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Optimal operation of trunk natural gas pipelines via an inertia-adaptive particle swarm optimization algorithm

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A B S T R A C T

The trunk natural gas pipeline is the main transmission line between the gas fields and consumers. In this paper, an optimization model is built for the trunk natural gas pipelines, aiming in balancing the maximum operation benefit and the maximum transmission amount. The weight sum method was used to combine these two optimization goals into one hybrid objective function, and the weight value of each single objective function was determined by the scale method which was derived from the Analytic Hierarchy Method (AHP). Besides, the constraints concerning about the node's pressure, flow rate and temperature. The compressor's power and status, the pipe's pressure and temperature equations were also incorporated into the model. In view of the non-linear characteristic of the model, the particle swarm optimization (PSO) algorithm was employed to solve it, and the adaptive inertia weight adjusting method was adopted to improve the basic PSO for its premature defect. The improved PSO is named the inertia-adaptive PSO (IAPSO) algorithm. Finally, the operation optimization model was applied to a real trunk gas pipeline, and the IAPSO as well as other four PSO algorithms were adopted to solve the model. The IAPSO shows faster convergence speed and better solution results than those of the other four PSO algorithms. The achievements provide a good way to balance the gas pipeline's operation benefit and transportation amount.

1. Introduction

Natural gas is a low-carbon, clean and high-quality energy source. The pipelines play an important role in the transmission and distribution of natural gases, because of its convenience, economy and reliability (Mokhatab and Poe, 2012). Based on the functions, the natural gas pipelines are usually divided into gathering pipelines, trunk pipelines and delivering pipelines. The trunk pipelines are the main transmission lines between the gas fields and consumers. Generally, they are long-distance and large-amount transmission pipelines with high pressures. By the end of the year 2012, the United States has the longest trunk gas transmission pipelines in the world, which had reached more than 330 000 km (Tubb, 2012). China had built more than 85 000 km trunk gas pipelines by the same time (Tubb, 2012).

Typically, there are four kinds of components in the trunk pipeline system: pipes, gas sources, consumers and compressors (Vasconcelos et al., 2013). A schematic of the long-distance trunk natural gas pipeline is depicted in Fig. 1. Theoretically, pipeline operators can make lots of feasible operation schemes with different flow rates and pressures, as long as sufficient gases are transported to the consumers. These schemes typically involve different operation benefits and pipeline's reliability (Chebouba et al., 2009). For example, larger amounts of gases require higher transmission pressures. As the pressures are mainly boosted by the installed compressors, more energy will be needed to drive the compressors. So, the increasing of gas transmission amount may not necessarily enhance the gas sales benefit. Besides, the higher pressures may reduce the reliability of the pipeline. Thus, how to balance the pipeline's transportation amount, operation benefits and reliability is a challenge for operators.

Generally, there are two kinds of methods to determine the pipeline's optimal operation scheme. The first method is named the schemes comparison method or comprehensive evaluation method (Li et al., 2012). Its principle is comparing and choosing the best scheme from a set of existed and feasible schemes. So the optimal scheme is limited by original scheme sets. The other method is called mathematical optimization method (Mohamadi et al., 2014;

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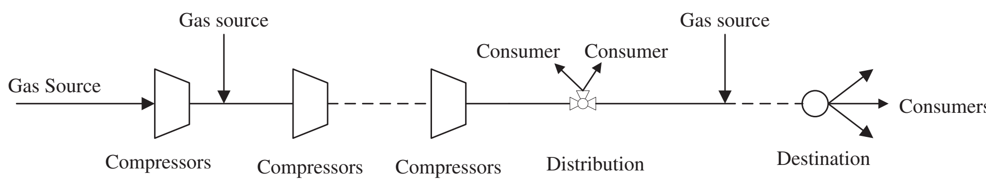

Fig. 1. A typical long-distance trunk gas pipeline system.

Pardalos and Resende, 2002). It determines the optimal scheme by building and solving a mathematical optimization model. The model typically contains an objective function and lots of constraints. The objective function represents the optimization goal, and the constraints are used to limit the variables within the specific bounds. Obviously, the latter method is more likely to get global optimal schemes when compared with the previous one (Borraz-Sánchez and Haugland, 2013; Wu et al., 2000). However, the operation optimization model of trunk natural gas pipelines usually contains both continuous and discrete optimization variables, linear and non-linear constraints. These features make the feasible domain of the optimization problem non-convex and discontinuous (Chebouba et al., 2009; Ehrhardt and Steinbach, 2005), and the solution of the model could be very difficult.

Many researchers have studied the solution method of gas pipeline's operation optimization model since Wong and Larson (1968) applied the dynamic programming (DP) to the fuel cost minimization problem in 1968. However, the computation amount of the DP algorithm increases exponentially with the amount of problem's dimension. So it is not practical to the large and complicate pipeline networks. Percell and Ryan researched the generalized reduced gradient (GRG) method (Percell and Ryan, 1987). Compared with the DP algorithm, the GRG method overcomes the dimensionality problem, and it can be applied to complicated structure networks. By using the linearization method, the non-linear model can be transformed into a linear model. Then the linear programming (LP) method can be used to solve the problem (De Wolf and Smeers, 2000). But the final results are dependent on the initial search point. In other words, the LP algorithm is also easily entrapped into the local optimum results if the initial search point is not set properly (Feldman, 1988).

Different with above traditional methods, some newly emerged evolutionary optimization algorithms and artificial intelligence algorithms explore the feasible domain based on stochastic evolution rather than on gradient information (Dong et al., 2012). Thus, they are effective to solve the discrete and nonlinear optimization problem. In recent years, many evolution algorithms have been applied to optimization problems successfully, such as the ant colony optimization (ACO) (Chebouba et al., 2009), differential evolution algorithm (DE) (Qin et al., 2009), simulated annealing optimization (Rodríguez et al., 2013) and the genetic algorithm (GA) (Li et al., 2011). Haddad solved the minimum fuel consumption problem by using three algorithms: particle swarm optimization (PSO) (Regis, 2014; Zheng and Wu, 2012), GA (Mohamadi et al., 2014) and the sequential quadratic programming. They found that the PSO algorithm has the best and fastest results.

