A method for the multi-objective optimization of the operation of natural gas pipeline networks considering supply reliability and operation efficiency

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Abstract

Reliable gas supply for minimum risk of supply shortage and minimum power demand for low energy cost are two fundamental objectives of natural gas pipeline networks. In this paper, a multi-objective optimization method is developed to trade-off reliability and power demand in the decision process. In the optimization, the steady state behavior of the natural gas pipeline networks is considered, but the uncertainties of the supply conditions and customer consumptions are accounted for. The multi-objective optimization regards finding operational strategies that minimize power demand and risk of gas supply shortage. To quantify the probability of supply

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interruption in pipeline networks, a novel limit function is introduced based on the mass conservation equation. Then, the risk of interruption is calculated by combining the probability of interruption and its consequences, measured in utility terms. The multi-objective optimization problem is solved by the NSGA-II algorithm and its effectiveness is tested on two typical pipeline networks, i.e., a tree-topology network and a loop-topology network. The results show that the developed optimization model is able to find solutions which effectively compromise the need of minimizing gas supply shortage risk and reducing power demand. Finally, a sensitivity analysis is conducted to analyze the impact of demand uncertainties on the optimization results.

Keywords: Natural gas pipeline network; Multi-objective optimization; Supply reliability; Power demand; NSGA-II algorithm

1. Introduction

Nomenclature			
A	cross sectional area of pipeline	Q	Volumetric flow rate
c	Sound speed	$Q_{i,j}$	Flow rate into delivery node i from connecting pipeline j
c_1-c_6	Constants depending on compressor units	R	Gas constant
C	Heat capacity	S_g	Specific gravity of natural gas
D	Diameter of the pipeline	SR	Shortage risk (SR) of Customer
EC	Energy cost	T	Temperature
f	Frictional factor	K	The factor for limited function
L_i	Gas uploaded to (L_i<0) or Downloaded from (L_i >0) the pipeline network	$U_i(L_i)$	Utility for Customer i of demand L_i
H	Value of headz	y_i	Mole fraction of component i
L_{mn}	Length of pipeline m-n	v	Gas velocity
M_{air}	Molecular mass of air	$v_{i,t}$, $k_{i,t}$	Constant parameters for untility calculation
$N_{R,min}$	Minimal speed of compressors	Z	Compressible factor
$N_{R,max}$	Maximal speed of compressors	α	Angle between pipeline and

			ground
N.F.S	No feasible solution	β	Reliability index
p_d	Outlet pressure of compressor	ρ_n	Density
p_s	Inlet pressure of compressor	η	Efficiency
p_m	Pressure at node *m*	ε	Absolute roughness of pipeline
p^{min}	Acceptable minimal pressure	μ , σ	Mean value and standard deviation of the stochastic variables, respectively
p^{max}	Acceptable maximal pressure	λ	Darcy friction factor
$p_{reference}$	Reference delivery pressure	Δt	Average duration of line-pack capacity consumption
$p_{i,potential}$	Delivery pressure after line-pack consumption	Δx	Length of pipeline influenced by line-pack capacity consumption
$P_{\text{lim},i}$	Required minimum delivery pressure	Φ	Standard normal distribution function

Natural gas plays a crucial role in the world energy consumption portfolio, as a clean energy resource. It is transported from resources to demands via pipeline systems. During the process of gas transportation in pipelines, there are pressure drops because of the friction between the pipe inner surface and the gas. To maintain reliable supply to the customers, the pressure drops are compensated by compressor stations located along the pipeline network system. These compressor stations are usually equipped with gas turbines, operated with spilled natural gas. According to the literature, the gas consumption of these stations accounts for 3-5% of the total amount of natural gas transported in the pipelines and the cost of compressors operation constitute 25-50% of the overall company operation budget (Demissie, Zhu, and Belachew 2017). Then, optimizing the compressors operation and minimizing the fuel cost of compressor stations are important issues.

