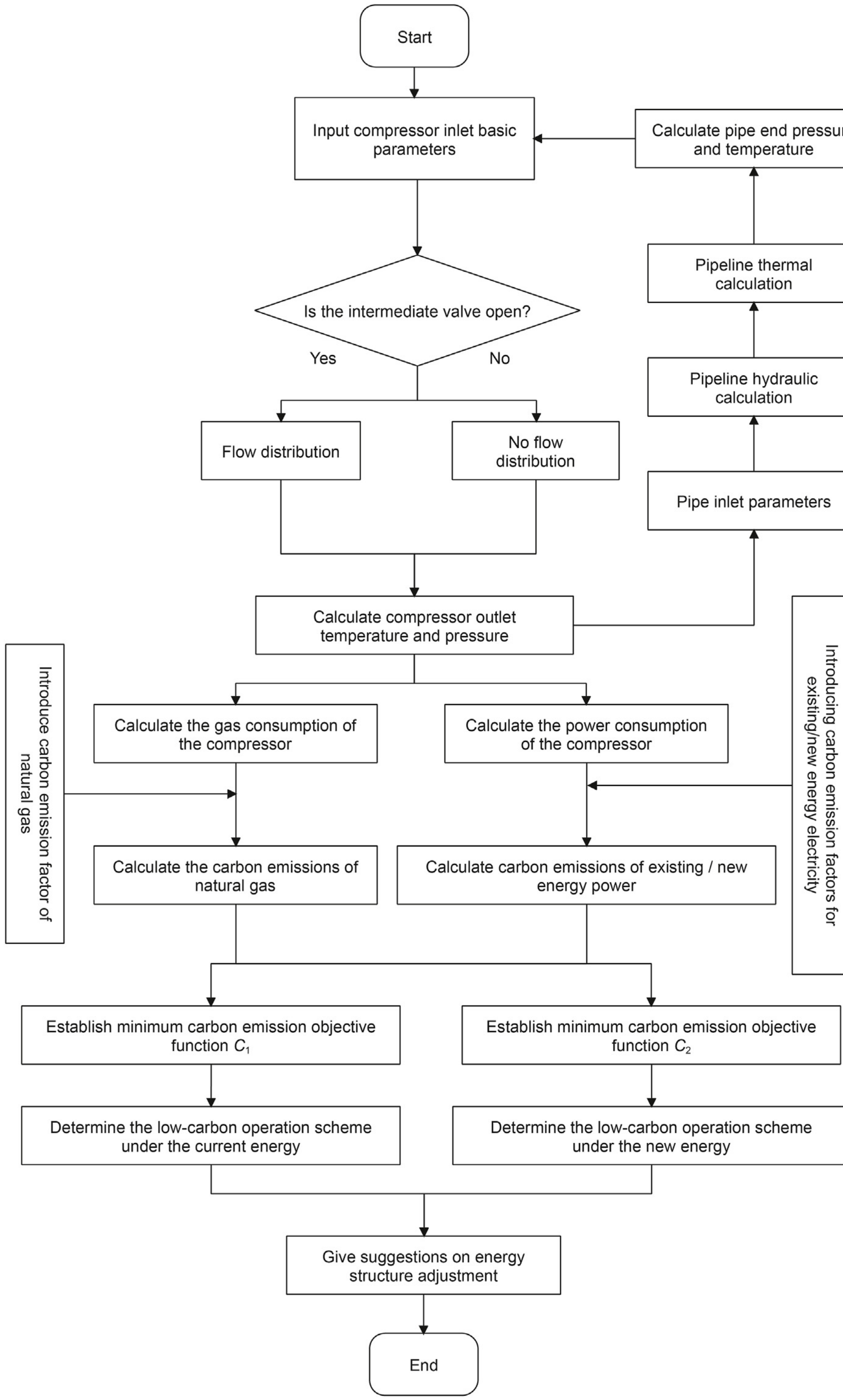


Fig. 2. Pipeline modeling flow chart.