Although many significant achievements have been met in the field of gas pipeline operation optimization, they mainly focus on the minimum fuel consumption problem or least gas purchase problem (Haddad and Behbahani, 2013). Scarcely literatures have considered both the operation benefits and transmission amount.

This paper builds an operation optimization model for natural gas pipelines, which considers the maximum operation benefits and transportation amount in a hybrid objective function. The nodes' pressure, flow rate and temperature constraints as well as the compressors' constraints are included in the model. The PSO algorithm is applied to solve model. However, the basic PSO (BPSO) easily entraps into the premature convergence. The premature convergence occurs when the most of the particles' positions of the swarm stop changing over successive iterations, although the global optimum remains undiscovered. In order to overcome the premature defect, the adaptive inertia weight adjusting method is introduced into the BPSO algorithm, and the IAPSO is developed and employed to solve the model successfully.

2. Mathematical model

The trunk natural gas pipeline system is composed of pipes, compressors, sources and consumers (Vasconcelos et al., 2013). We define the pipes and compressors as elements, gas sources and consumers as nodes (Li et al., 2011). So the elements are connected by nodes. Based on these definitions, this section illustrates the objective functions and constraints of the operation optimization model in details.

2.1. Objective functions

(1) Maximum operation benefit objective function

The maximum operation benefit is defined as the sales income minus the costs. These costs include gas purchasing cost, pipeline's operation cost, management cost and compressors running cost. Finally, it can be written as follows (Li et al., 2011).

$$\max f_1 = \sum_{i=1}^{N_n}(S_i Q_{ni}) - \sum_{j=1}^{N_p}(R_j f_m) - \sum_{l=1}^{N_c}(H_l C_l W_l) \tag{1}$$

where Q_{ni} is the inflow/outflow rate at the ith node, inflow rate is set as a positive value and outflow rate as a negative value, m^3/s; S_i is the sale income or purchase cost coefficient of gas at the ith node, dollar/m^3; f_m is a function of management and operation, it is dependent on pressure, flow rate and pipeline length; R_j is the management and operation cost coefficient of the jth pipeline, dollar/km; H_l is the status of the compressor ($H_l = 0$ if the compressor is OFF; $H_l = 1$ if the compressor is ON); C_l is the cost coefficient of the lth compressor station, dollar/kW; W_l is the power of the lth compressor station, kW; N_n, N_p, N_c are the total number of nodes, pipelines and compressors respectively.

(2) Maximum transmission amount objective function

Sometimes, the operators need large amount of gases in order to meet the contract matters. However, the maximum transmission amount may not lead to the maximum operation benefit. So the maximum transmission amount function is necessary and irreplaceable. This function is defined as the total gas volume that flows into the pipeline (Li et al., 2011). It can be calculated by Eq. (2):

$$\max f_2 = \sum_{i=1}^{N_n} (\beta Q_{ni}) \quad (2)$$

where β is a coefficient. If the node is a gas source, $\beta = 1$; Otherwise, $\beta = 0$.

(3) Hybrid objective function

Generally, both the operation benefit and transportation amount are important goals in the operation scheme. In some cases, the pipeline operators need to balance the operation benefit and the transportation amount. Then, above two objective functions should be integrated into one new function. The weight sum method is used here to build the hybrid objective function, and is expressed as follows:

$$\max f = af_1 + bf_2 \quad (3)$$

where f_1 is the maximum operation benefit objective function; f_2 is the maximum transmission amount objective function; a and b are weight factors, $a + b = 1$.

Due to the objective functions f_1 and f_2 have different dimensions, the logarithms dimensionless method is used to make those two functions dimensionless. This method is commonly used in the artificial neural network (Psichogios and Ungar, 1992).

The weights a and b reflect the relative importance between the operation benefit and transmission amount objectives. Hence, their values have a crucial influence on the optimization results. Generally, the weights can be determined according to the operator's intentions and experiences. In order to compare the relative importance of the two objectives and determine the weights quantity, this paper adopts the scale method derived from the Analytic Hierarchy Method (AHP) (Li et al., 2012). The scales and their definitions are listed in Table 1.

2.2. Constraints

The trunk natural gas pipeline is designed for running in specific pressure, temperature and flow rate ranges. The optimization results must not fall beyond the limitations of these design parameters. Besides, the natural gas flowing within the pipeline should satisfy the basic mass, momentum and energy conservation laws (Mokhatab and Poe, 2012). All of these limitations are summarized as the constraints of the model. The details are illustrated as follows.

(1) The outflow and inflow rate constraint

The long-distance trunk gas pipeline always has many consumer and source nodes. At the consumer node, the gas flow rate should not fall below the request minimal outflow rate. At the source node, the gas inflow rate should not fall beyond the maximum production amount of the gas field. So the flow rate constraint can be written as follows (Zheng et al., 2010).

Table 1
The scales and definitions of relative importance.

Value a/b	Explanation
1	f_1 is of the same importance as f_2
3	f_1 is a slightly more important than f_2
5	f_1 is significantly more important than f_2
7	f_1 is much more important than f_2
9	f_1 is extremely more important than f_2
2, 4, 6, 8	Intermediate values of importance
Cut down	The ratio, b/a

$$Q_{nimin} \le Q_{ni} \le Q_{nimax} \quad i = 1, 2, \ldots N_n \quad (4)$$

where Q_{ni} is the flow rate of the ith node, m^3/s; Q_{nimin} is the minimum allowable inflow/outflow rate of the ith node, m^3/s; Q_{nimax} is the maximum allowable inflow/outflow rate of the ith node, m^3/s.