Many efforts have been done for the optimization of natural gas pipeline networks. Literature reviews have been written to summarize the methods and the achievements (Ríos-Mercado and Borraz-Sánchez 2015). In general, the optimization problems can be classified into operation problems and design problems (Demissie et al. 2017; Guerra et al. 2016). The optimization methods for design problems focus on the system structure design, material selection, compressor station configuration and components location (Üster and Dilaveroğlu 2014). The target of design optimization is to optimize system transmission capacity (Alves, Souza, and Costa 2016), operation flexibility (Fodstad, Midthun, and Tomasgard 2015) and future expansion plans (Mikolajková et al. 2017), with the minimum cost of investment. The optimization of operation considers different targets, such as operation cost minimization (Misra et al. 2015; Ríos-Mercado, Kim, and Boyd 2006), delivery capacity maximization (Fasihizadeh, Sefti, and Torbati 2014), line-pack maximization (Ernst et al. 2011; Ríos-Mercado and Borraz-Sánchez 2015), greenhouse gas emission minimization (Yang et al. 2017), etc. Due to the complexity of these optimization problems including non-linearity and non-convexity, they are very difficult to solve with feasible computational efforts. Methods have been developed, including Dynamic Programming (Ahmadian Behrooz and Boozarjomehry 2017), Mixed Integer Non-Linear Programming (Wang, Liang, et al. 2018; Wang, Yuan, et al. 2018; Zhou et al. 2019), Graph Theory (Praks, Kopustinskas, and Masera 2015; Su, Zhang, et al. 2018), Intelligence algorithm (Cortinovis et al. 2016; MohamadiBaghmolaei et al. 2014; Su, Zio, Zhang, Yang, et al. 2018; Zhang et al. 2018), distributed optimization(Won and Kim 2017) and so on. Among these methods, the nondominated sorting genetic algorithm (NSGA) has been chosen to achieve very good results in many applications (Deb et al. 2007). However, in most cases, the multi-objective optimization problem is simplified to a single-objective optimization problem, by converting part of the objectives to constraints. With the increase in computational capacity, some efforts have been conducted to solve multi-objective optimization problems in natural gas pipeline systems (Demissie et al.

2017).

In light of the occurrences of the disasters of natural gas interruption in recent years (Flouri et al. 2015), reliability of supply of natural gas pipeline systems has become an important concern: A number of methods have been developed to analyze the reliability of critical infrastructures from different perspectives (Lappas and Gounaris 2018; Mo, Li, and Zio 2016; Su et al. 2017; Zio 2016). According to the literature survey, most of the supply reliability analyses of natural gas pipeline networks are concerned with the long-term design (McCarthy, Ogden, and Sperling 2007; Praks et al. 2015; Su et al. 2017; Su, Zio, Zhang, and Li 2018), and the short-term supply reliability is always addressed either by putting a pressure buffer dimensioned according to the contract required pressures and engineering experience, or by maximizing the line-pack at the demand side (Ahmadian Behrooz and Boozarjomehry 2017). Demand uncertainty is also considered as an important factor in the optimization. (Ahmadian Behrooz 2016; Ahmadian Behrooz and Boozarjomehry 2017).

In spite of these efforts, the relationship between operation strategies and short-term supply reliability have been mainly developed based on engineering experience. Generally, a high level of supply reliability requires large pressure buffers for the overall system, which needs more fuel consumption by the compressor stations to maintain the high pressures. To effectively enhance the supply reliability and the system efficiency at the same time, a scientific method to optimize the pressure buffer and the operation cost in natural gas pipeline networks is in need.

In this work, a multi-objective optimization method is developed to find operational strategies for optimize the two conflicting objectives, i.e., minimize supply shortage risk and power demand. To quantify the risk of shortage in a short-term (hourly), the shortage probability is calculated based on a simplified hydraulic model of pipelines and demand uncertainties. The consequences of shortages are quantified via Utility Theory (Sheikhi, Bahrami, and Ranjbar 2015). Power demands of pipeline networks are calculated by a steady-state hydraulic model including pipelines and compressor stations. Finally, the developed multi-objective optimization problem is solved by a powerful Genetic Algorithm, NSGA-II (Azadeh et al. 2017; Deb et al. 2007; Kuznetsova et al. 2014).