2.3.2. *Traditional particle swarm optimization*

In particle swarm optimization (PSO), each particle has a position vector *P* and a velocity vector *V*. the traditional calculation formula is as follows:

$$v_{i,j}^{Iter+1} = v_{i,j}^{Iter} + h_1^{Iter} r_{1,j}\left(p_{i,j}^{Iter} - x_{i,j}^{Iter}\right) + h_2^{Iter} r_{2,j}\left(p_{g,j}^{Iter} - x_{i,j}^{Iter}\right) \quad (17)$$

$$X_i^{Iter+1} = V_i^{Iter+1} + X_i^{Iter} \quad (18)$$

2.3.3. *NHPSO-JTVAC algorithm*

The NHPSO-JTVAC algorithm refers to a new self-organizing hierarchical particle swarm algorithm with a jumping time-varying acceleration coefficient. This algorithm is upgraded from

Table 4
Solution results of four optimization algorithms.

Objective function		PPSO	NHPSO-JTVAC	CPSO	EDW-PSO
Objective function 1	Best	27.51×10^{7}	$\mathbf{27.26 \times 10^{7}}$	12.83×10^{12}	53.21×10^{12}
	Worst	40.25×10^{7}	$\mathbf{29.85 \times 10^{7}}$	17.51×10^{22}	44.53×10^{21}
	Mean	31.55×10^{7}	$\mathbf{28.09 \times 10^{7}}$	10.56×10^{20}	16.57×10^{19}
	SD	3.23	**0.74**	39.32×10^{21}	81.42×10^{20}
Objective function 2	Best	27.43×10^{7}	$\mathbf{26.12 \times 10^{7}}$	14.06×10^{12}	89.35×10^{7}
	Worst	29.82×10^{21}	$\mathbf{42.32 \times 10^{7}}$	33.92×10^{19}	59.92×10^{21}
	Mean	10.01×10^{21}	$\mathbf{29.76 \times 10^{7}}$	21.22×10^{18}	19.74×10^{20}
	SD	54.48×10^{20}	**4.38**	72.71×10^{18}	10.71×10^{21}

another improved particle swarm algorithm HPSO-TVAC. Compared with the traditional particle swarm algorithm PSO, there are two main differences.

(1) The calculation method of the learning factor is different

In the traditional particle swarm optimization algorithm, the learning factors b_1 and b_2 are usually fixed, but the fixed value will make the local and global search ability of the particle swarm optimization algorithm insufficient. The calculation method of b_1 and b_2 in the NHPSO-JTVAC algorithm is as follows:

$$b^{Iter_{Iter}} = \left(b_f - b_i\right)\frac{Iter}{Iter_{max}} + b \tag{19}$$

$$b_1^{Iter} = |w|\left(b^{Iter} * w\right) \tag{20}$$

$$b_2^{Iter} = |1-w|^{\left(\frac{b^{Iter}}{1-w}\right)} \tag{21}$$

In Eq. (19), b^{Iter}will change from $b^1 = b_i = 0.5$ to $b^{Iter\ max} = b_f = 0.0$.

(2) The speed update formula is different

The velocity calculation formula of the traditional particle swarm optimization algorithm is Equation (17). The study of Cheng and Jin (2015) shows that the $P_g^{Iter} - X_i^{Iter}$ is easy to make the algorithm fall into the local optimum. Therefore, in the NHPSO-JTVAC algorithm, Ghasemi et al. (2017) introduced the optimal individual value of random particles, P_r^{Iter}, and used $(P_g^{Iter} + P_r^{Iter}) - 2*X_i^{Iter}$ to replace the original $P_g^{Iter} - X_i^{Iter}$, transforming Eq. (17) into Eq. (22).

$$v_{i,j}^{Iter+1} = b_1^{Iter} r_{1,j}\left(P_{i,j}^{Iter} - x_{i,j}^{Iter}\right) + b_2^{Iter} r_{2,j}\left(\left(P_{g,j}^{Iter} + P_{r,j}^{Iter}\right) - 2x_{i,j}^{Iter}\right) \tag{22}$$

3. Case introduction and model verification

3.1. Case introduction

The parallel pipeline diagram is shown in Figure 1. Each pipeline has 14 stations with an inner diameter of 1.177 m, and the operation time is calculated by one month (31 days). The trend diagram of the pipeline is shown in Fig. 3.

According to the operation data of the compressor station investigated on-site, the operation data of two pipelines in a month are shown in Table 5 and Table 6.

3.2. Model validation

Because natural gas itself is compressible, it is very important to calculate the correct pressure and temperature. Here, we input the actual operation data of the pipeline into the optimization model and calculate the pressure and temperature along the pipeline for model verification. The pressure change is shown in Fig. 4.