(2) The node pressure constraint

Similar to the flow rate constraint at each node, the node pressure must be limited by the maximum and minimum values. For instance, the pressure at the compressor's inlet must maintain beyond the required minimum suction pressure, and the distribution pressure must not be higher than pipeline's maximum allowable operation pressure. Thus, the node pressure constraint can be expressed as follows (Li et al., 2011):

$$P_{nimin} \le P_{ni} \le P_{nimax} \quad i = 1, 2, \ldots, N_n \quad (5)$$

where P_{ni} is the pressure at the ith node, Pa; P_{nimin} is the minimum allowable pressure at the ith node, Pa; P_{nimax} is the maximum allowable pressure of the ith node, Pa.

(3) The node temperature constraint

The volume of the natural gas expands with the temperature increasing. As a result, the volume flow rate increases, and the pipeline's transmission ability is decreased. Besides the high temperature constraint, there is also a low temperature limitation. The lowest temperature must maintain beyond the natural gas's hydrocarbon dew point and water dew point (Mokhatab and Poe, 2012). Otherwise, the liquid hydrocarbon or water condensation appears in the pipeline (Galatro and Marín-Cordero, 2014), which will decrease the pipeline's transportation efficiency and induce the pipe material's corrosion. Thus, the node pressure constraint can be expressed as follows (Li et al., 2011):

$$T_{nimin} \le T_{ni} \le T_{nimax} \quad i = 1, 2, \ldots, N_n \quad (6)$$

where T_{ni} is the temperature at the ith node, K; T_{nimin} is the minimum temperature at the ith node, K; T_{nimax} is the maximum allowable pressure of the ith node, K.

(4) Flow rate balance equation of nodes

According to the mass conservation law, the mass inflow rate should be equal to the outflow rate at any node. This constraint can be expressed by Eq. (7):

$$\sum_{k \in U_i} \alpha_{ik} M_{ik} = 0 \quad i = 1, 2, \ldots, N_n; \quad k = 1, 2, \ldots, N_e \quad (7)$$

where U_i is the set of elements that connect to the ith node; M_{ik} is the absolute mass flow rate of the kth element that connect to the ith node, kg/s; α_{ik} is constant, $\alpha_{ik} = 1$ if the kth element comes out from the ith node t; $\alpha_{ik} = -1$ if kth element goes into the ith node; $N_e = N_c + N_p$.

(5) The centrifugal compressor's power constraint

The centrifugal compressor is the most complicate equipment in the long-distance gas pipeline system. The compressor must be operated between the surge zone and the stonewall zone. Typically, the details of the compressor's model contains a set of polynomial formulations which depicts relationship between the inlet volumetric flow rate, speed, adiabatic head, adiabatic efficiency as well as the stone zone and surge zone (Wu et al., 2000). Many literatures concluded that the optimization of the compressor's operating parameters is a very difficult task (Haddad and Behbahani, 2013; Wu et al., 2000). In this paper, a simplified compressor model is introduced to reduce the complexity of the optimization model.

The simplified model uses the maximum and minimum powers to guarantee the normal operation of the compressor. The compressor's power constraint is expressed by Eq. (8).

$$W_{l\min} \le W_l \le W_{l\max} \quad l = 1, 2, \ldots, N_c \tag{8}$$

where W_l is the power of the lth compressor, kW; $W_{l\min}$ is minimum allowable power of the lth compressor station, kW; $W_{l\max}$ is maximum allowable power of the lth compressor station, kW.

The centrifugal compressor's power can be calculated by Eq. (9).

$$W = \frac{0.0167 P_s Q_s \frac{m}{m-1}}{\eta_p}\left[\varepsilon^{\frac{m-1}{m}} - 1\right] \tag{9}$$

where ε is the compressor ratio, P_d/P_s; P_d is the compressor's discharge pressure, kPa; P_s is the compressor's suction pressure, kPa; Q_s is the volume flow rate at the suction pressure P_s, m^3/min; η_p is the compressor's efficiency; m is the polytropic exponent of the gas (Khan and Lee, 2012).

There are five variables in Eq. (9), but only three of them, which are P_d, P_s and Q_s, are independent. The parameter m is determined by the pressure and gas composition, and the parameter η_p is dependent on the compressor's inherent performance. Furthermore, if the lengths of the suction and discharge pipes are ignored, P_d and P_s are approximately equal to the pressures at downstream/upstream nodes. This approximation method can be illustrated by Fig. 2.

(6) Compressor's status constraint

There are two statuses of the compressor: On or OFF. The constraint is explained by following equation.

$$H_l\begin{cases} = 1 & \text{if the compressor in ON} \\ = 0 & \text{if the compressor in OFF}\end{cases} \tag{10}$$

On the other hand, the compressor's status can be obtained based on the compressor ratio. If the compressor ratio is equal to unity, the status is OFF. If the compressor ratio is larger than unity, the status is ON.

(7) The compressor's temperature equation

The temperature of the natural gas also changes with the compression of the gas. The temperature change across the compressor can be calculated by Eq. (11)

$$T_d = T_s \varepsilon^{\frac{m-1}{m}} \tag{11}$$

where T_s is the suction temperature, K; T_d is the discharge temperature, K.

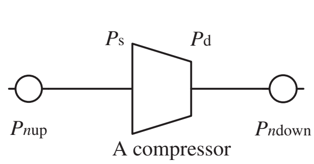

Fig. 2. Approximation method of the compressor's pressures.

Similar to the compressor's suction and discharge pressures, above two temperatures also can be replaced by the upstream and downstream nodes' temperatures.