The main contribution of this work is to propose a multi-objective decision-making method, considering two critical targets in natural gas pipeline systems, namely supply shortage risk minimization and power demand reduction. To support this decision-making process, a novel method to quantify the short-term risk of supply is developed based on hydraulic properties of pipelines, uncertainties of gas demands and characteristics of customers.

The rest of this paper is organized as follows: Section 2 illustrates the method, in three parts: Natural gas pipeline network modeling and power demand calculation (Section 2.1), Shortage risk of supply calculation for customers (Section 2.2) and multi-objective optimization modeling of the operation of natural gas pipeline networks (Section 2.3). The case study is performed in Section 3 to verify the effectiveness of the developed method and the results are analyzed from different perspectives. Finally, Section 4 discusses the conclusions and the plans for future research on the topic.

2. Methodology

In natural gas transmission systems, a large part of energy is consumed by compressor stations. Hence, reducing their power demands can effectively increase the efficiency of the pipeline system and the operating profit. Besides, considering that most of the compressors are driven by the gas turbine, reducing the power demand of the compressor stations can also benefit the environment by reducing greenhouse gas emission. Considering this, it is no surprise that power demand reduction of compressors is a main target of optimization of gas transmission systems.

Furthermore, in a natural gas pipelines system, there are various types of customers with different demands and the system needs to be operated in a way as to maintain the delivery pressures above the minimum contract pressure in order to satisfy the requirements. Because of unpredicted events, such as extreme weather conditions, the demands of customers can be quite uncertain, which requires "margins" in delivery pressures, i.e., pressure buffers at the demand points to make sure the minimum contract pressure can be satisfied in any case.

However, the pressure buffers require extra power demands in the compressor stations, to maintain a high level of operating pressures in the overall pipeline network. Accordingly, the main challenge of operation optimization in natural gas pipeline systems is to figure out the trade-off between efficiency and security of supply. In real application, the delivery pressures at the demand sites are always determined by experience of operators and historical data of customers' demands. In general, because of the complexity and nonlinear properties of natural gas pipeline networks, this kind of experience-based methods may not always give a good choice. In this part, the method introduced is able to help finding out the optimal pressure buffers to maintain a reliable supply with minimum cost of energy.

2.1 Natural gas pipeline network modeling and power demand calculation

Natural gas pipeline networks are complex systems. The following assumptions are made for their modeling (Ríos-Mercado and Borraz-Sánchez 2015; Szoplik 2016; Zhang, Wu, and Zuo

2016):

A. In this work, the optimization is carried out based on the system steady-state behavior, which means that it aims at finding optimal reference values of delivery pressure at demand sites;

B. The pipeline segments are horizontal;

C. Directions of gas flow in pipelines are specified;

D. Gas flows in pipelines are isothermal;

E. The compressibility factor remains constant throughout the transportation process.

Based on the assumptions, the pipeline equations can be simplified as follows (Demissie et al. 2017):

$$Q = \frac{3.629 D_{mn}}{Z S_g T f_{mn} L_{mn}} \left(p_m^2 - p_n^2 \right) \quad (1)$$

where Q denotes the flow rate in Nm^3/s; D_{mn} denotes the diameter of the pipeline m-n; p_m and p_n represent the pressure at nodes m and n in Pa; Z is the compressible factor; T is the temperature of gas in K; f_{mn} denotes the frictional factor; L_{mn} denotes the length of pipeline m-n in m; S_g denotes the specific gravity.

The frictional factor can be obtained by solving Nikuradse's Equation (Coelho and Pinho 2007):

$$\frac{1}{f_{mn}} = -2 \log_{10} \left(\frac{\varepsilon_{ij}}{3.71 D_{ij}} \right) \quad (2)$$

where ε_{ij} is the pipe absolute roughness in mm.