When the absolute pressure difference is within 5%, it meets the requirements. In Fig. 4, the maximum outgoing pressure difference of pipeline 1 is 0.17 MPa, that is, the maximum pressure error of pipeline 1 is 1.58%; The maximum outgoing pressure difference of pipeline 2 is 0.21 MPa, that is, the maximum pressure error of pipeline 2 is 1.91%, so the pressure calculation of the model meets the requirements. In addition, the outgoing temperature change along the pipeline is shown in Fig. 5.

When the temperature difference is within 5%, it meets the calculation requirements. In Fig. 5, the maximum temperature difference of pipeline 1 is 1.79 °C, that is, the maximum temperature error of pipeline 1 is 3.79%. The maximum temperature difference of pipeline 2 is 1.61 °C, that is, the maximum temperature error of pipeline 2 is 3.38%, so the temperature calculation of the model meets the requirements.

4. Results and discussion

4.1. Optimization results

NHPSO-JTVAC algorithm is used for optimization. The initial population is 50 and the number of iterations is 150.

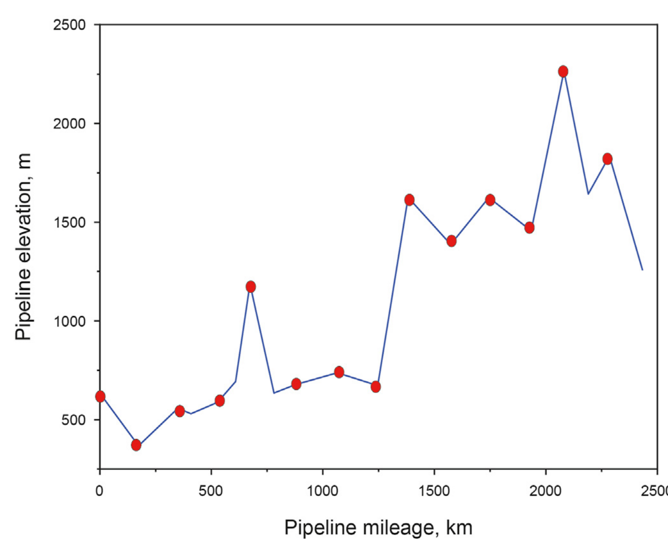


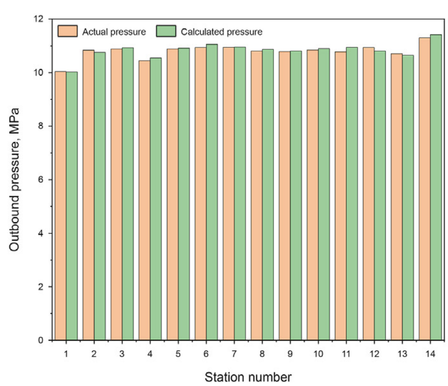
Fig. 3. Elevation-mileage data of the parallel pipeline.

Table 5
Actual operation data of pipeline 1.

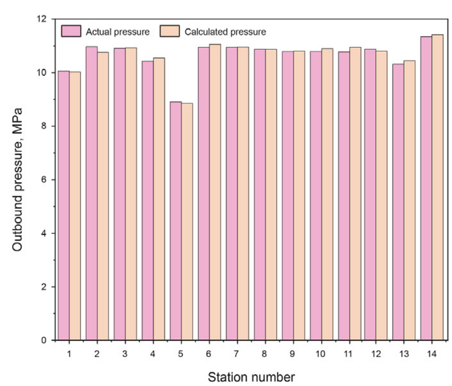
Station number	Inlet pressure, MPa	Outlet pressure, MPa	Inlet temperature, °C	Outlet temperature, °C	Number of compressors	Compressor power, kW	Compressor type	Valve status
1	6.48	10.04	20.37	54.7	2	13326.03	Gas	Open
2	8.10	10.84	24.76	51.12	1	6623.86	Gas	Open
3	8.80	10.89	25.00	44.00	1	4257.58	Gas	Open
4	8.98	10.45	22.55	35.60	1	3382.53	Gas	Open
5	7.40	10.89	12.88	44.70	3	15425.00	Electric	Close
6	7.92	10.94	16.03	42.65	2	12969.13	Gas	Open
7	8.19	10.95	22.46	47.16	2	10517.14	Gas	Open
8	8.41	10.81	26.00	50.00	1	2982.66	Gas	Open
9	8.14	10.79	24.2	48.5	1	14221.24	Gas	Open
10	8.02	10.85	26.6	51.9	2	18616.48	Electric	Open
11	7.97	10.78	21.22	46.61	1	5693.25	Gas	Open
12	8.11	10.94	20.61	49.50	1	5839.12	Gas	Open
13	8.08	10.71	20.75	45.15	2	17627.30	Electric	Open
14	8.24	11.30	20.31	46.88	1	5951.70	Gas	Open

Table 6
Actual operation data of pipeline 2.