(8) The pipeline's pressure equation

The pipeline's pressure equation describes the relationship between the gas flow rate and pressures at inlet and outlet of the pipe. The equation is derived from the one-dimensional momentum conservation equation. It takes the following form (Li, 2008).

$$M_j = \frac{\pi}{4}\sqrt{\frac{\left[P_{Qj}^2(1 - C_1\Delta h) - P_{Zj}^2\right]D^5}{\lambda Z R T_a L\left(1 - \frac{C_1 \Delta h}{2}\right)}} \quad j = 1, 2, \ldots, N_p \tag{12}$$

$$C_1 = \frac{2g}{ZRT_a} \tag{13}$$

where P_{Qj} is the jth pipe's inlet pressure, Pa; P_{Zj} is the jth pipe's outlet pressure, Pa; M_j is the mass flow rate in the jth pipe, kg/s; T_a is the pipe's average temperature, K; L is the pipe length, m; D is the internal diameter, m; Δh is the elevation difference between the inlet and outlet of the pipe, m; Z is the compressibility factor, which can be obtained by equation of state (Poling et al., 2000); g is the gravity acceleration, 9.8 m/s^2; R is the gas constant, 8.314 J/(mol K); λ is the friction factor, which can be calculated by the Colebrook–White correlation (Mokhatab and Poe, 2012):

$$\frac{1}{\sqrt{\lambda}} = -2\lg\left(\frac{\kappa}{3.7D} + \frac{2.51}{\mathrm{Re}\sqrt{\lambda}}\right) \tag{14}$$

where κ is the absolute roughness of the pipe's internal wall, m; Re is the Reynold number.

Based on the environment temperature and the inlet temperature, the average temperature T_a can be calculated by Eq. (15) (Mokhatab and Poe, 2012).

$$T_a = T_0 + (T_{nup} - T_0)\frac{1 - \exp\left(-\frac{K\pi D}{MC_p}\right)}{-\frac{K\pi D}{MC_p}L} \tag{15}$$

where C_p is the specific heat capacity of the gas, J/(kg K); T_{nup} is the temperature at the pipe's inlet node, K; T_0 is the environment temperature, K; K is the pipe's overall heat transfer coefficient, W/(m^2 K).

Similar to Fig. 2, a pipeline is typically connected with its upstream node and downstream node. Thus, pipe's inlet pressure P_{Qj} and outlet pressure P_{Zj} are equal to the upstream node and downstream node pressures P_{nup}, P_{ndown} respectively. Finally, there is only one independent variable in Eq. (12), which is the mass flow rate M_j in the pipe.

(9) The pipeline's temperature equation

The pipeline's temperature equation is used to predict the temperature along the pipe. Based on the one-dimensional energy equation, the pipeline's temperature equation can be derived as Eq. (16):

$$T_{ndown} = T_0 + (T_{nup} - T_0)\exp\left(\frac{-L}{F_r}\right) + \frac{F_r}{C_p}\left[JC_p(P_{nup} - P_{ndown}) - g\sin\theta\right] \tag{16}$$

$$F_{\mathrm{r}} = \frac{MC_p}{K\pi D} \tag{17}$$

where T_{ndown} is the pipeline's downstream node temperature, K; J is the Joule–Thomson coefficient, K/Pa; is the pipe inclination angle, rad.

(10) Node–element matrix

Eqs. (7), (9), (11)–(17) represent the steady state simulation model for the trunk natural gas pipeline network. When the equations are applied to a complicated pipeline network, the node–element matrix can be used to describe the network's topology. If a network is composed of N_{n} nodes and N_{e} elements, the size of the matrix should be $N_{\mathrm{n}} \times N_{\mathrm{e}}$.

A simple trunk gas pipeline network is shown in Fig. 3. Its node–element matrix is expressed by Eq. (18).

$$\alpha = \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & -1 \\ 0 & 1 & 0 & -1 \end{bmatrix} \tag{18}$$

In the matrix, each row corresponds to an element, and each column corresponds to a node. Thus, the upstream and downstream node of each element can be found by searching a fixed row. All the inflow and outflow elements that connect to the same node can be found by searching a fixed column. By using this method, the pipeline network with arbitrary structure can be described easily, and the optimization model can be built for any network with any structures.

2.3. Optimization model

According to the objective functions and constraints illustrated previously, the optimization variables in the model are: the pressure, temperature, inflow rate and outflow rate at every node, the flow rate in every elements (pipes, compressors), status and power of every compressor. The variables are summarized in Eq. (19).

$$\mathbf{X} = \left[P_{n1}, Q_{n1}, T_{n1}, P_{n2}, Q_{n2}, T_{n2}, \ldots, P_{nN_{\mathrm{n}}}, Q_{nN_{\mathrm{n}}}, T_{nN_{\mathrm{n}}}, M_1, M_2, \ldots, M_{N_{\mathrm{e}}}, W_1, W_2, \ldots, W_{N_{\mathrm{C}}}, H_1, H_2, \ldots, H_{N_{\mathrm{C}}}\right] \tag{19}$$

In Eq. (19), the pressures, flow rate and compressors' power are continuous parameters, whereas the compressors' statuses are discrete parameters. So it is a combinational optimization problem, which is difficult to be solved. In order to simplify the model, the status of the compressors is replaced by the compressor ratio ε. If the compressor is stopped, $\varepsilon = 1$; if the compressor is working, $\varepsilon > 1$. Then, all the discrete variables are transformed into continuous variables.

The mass flow rate M is defined as the volume flow rate multiplied the gas density, $M = Q\rho$. Then, Eq. (19) can be transformed into the following form.

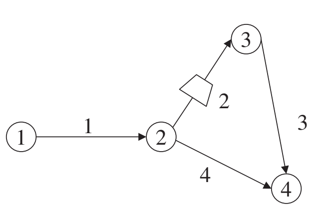

Fig. 3. A simple trunk gas pipeline network.

$$\mathbf{X} = \left[P_{n1}, Q_{n1}, T_{n1}, P_{n2}, Q_{n2}, T_{n2}, \ldots, P_{nN_{\mathrm{n}}}, Q_{nN_{\mathrm{n}}}, T_{nN_{\mathrm{n}}}, Q_1, Q_2, \ldots, Q_{N_{\mathrm{e}}}, W_1, W_2, \ldots, W_{N_{\mathrm{C}}}, \varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{N_{\mathrm{C}}}\right] \tag{20}$$

Based on Eqs. (1)–(18) and (20), the optimization model for the trunk natural gas pipeline operation can be written as follows.

$$\min f(\mathbf{X}) \tag{21}$$

$$\text{Subject to :} \quad h_i(X) = 0 \quad i = 1, 2, \ldots, \gamma \tag{22}$$

$$g_i(\mathbf{X}) \geq 0 \quad i = 1, 2, \ldots, \xi \tag{23}$$

where f is the objective function; h_i represents equality constraints; g_i represents inequality constraints; γ and ξ represent the total number of the equality constraints and inequality constraints, respectively.