The specific gravity can be calculated by the following equation:

$$S_g = \frac{M_{NG}}{M_{air}} \quad (3)$$

where M_{air} is the Molecular mass of air, g/mole; M_{NG} is the Molecular mass of natural gas, which can be obtained via:

$$M_{NG} = \sum M_i y_i \quad (4)$$

where M_i represents the Molecular mass of component i in g/mole; y_i is the mole fraction of component i.

Compressors provide energy to natural gas to supplement pressure losses during the gas transmission process. The energy supplemented by the compressor is calculated as head, i.e., the amount of energy supplied per unit mass of gas. The value of head can be obtained by the following equation (Hesam Alinia Kashani and Molaei 2014):

$$H = ZRT \frac{k}{k-1}\left[\left(\frac{p_d}{p_s}\right)^{\frac{k-1}{k}} - 1\right] \quad (5)$$

in which k is calculated by (Pambour, Bolado-Lavin, and Dijkema 2016):

$$k = \frac{\sum C_{pi} M y_i}{\sum C_{pi} M y_i - \bar{R}} \quad (6)$$

On the basis of Equation 6, we can further calculate the energy provided to the gas in the compressor (Demissie et al. 2017):

$$Power = \frac{Q_m H}{\eta_{is}} \quad (7)$$

The performance of centrifugal compressors can be described in terms of the specific properties of adiabatic head, adiabatic efficiency, inlet volumetric flow rate and compressor speed. The relationships between them are usually represented via performance maps in which H is plotted as a function of Q at different compressor speeds N_R (in rpm). The performance map is different for different compressors. In this work, the performance maps are adopted from Reference (Demissie et al. 2017). To analyze the working conditions of the compressor, the curves on the map are approximated by quadratic polynomial functions (Equations 8-9), and the constants in the fitting functions are obtained via the least squares method.

$$\frac{H}{N_R^2} = c_1 + c_2\left(\frac{Q_{ac}}{N_R}\right) + c_3\left(\frac{Q_{ac}}{N_R}\right)^2 \quad (8)$$

$$\eta_{is} = c_4 + c_5\left(\frac{Q_{ac}}{N_R}\right) + c_6\left(\frac{Q_{ac}}{N_R}\right)^2 \quad (9)$$

The performance of the compressor is mainly limited by two constraints: (1) the rotational speed N_R must remain within the operational range in Equation 10, (2) the operational range of the compressor is limited by its surge and stone wall, as in Equation 11.

$$N_{R,\min} < N_R < N_{R,\max} \quad (10)$$

$$\left(\frac{Q_{ac,Low}}{N_{R,\min}}\right) \le \left(\frac{Q_{ac}}{N_R}\right) \le \left(\frac{Q_{ac,Up}}{N_{R,\max}}\right) \quad (11)$$

2.2 Shortage risk of supply calculation for customers

The reliable supply of natural gas in pipeline networks is a fundamental requirement for operation optimization. However, most optimization works focus on economic efficiency improvement or greenhouse gas emission reduction. The reasons of that are: (1) supply reliability of natural gas is always considered as a long-term issue and should be dealt with at the design stage; (2) it is difficult to properly evaluate the supply reliability from the perspective of short-term operations which relates to the operation strategy, the hydraulic properties of the natural gas flow and the uncertainties of consumption. Considering these problems, here we propose a novel method to evaluate the short-term supply reliability of natural gas pipeline networks.

Generally, pipeline systems must maintain the supply pressures at the customers higher than the minimum pressures required by contract (Fig. 1). In some conditions, the gas flows into the pipeline may be less than the consumption by its connected customer, which generates an imbalance between the supply and the demand of the customer. To fill the gap of gas from the imbalance, gas is supplemented by the line-pack capacity, which leads to the decrease of the delivery pressure at the customer. For this reason, gas pipeline operators need to retain a pressure buffer between the delivery pressure and the minimum required pressure.