Station number	Inlet pressure, MPa	Outlet pressure, MPa	Inlet temperature, °C	Outlet temperature, °C	Number of compressors	Compressor power, kW	Compressor type	Valve status
1	6.48	10.06	16.80	52.00	2	11904.27	Gas	Open
2	8.22	10.97	26.3	52.5	2	7989.06	Electric	Open
3	8.82	10.91	25.52	44.13	2	5382.93	Electric	Open
4	8.96	10.43	23.01	35.81	2	6765.28	Electric	Open
5	8.91	8.91	29.23	29.60	0	0	Electric	Close
6	7.89	10.95	16.00	44.00	1	5145.83	Gas	Open
7	8.19	10.95	24.00	50.00	2	11347.18	Gas	Open
8	8.39	10.88	25.40	46.70	2	5951.15	Gas	Open
9	8.12	10.79	25.12	49.62	2	25941.94	Gas	Open
10	8.01	10.79	26.2	53.9	2	14784.70	Electric	Open
11	8.00	10.78	20.84	47.6	3	11331.28	Electric	Open
12	7.79	10.88	18.80	46.96	3	11692.33	Electric	Open
13	8.22	10.32	23.30	41.70	2	13088.13	Electric	Open
14	8.08	11.35	18.7	48.2	3	11227.24	Electric	Open



(a) Outlet pressure of each station in pipeline 1



(b) Outlet pressure of each station in pipeline 2

Fig. 4. Comparison between actual pressure and calculated pressure.

(1) Objective 1 optimization results

The optimization process is shown in Fig. 6.

As can be seen from Fig. 6, when the algorithm iterates to 82 steps, the calculation results tend to be stable. The operation data of each station under this objective is shown in Table 7.

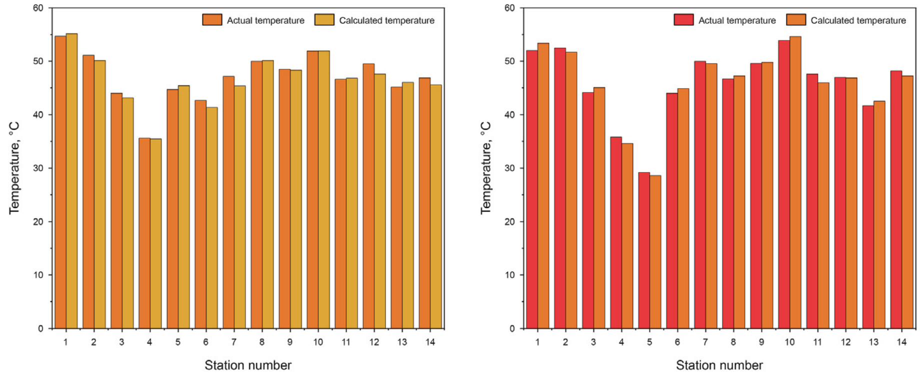
As can be seen from Table 7, in Objective 1, there are 23 gas compressors and 17 electric compressors in the pipeline system.

(2) Optimization results of objective 2

The optimization process is shown in Fig. 7.

As can be seen from Fig. 7, when the algorithm iterates to 93 steps, the calculation results tend to be stable. The operation data of each station under this objective is shown in Table 8.

As can be seen from Table 8, in Objective 2, there are 21 gas compressors and 18 electric compressors in the pipeline system.



(a) Outlet temperature of each station of pipeline 1 (b) Outlet temperature of each station of pipeline 2

Fig. 5. Comparison between the actual temperature and calculated temperature.

4.2. Result discussion

4.2.1. Analysis of carbon emissions from different energy sources

(1) Carbon emission analysis of natural gas

The carbon emissions of natural gas in each station of the actual scheme, objective 1 optimization scheme, and objective 2 optimization scheme are shown in Fig. 8.