Based on the objective function and all the constraints, the optimization model establishment procedure can be depicted by Fig. 4.

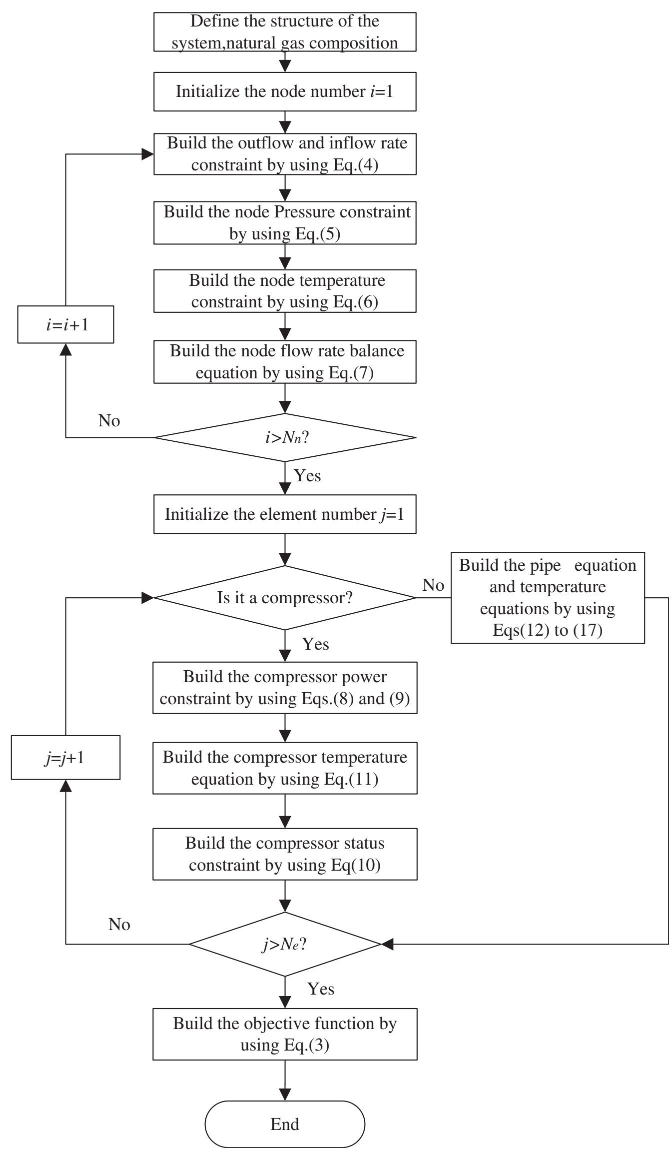

Fig. 4. The optimization model establishment procedure.

Although the objective function is linear, there are both linear and non-linear constraints in the model. So the optimization model is a non-linear model. Based on the particle swarm optimization algorithm, the following section researched an efficient solution method for the model.

3. Model solution

3.1. Basic particle swarm optimization (BPSO)

Particle swarm optimization (PSO) is a population-based evolutionary optimization algorithm, which is inspired by social behavior of bird flocking (and school of fish) (Kennedy, 2010). In PSO, a swarm contains a set of population members, which is called the particle. Every particle has both a position and velocity. The position represents a candidate solution in the multi-dimensional solution space, and the velocity moves it from one position to another over the solution space. For every position, a fitness function is applied to evaluate the particle quantitatively until the convergence criteria are met. The particle with the best fitness value in the neighborhood is marked as the global/local best particle. Every particle also keeps a record of its personal best position searched so far. For the trunk natural gas pipeline, every particle represents a candidate optimum operation solution.

In a D-dimensional solution space, the position vector of the i-th solution is written as $\mathbf{X}_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,D})$, and the corresponding velocity vector is given by $\mathbf{V}_i = (v_{i,1}, v_{i,2}, \ldots, v_{i,D})$. The velocity and position updating methods for the d-th dimension of i-th solution at the $(k+1)$-th iteration step are expressed by Eqs. (24) and (25) (Bansal et al., 2011).

$$v_{i,d}^{k+1} = \omega^k \cdot v_{i,d}^k + c_1 r_1 \left(\text{pbest}_{i,d} - x_{i,d}^k\right) + c_2 r_2 \left(\text{gbest}_d - x_{i,d}^k\right) \tag{24}$$

$$x_{i,d}^{k+1} = x_{i,d}^k + v_{i,d}^{k+1} \tag{25}$$

where ω is the inertia weight, which is used to balance the global and local search ability; a large inertial weight is more appropriate for global searches and a small inertia weight facilitates local searches. c_1 and c_2 represent the cognition parameter and social parameter respectively, which determine the balance influence of the individual's knowledge and that of the group; r_1 and r_2 are random numbers ranging from 0 to 1; x is the position of the particle; v is the velocity of the particle; $\text{pbest}_{i,d}$ is the personal best position found so far by the d-th dimensional in the i-th solution. gbest_d is the best position found so far by all of the solutions; the subscript i represents the solution's number; the subscript d represent the variable number in the solution vector; the superscript k represents the number of generation (iteration).