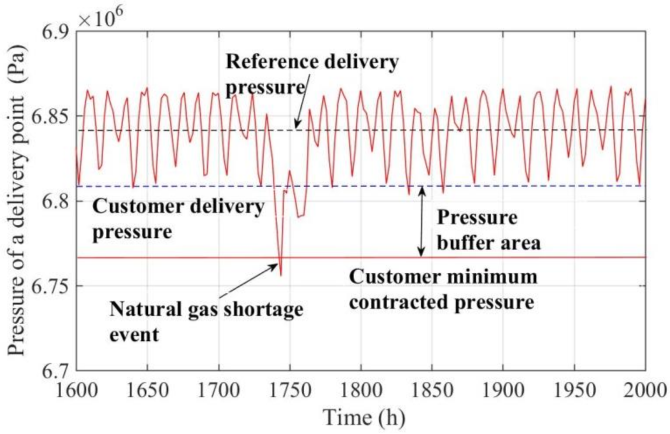

Fig. 1 Dynamic behavior of pressure at a delivery point

The key point to perform the operation optimization with the consideration of supply reliability is to mathematically describe the relationship between the delivery pressure, the customer's consumption of gas and the conditions of the pipeline network system, and, then, inject the uncertainties into this relationship.

$$\frac{\partial p}{\partial t}+\frac{\rho_n c^2}{A}\frac{\partial Q}{\partial x}=0 \quad (12)$$

$$\frac{\partial\left(\rho_{\mathrm{n}} v\right)}{\partial t}+\frac{\partial\left(\rho_{\mathrm{n}} v^2\right)}{\partial x}+\frac{\partial p}{\partial x}+\frac{\lambda \rho_{\mathrm{n}} v|v|}{2D}+\rho_{\mathrm{n}} g \sin\alpha=0 \quad (13)$$

The mass equation and the momentum equation (Equations 12-13) are typically the basics to model the hydraulic properties of the natural gas flow in the pipelines. We here use the mass equation to model the relationship between the delivery pressure, the customer's consumption of gas and the system condition, by transforming Equation 12 as Equation 14 (Pambour et al. 2016).

We consider the continuity equation at the nodes in the network system, and Eq. 12 shows that the change of pressure at a node is caused by the imbalance between its inflows and outflows of natural gas. Based on this assumption and referring to the mathematical transformation in Ref (Pambour et al. 2016), we replace the term ∂Q in Eq. 12 by $\left(\sum_{j=1}^{k} Q_{i,j} - L_i\right)$. Then, Eq. 12 can be transformed by Eq. 14.

$$\frac{dp_i}{dt} = -\frac{\rho_n c^2}{\sum_{j=1}^{k} A_{i,j} \Delta x_{i,j}} \left(\sum_{j=1}^{k} Q_{i,j} - L_i\right) \quad (14)$$

where, $Q_{i,j}$ represents the gas flow into delivery node i from the connecting pipeline j; when gas flows from the pipeline j to the delivery node i, $Q_{i,j}$ is positive; otherwise $Q_{i,j}$ is negative. L_i represents the gas uploaded to (L_i<0) or downloaded from (L_i >0) the pipeline network; when the node represents a junction, L_i =0. Hence, Eq. 14 represents the changes in the delivery pressures at the demand sides along with the fluctuations of the line-pack values.

To clearly present this relationship, Equation 14 is further transformed as Equation 15 by the finite difference method, which is a numerical method to transform the differential equations in time into algebraic equation:

$$p_{i,potential} = -\frac{\rho_n c^2 \Delta t}{\sum_{j=1}^{k} A_{i,j} \Delta x_{i,j}} \left(\sum_{j=1}^{k} Q_{i,j} - L_i\right) + p_{reference} \quad (15)$$