In Fig. 8, the carbon emission of the actual scheme is 174,100 tons, the carbon emission of objective function 1 is 154,100 tons, and the carbon emission of objective function 2 is 151,300 tons. It shows that after optimization, both objective function 1 and objective function 2 reduce the use of natural gas, in which the existing energy structure (Objective 1) can reduce carbon emissions by 11.49%, and the addition of new energy (Objective 2) can reduce carbon emissions by 13.10%.

(2) Carbon emission analysis of electric power

The carbon emission of electric energy of each station in the actual scheme, objective 1 and objective 2 is shown in Fig. 9.

In Fig. 9, the startup number of the fourth electric drive compressor station of pipeline 2 is 0 in different operation schemes, so there is no carbon emission in the station. Among the three operation schemes, the carbon emission of the actual scheme is 221,800 tons, the carbon emission of objective 1 is 118,500 tons, and the carbon emission of objective 2 is 109,900 tons. It shows that after the addition of new energy, the carbon emission can be reduced by 50.45%.

4.2.2. Energy consumption analysis of different energy sources

Natural gas and electric energy consumption of the three schemes are shown in Fig. 10.

It can be seen from Fig. 10 that the natural gas and electric energy consumption of objective 1 and objective 2 have decreased

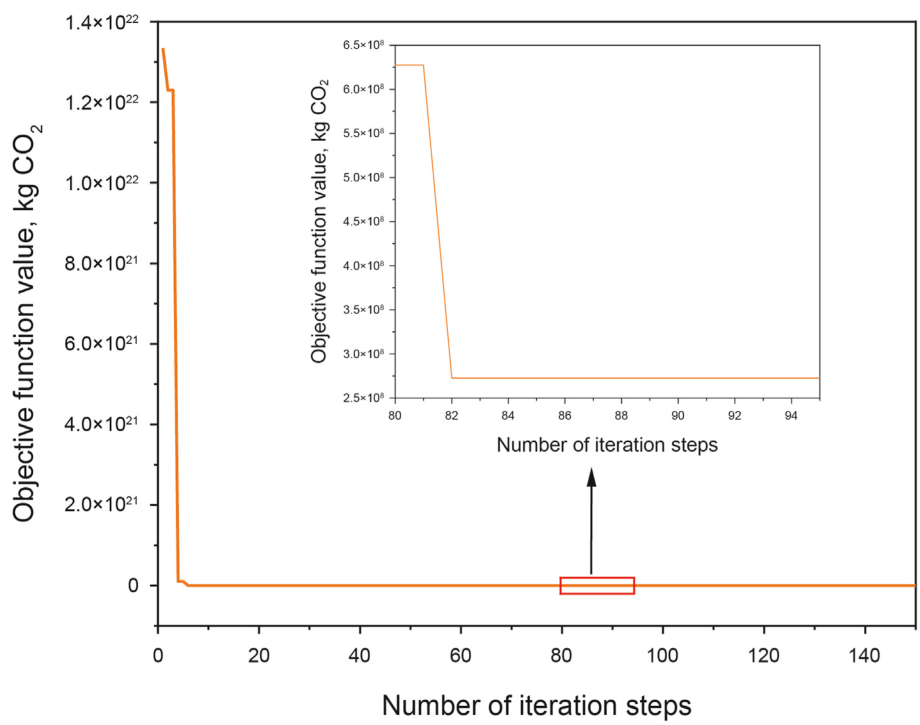


Fig. 6. Iteration diagram of objective function 1.

Table 7
Operation data of each station in Objective 1.

Station number	pipeline 1			pipeline 2			Valve status
	Number of compressors	Compressor power, kW	Compressor type	Number of compressors	Compressor power, kW	Compressor type	
1	3	13131.09	Gas	3	14030.75	Gas	Open
2	1	5174.33	Gas	3	5490.52	Electric	Open
3	0	0	Gas	0	0	Electric	Open
4	2	7106.59	Gas	3	17927.09	Electric	Open
5	0	0	Electric	0	0	Electric	Open
6	2	10486.16	Gas	1	1605.56	Gas	Open
7	1	6816.98	Gas	2	4677.80	Gas	Open
8	1	4923.05	Gas	2	7988.26	Gas	Open
9	0	0	Gas	0	0	Gas	Open
10	1	11086.30	Electric	2	12939.54	Electric	Open
11	2	13425.62	Gas	1	3603.43	Electric	Open
12	1	7194.27	Gas	1	1649.16	Electric	Open
13	2	16270.64	Electric	1	6857.75	Electric	Open
14	2	9863.95	Gas	3	8925.60	Electric	Close