Besides, Eqs. (26) and (27) are used to constrain the upper and lower bounds of particles' velocities (Kennedy, 2010).

$$\text{If} \quad v_{i,d} > v_{\max}, \quad v_{i,d} = v_{\max} \tag{26}$$

$$\text{If} \quad v_{i,d} < -v_{\max}, \quad v_{i,d} = -v_{\max} \tag{27}$$

3.2. Fitness function

Generally, the objective functions must be included in the fitness function, and the candidate solution must satisfy the equality constraints. In this paper, the equality constraints are incorporated into the fitness function in the way of a penalty function. Finally, the fitness function is expressed as follows (Tang and Zhao, 2009).

$$F(\mathbf{X}) = -f(\mathbf{X}) + G\sum_{i=1}^{\gamma} |h_i(\mathbf{X})| \tag{28}$$

where $F(\mathbf{X})$ is the fitness function; $f(\mathbf{X})$ is the objective function; G is a large positive constant; $h_i(\mathbf{X})$ is the real results of the equality constraints.

3.3. Convergence criteria

Similar to some traditional iteration methods, the evolution process of the PSO are finished when certain converge criteria are met. Many studies (Kennedy, 2010; Zheng and Wu, 2012) have shown that the particles aggregate if the swarm reaches a convergence state. Because the aggregate particles have similar fitness values, the variance of the fitness functions can be used to develop the convergence criteria (Tang and Zhao, 2009). The variance is calculated by Eq. (29).

$$\xi^2 = \sum_{i-1}^{\zeta} \left[\frac{F(\mathbf{X}_i) - F_\text{a}}{F^*}\right]^2 \tag{29}$$

where ζ is the total number of the particles; $F(\mathbf{X}_i)$ is the fitness value of the i-th particle; F_a is the average fitness value of all the particles; F^* is a normalization calibration factor, which is calculated by Eq. (30).

$$F^* = \begin{cases} \max\limits_{1\le i\le\zeta}[|F(\mathbf{X}_i) - F_\text{a}|], & \text{if } \max\limits_{1\le i\le\zeta}[|F(\mathbf{X}_i) - F_\text{a}|] > 1 \\ 1, & \text{others} \end{cases} \tag{30}$$

If the particles aggregate in a small space, the value of the variance ξ^2 will be smaller than a specific value. Thus, we can judge the particles' converge state.

The BPSO has the advantages of simple and high calculation speed. However, by far the most problematic characteristic of PSO is its propensity to converge, prematurely, on early best solutions. Many methods have been developed in attempts to overcome these defects. One of the most popular methods is adjusting the inertia weight ω (Bansal et al., 2011; Nickabadi et al., 2011).

3.4. Improvement of the particle swarm optimization

In Eq. (24), the inertia weight is used to balance the global and local search ability. It can be seen that the term $\omega \cdot v_i^k$ increase as the inertia weight. If ω has a large value, the particle will search broader solution space. If ω has a small value, the evolution process will focus on the space that near to the local best particle. Thus, the global and local optimization performances of the algorithm can be controlled by adjusting the inertial weight value.

In order to overcome the premature defect and enhance the computation speed of the BPSO, this paper adopts an adaptive inertia weight strategy to adjust the ω value dynamically. This method adjusts the inertia weight adaptively based on the distance from the particles to the global best particle (Suresh et al., 2008). It is expressed by Eq. (31) .

$$\omega^{k+1} = \omega^k \left(1 - \frac{\text{dist}_i}{\text{dist}_{\max}}\right) \tag{31}$$

where ω^0 is a random number ranging from 0.5 to 1.0; dist_i is the current Euclidean distance from the i-th particle to the global best particle; $\text{dist}_{\max}$ is the maximum distance from a particle to the global best particle. The two distances are defined by Eqs. (32) and (33).

$$\text{dist}_i = \left(\sum_{d=1}^{D}(\text{gbest}_d - x_{i,d})^2\right)^{1/2} \tag{32}$$

$$\text{dist}_{\max} = \max_i(\text{dist}_i) \tag{33}$$

As expressed by Eq. (31), the weight will increase automatically if the particle is apart from the global best value. Otherwise, the inertia weight will decrease. This adaptive adjustment approach gives the PSO greater global search ability when the particles are apart from the global best. It also gives the improved algorithm finer local search ability when the particles approach toward the global best particle.

Moreover, the update position of the particle is modified as follows avoiding the premature convergence.

$$x_{i,d}^{k+1} = (1-r_3)x_{i,d}^{k} + v_{i,d}^{k+1} \tag{34}$$

where r_3 is a uniformly distributed random number ranging from −0.25 to 0.25.

The performance of IAPSO algorithm is studied by Suresh et al. (2008). They used eight well-known benchmarks to evaluate its performance. These benchmark functions are Sphere, Rosenbrock's, Rastrigin's, Griewank's, Ackley's, Weierstrass. The performance of the IAPSO algorithm was also compared with other four PSO algorithms which are PSO-TVIW, HPSO-TVAC, MPSO-TVAC and CLPSO algorithms (Suresh et al., 2008). They found that the IAPSO has better solution quality and higher convergence speed than the other four PSO algorithms.

3.5. Procedures of solving the model with the PSO algorithms

Based on the PSO algorithms, the optimization model can be solved by the following procedures.

Step 1: Set the total number of the particles, the maximum number of the evolution generation $k_{\max}$, the maximum velocity $v_{\max}$, cognition parameter c_1, social parameter c_2 and initial weight ω^0.
Step 2: Initialize the velocity randomly and position of all particles. Because the each one particle's position represents a feasible operation scheme of the gas pipeline, the initial positions can be obtained from the pipeline's operation database or by the pipeline steady-state simulation software. Nowadays, lots of commercial software packages can be utilized in implementing the pipeline simulation, such as the PipelineStudio and Stoner Pipeline Simulator (SPS) (Wu et al., 2009).
Step 3: Set the generation number count $k = 1$.
Step 4: Evaluate the fitness of each particle in the population according to the fitness function Eq. (28).
Step 5: Compare the particle's fitness value with $\text{pbest}_{i,d}$ and gbest_d. Update the $\text{pbest}_{i,d}$ and gbest_d according to the comparison results.
Step 6: Calculate the new inertia weight ω^{k+1} by using Eq. (31).
Step 7: Calculate the new velocity $v_{i,d}^{k+1}$ by using Eq. (24).
Step 8: Update the position of each particle by using Eq. (34).
Step 9: Calculate the variance of the all the particles' fitness functions and check whether the converge criterion is met by using Eq. (29). If it is met, go to Step 11. Otherwise, go to Step 10.
Step 10: If $k > k_{\max}$, go to Step 11. Otherwise, increment the generation number count $k = k + 1$ and go to Step 4.
Step 11: Stop the program and output optimization results.