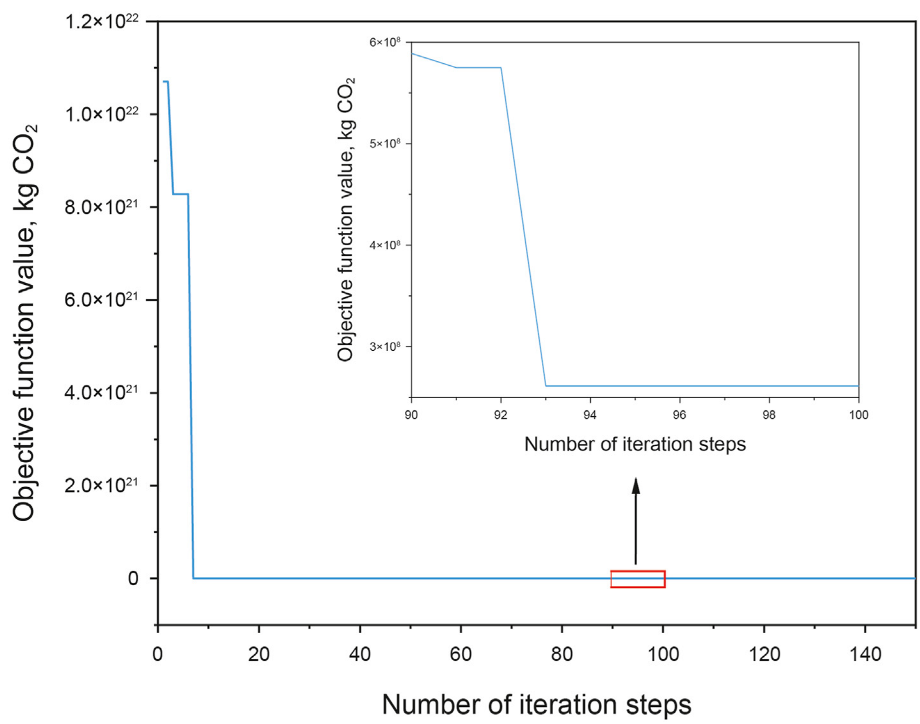


Fig. 7. Iteration diagram of objective function 2.

Table 8
Operation data of each station in Objective 2.

Station number	pipeline 1			pipeline 2			Valve status
	Number of compressors	Compressor power, kW	Compressor type	Number of compressors	Compressor power, kW	Compressor type	
1	3	17023.83	Gas	2	10935.14	Gas	Open
2	1	5580.02	Gas	0	0	Electric	Close
3	1	5662.70	Gas	2	7419.34	Electric	Open
4	1	5389.82	Gas	1	7865.46	Electric	Open
5	0	0	Electric	0	0	Electric	Close
6	2	9636.26	Gas	2	12331.80	Gas	Open
7	2	10290.82	Gas	1	3027.95	Gas	Open
8	0	0	Gas	0	0	Gas	Open
9	2	22484.36	Gas	1	5601.85	Gas	Open
10	3	13653.52	Electric	2	15027.61	Electric	Open
11	1	5640.86	Gas	2	7012.05	Electric	Open
12	1	7653.75	Gas	1	6500.37	Electric	Open
13	3	18516.79	Electric	1	6902.12	Electric	Open
14	1	3085.43	Gas	3	8586.21	Electric	Open

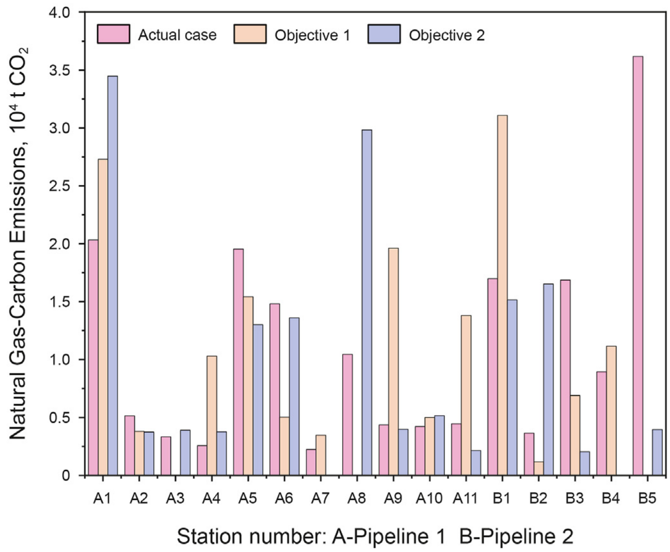


Fig. 8. Carbon emission of natural gas in each station of the pipeline system.

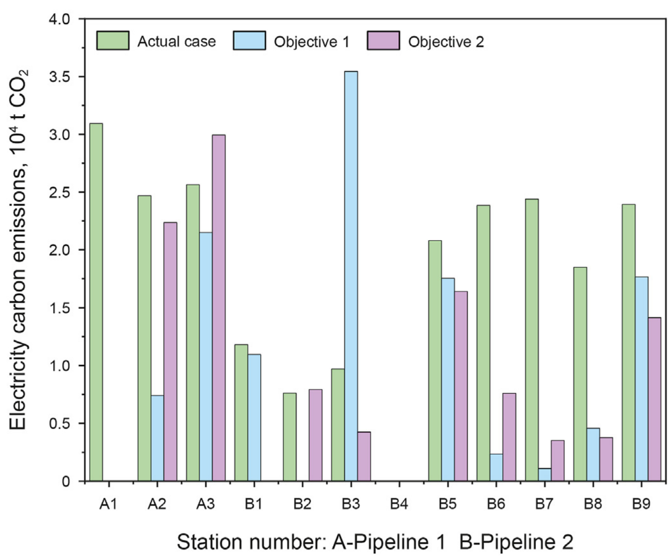


Fig. 9. Carbon emission of electric energy of each station of the pipeline system.

after optimization. The natural gas consumption of objective 1 is greater than that of objective 2, that is, the pipeline system is more inclined to consume natural gas under the existing energy structure. The electric energy consumption of objective 2 is greater than that of objective 1, that is, after adding new energy, the pipeline system is more inclined to consume electric energy. The optimization results of the two objectives comply with chapter 2.2.1.

4.2.3. Suggestions on energy structure adjustment

The total carbon emissions of the three schemes are shown in Fig. 11.

As can be seen from Fig. 11, the carbon emissions of the two objective functions are reduced, of which objective 1 can reduce the total carbon emissions by 31.14% and objective 2 can reduce the total carbon emissions by 34.02%. Therefore, after the introduction of new energy power, the carbon emission of the natural gas pipeline can be reduced more. At this time, the energy consumption values of the three schemes are shown in Table 9.

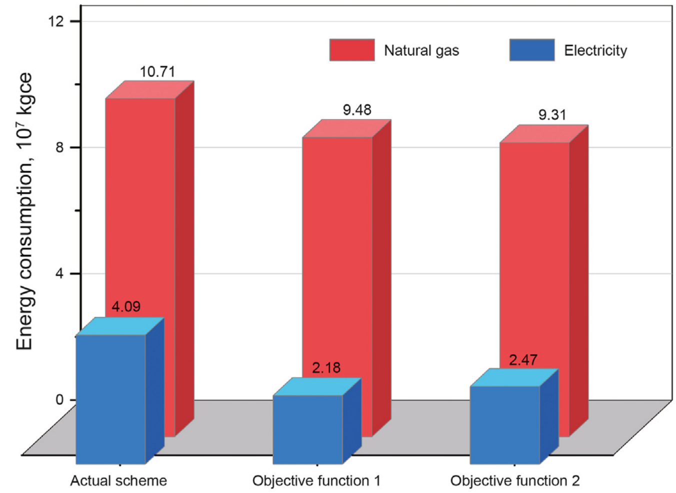


Fig. 10. Natural gas and electric energy consumption of three schemes.

In Table 9, the energy consumption of objective 1 can be reduced by 21.19%, and the energy consumption of objective 2 can be reduced by 20.40%. It shows that after adding new energy, under the minimum carbon emission objective, the lowest carbon emission can be guaranteed, but the lowest energy consumption cannot be guaranteed. At this time, carbon emissions and energy consumption do not increase at the same time. The energy structure diagram of objective 1 and objective 2 is shown in Fig. 12.

Fig. 12 shows the proportion of energy under different objectives. In general, the introduction of new energy is more conducive to reducing carbon emissions. Due to the instability of new energy, it is suggested to introduce new energy in stages to reduce carbon emissions.