Above procedures also can be depicted by a flow chart as shown in Fig. 5.

Based on the above optimization and its solution method, a Visual C# computer program was developed so that optimization results can be obtained.

4. Results and discussions

4.1. Introduction of the Se–Ning–Lan gas pipeline

Sebei–Ningxia–Lanzhou gas transmission pipeline was built in 2001. Its total length is 922 km, and the internal diameter is 660 mm. The pipe's wall thickness is 17 mm. Nine stations along the pipeline distribute gases to sixteen consumers. There are four compressor stations with eight compressors to boost the gas pressure. The topological structure of the pipeline is depicted in Fig. 6.

The maximum allowable operation pressure is 6.4 MPa, and the design annular gas transportation amount is 37×10^8 m^3. The absolute roughness of the pipe's internal wall is 0.01 mm. The environment temperature is 2.1 °C, and the pipeline's overall heat transfer coefficient is 1.47 W/(m^2 K). The composition of the natural gas is listed in Table 2. Based on the gas composition, the Peng–Robinson Equation of State (Mokhatab and Poe, 2012) is utilized

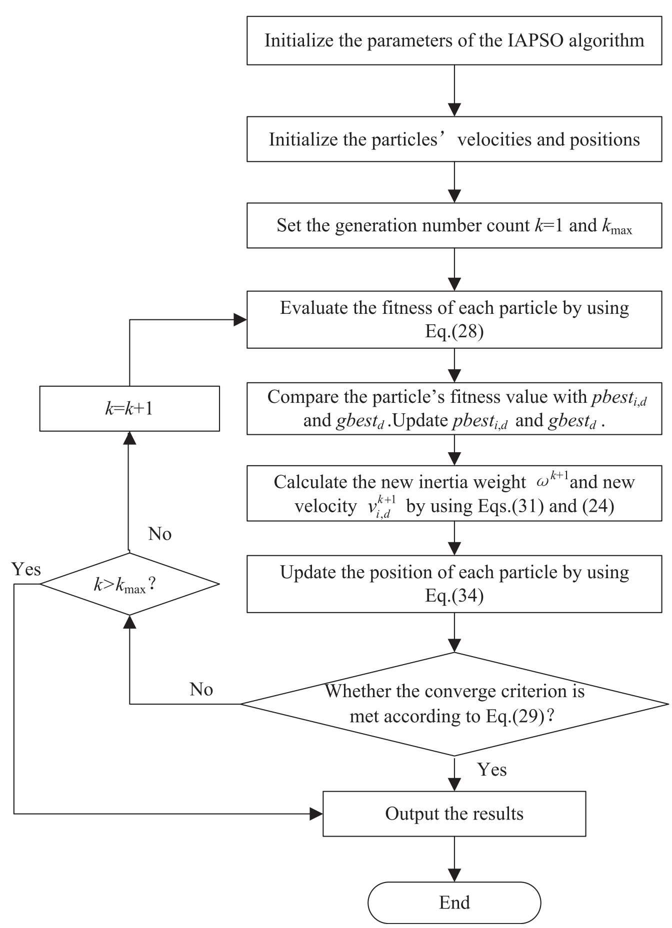

Fig. 5. The optimization model solution procedure.

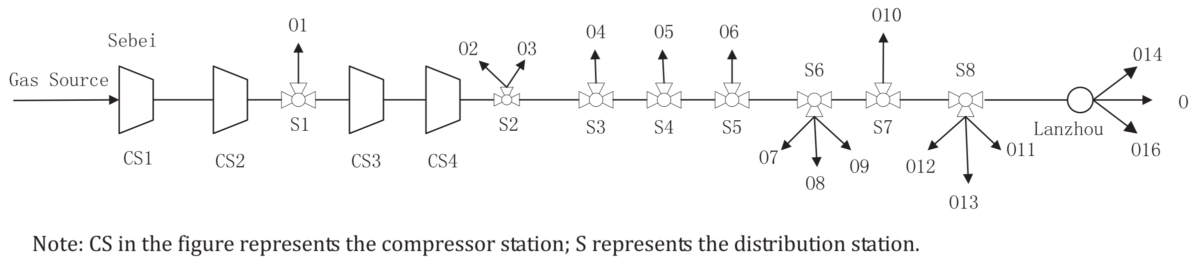

Fig. 6. The Schematic diagram of Se–Ning–Lan gas pipeline.

Table 2
The composition of the natural gas.

Component	N_2	CO_2	CH_4	C_2H_6	C_3H_8
Mole fraction	0.0020	0.0250	0.9684	0.0036	0.0010

to calculate the physical parameters, including the compressibility factor, density, specific heat capacity, Joule–Thomson coefficient.

4.2. Optimization results

Set the total number of particles is 30, the maximum number of the evolution generation $k_{max} = 600$, the cognition parameter $c_1 = 1$, social parameter $c_2 = 1$ and initial weight $\omega^0 = 0.5$, the convergence value of swarm's fitness variance is 10^{-7}. Besides, in the objective function Eq. (3), we set $a/b = 2$, which means $a = 0.666$ and $b = 0.333$.