5. Conclusion

This paper studies the method of low carbon emission of natural

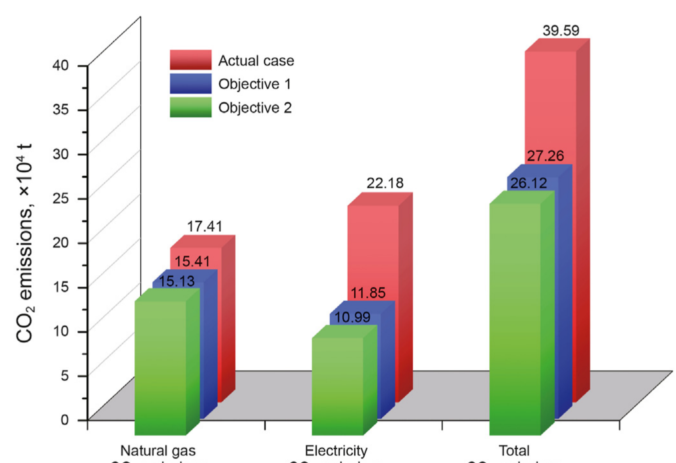


Fig. 11. Comparison of total carbon emissions of various schemes.

Table 9
Energy consumption of three operation schemes.

Category	Actual scheme	Objective 1	Objective 2
energy consumption, 10^8 kgce	1.4800	1.1664	1.1781

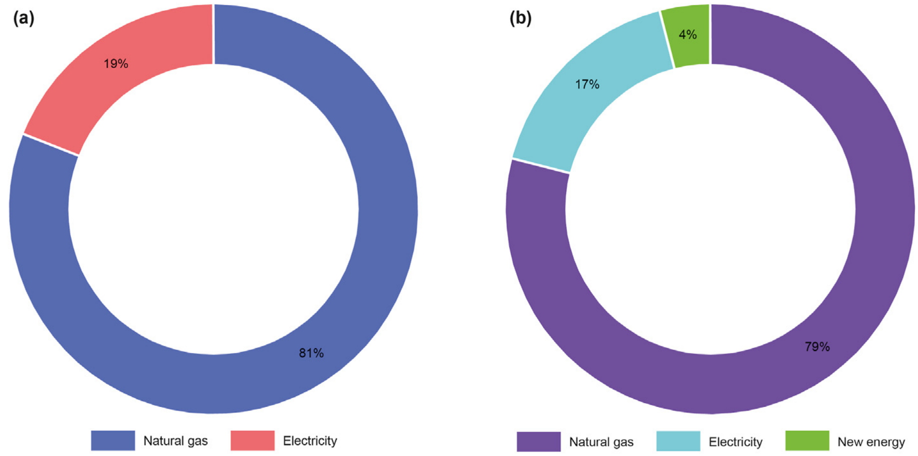


Fig. 12. Energy structure a: Objective 1; b: Objective 2.

gas pipelines, and the following conclusions can be drawn:

(1) The established optimization model of the natural gas pipeline network is verified by practical engineering cases. The maximum calculation error of pressure and temperature is 1.91% and 3.79%, which is in line with the actual situation and has guiding significance for on-site operation.
(2) After optimizing the energy types in the existing pipeline system, the CO_2 emission can be reduced by 34.02% and the energy consumption can be reduced by 21.19%.
(3) By changing the energy structure of the pipeline system, the introduction of wind power and photoelectric can reduce CO_2 emission by 34.02% and energy consumption by 20.40%. In this case, the lowest energy consumption cannot be guaranteed when the carbon emission is the lowest.

Based on the research of this paper, the following problems can be considered for the calculation of carbon emission of the natural gas pipeline system in the future:

(1) If multiple energy sources are introduced, the switching mechanism of different power needs to be further studied.
(2) Many standards related to carbon emissions are not perfect, such as carbon emission factors of new energy power, and many countries do not have relevant databases.
(3) For specific pipelines, each region should establish corresponding carbon emission measurement methods.
(4) In the case of thermal power generation, carbon emissions have been generated in the power generation process, but users consume a large amount of electricity. Therefore, it is necessary to clarify whether carbon emissions should belong to users or power production departments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the CNPC Science and Technology Major Project (2013B-3410) and the Graduate Research And Innovation Fund project of Southwest Petroleum University in 2021 (2021CXYB51).

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