In order to ensure the initial particles satisfy all the constraints, the pipeline simulation software Stoner SPS version 9.5 was used to generate 30 initial particles of the swarm. According to the pipeline's design parameters, the limitations of the optimization variables are listed as follows: $970 \times 10^4\ m^3/d \le Q \le 0 m^3/d$, $6.4\ MPa \le P \le 2.0\ MPa$, $4800\ kW \le W \le 1300\ kW$, $1.0 \le \varepsilon \le 3.0$, $-10\ °C \le T \le 60\ °C$.

The optimization model is solved by five PSO algorithms: IAPSO, PSO-TVIW, HPSO-TVAC, MPSO-TVAC and CLPSO. The convergence curves of these five algorithms are shown in Fig. 7. The optimized values related to the objective function are listed in Table 3.

Fig. 6 presents that the IAPSO algorithm has faster convergence speed and smaller final converge fitness variance than the other four PSO algorithms. Table 2 shows the scheme obtained by the IAPSO method has larger flow rate and higher operation benefit than those obtained by other methods. It should be noted that the IAPSO optimization scheme has lower maximum pressure than other schemes, which means the scheme has greater security.

Based on the IAPSO algorithm's results, the optimal operation parameters of the pipeline are obtained. The details of the optimization results are listed in Tables 4 and 5.

The results prove that the IAPSO method is efficient and reliable when applied to solve the operation optimization model for natural gas pipelines.

It should be noted that although above five algorithms start with the same initial particles, they finally get different results. The different updating methods with regard to their weights, velocities and positions may contribute to the difference results (Suresh et al., 2008). In the future, the internal mechanism that causes these differences should be researched.

5. Conclusions

This paper built an operation optimization model for the natural gas pipeline including compressors, in order to balance the operation benefit and gas transmission amount. The weight sum method was used to combine the maximum operation benefit and transmission amount goals into one hybrid objective function, and the weight value of each single objective function was determined

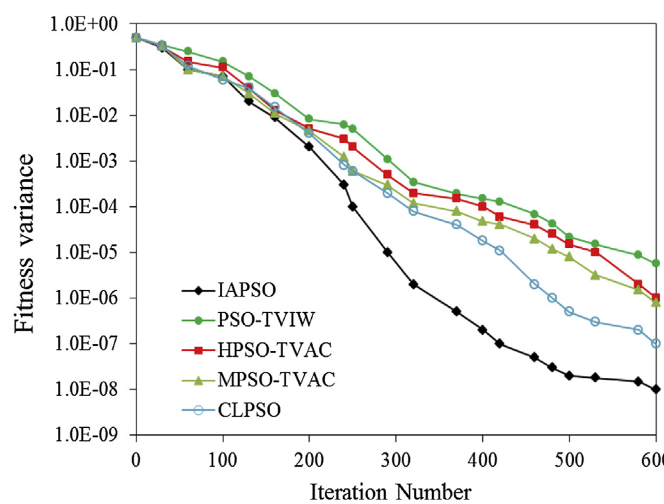

Fig. 7. The converge curves of Se–Ning–Lan gas pipeline.

Table 3
Optimized values related to the objective function obtained by five PSO algorithms.

Algorithm	Maximum flow rate ($10^4\ m^3/d$)	Operation benefit (10^4 dollar/d)	Maximum pressure (MPa)	Minimum pressure (MPa)
IAPSO	960.8	75.2	5.51	3.00
PSO-TVIW	893.7	65.6	5.70	2.02
HPSO-TVAC	902.6	64.9	5.65	2.56
MPSO-TVAC	932.5	70.6	5.50	2.35
CLPSO	925.3	71.8	5.67	2.68

Table 4
Inlet and outlet parameters of stations.

Station name[a]	Inlet temperature (°C)	Outlet temperature (°C)	Inlet pressure (MPa)	Outlet pressure (MPa)	Flow rate ($10^4\ m^3/d$)
CS1	4.6	23.3	4.15	5.30	960.8
CS2	−0.9	33.5	3.13	5.44	953.3
S 1	4.3	4.3	4.48	4.48	933.3
CS3	−2.0	33.9	3.09	5.51	912.2
CS4	−1.8	34.7	3.00	5.32	895.7
S 2	8.7	8.6	4.40	4.40	642.7
S 3	5.7	−5.9	4.30	4.30	629.1
S 4	5.6	20.0	4.40	4.40	625.3
S 5	3.6	20.0	4.30	4.30	617.2
S 6	1.7	1.7	4.20	4.20	614.5
S 7	1.7	1.7	4.20	4.20	602.6
S 8	1.1	−9.6	4.10	4.10	593.5
Lanzhou	0.7	0.4	4.00	3.90	256.0

[a] The station names can be located in Fig. 5.

Table 5
Optimized results for each compressor.

Station	Compressor Name	Suction Pressure (MPa)	Discharge pressure (MPa)	Compressor ratio	Status
CS1	CS1 A	4.15	4.15	1.00	OFF
	CS1 B	4.15	5.30	1.28	ON
CS2	CS2 A	3.13	3.13	1.00	OFF
	CS2 B	3.13	5.44	1.74	ON
CS3	CS3 A	3.09	5.51	1.78	OFF
	CS3 B	3.09	3.09	1.00	ON
CS4	CS4 A	3.00	3.00	1.00	OFF
	CS4 B	3.00	5.32	1.77	ON

by the scale method which was derived from the Analytic Hierarchy Method (AHP). Besides, the constraints concerning about the node's pressure, flow rate and temperature. The compressor's power and status, the pipe's pressure and temperature equations were also incorporated into the model. Especially, the compressor ratio was adapted to replace the compressor's status. As a result, all the discrete variables are eliminated in the model.

The operation optimization model was applied to a real trunk gas pipeline in China, and an adaptive inertia weight adjusting based particle swarm optimization (IAPSO) algorithm and other four PSO algorithms were adopted to solve the non-linear optimization model. The results show that IAPSO has faster convergence speed and better solution quality than those of the other four PSO algorithms. These achievements show that it is feasible to balance the gas pipeline's operation benefit and transportation amount by using the optimization model and the IAPSO algorithm.

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