where $p_{i,potential}$ represents the delivery pressure after the time interval Δt with the line-pack consumption rate of $\left(\sum_{j=1}^{k} Q_{i,j} - L_i\right)$. $p_{reference}$ represents the reference delivery pressure, obtained by adjusting the operating conditions of the compressors in the pipeline network. In general, the flow rate should be calculated based on both the mass equation and the momentum equation, by mathematical iteration methods. But in this work, to evaluate the supply reliability at the delivery node, we need to know the probability rather than an exact value of pressure. For this reason, we consider as stochastic variables both the flow rate Q and the customer consumption L and predict the potential risk of supply shortages. Here the uncertainties of the flow rates, which is hypothetically represented by their standard deviations, in the pipelines connecting the customers are used to represent the uncertainties of the system supply capacity, due to the uncertain changes in the system running conditions. This is because the changes of working conditions in the pipeline network will eventually reflect on the flow rates to the customers, from the supply reliability perspective. Based on that, a limit function is developed as:

$$g_i\left(Q_{ij}, L_i, P_{i,t}, P_{\lim,i}\right) = K\left(\sum a_{ij}Q_{ij} - L_i\right)\Delta t + p_{reference} - P_{\lim,i} \quad (16)$$

in which $P_{\lim,i}$ denotes the contract required minimum delivery pressure; g_i<0 represents the occurrence of supply shortage at Customer i; the factor K is calculated by Equation 17:

$$K = -\frac{\rho_n c^2}{\sum_{j=1}^{k} A_{i,j}\Delta x_{i,j}} \quad (17)$$

in which Δt is the average duration of time that the consumption of the line-pack capacity may continue; $\Delta x_{i,j}$ is the length of the pipeline j influenced by the imbalance between the delivery gas volume and the demand of Customer i. Hence, g_i<0 represents the fact that the future delivery pressure, $p_{i,potential} = K\left(\sum a_{ij}Q_{ij} - L_i\right)\Delta t + p_{reference}$, is incapable of fulfilling the needs of Customer i.

Usually, the limit state function needs to be solved by a huge number of Monte-Carlo simulations. However, in this work the limit state function is conveniently built up as a linear function of the stochastic variables, by which the probability of shortage of natural gas can be directly obtained by Equations 18-19. The process derivation is performed based on the First order second moment method (Beck et al. 2015), which is always used for analysis of structure reliability. The key point of the method is to obtain the reliability index β, according to the moments of the linear limited function (Eq. 16). The reliability index β, is, then, used to calculate the failure probability, based on the assumption that the variables follow the Gaussian distribution.

$$P\left[g_i < 0\right] = \Phi(-\beta_i) \quad (18)$$

$$\beta_i = \frac{K\left(\sum a_{ij}\mu_{Q_{ij}} - \mu_{L_i}\right)\Delta t - \mu_{P_{\lim,i}} + p_{reference}}{\sqrt{K^2\left(\sum a_{ij}{}^2\sigma_{Q_{ij}}^2 - \sigma_{L_i}^2\right)\Delta t - \sigma_{P_{\lim,i}}^2}} \quad (19)$$

in which μ and σ represent the mean value of the stochastic variables, respectively.

For the consequences, we use utility, a concept from microeconomics. More specifically, in this paper, we use a quadratic utility function to describe the utilities of the natural gas customers (Sheikhi et al. 2015) (Equation 20).

$$U_i\left(L_i\right) = v_{i,t}L_i - \frac{k_{i,t}}{2}L_i^2 \quad (20)$$

in which $U_i(L_i)$ represents the utility for the Customer i of the demand of L_i; $v_{i,t}$ and $k_{i,t}$ are positive parameters.

The supply shortage risk (*SR*) of Customer i can be calculated by Equation 21, by combining Eqs. 18 and 20:

$$SR_i = U_i\Phi\left(-\beta_i\right) \quad (21)$$

2.3 Multi-objective optimization modeling of the operation of natural gas pipeline networks

In many works, the operation optimization problems are simplified as single-objective optimizations. In this paper, we develop a multi-criteria decision-making process to obtain the optimal trade-off of supply reliability maximization and operation cost minimization.

The decision variables of the multi-criteria decision-making process are the rotational speed of the compressors and the pressures of the nodes. The two objective functions are given Equations 22-23 below:

Objective 1: minimizing the supply shortage risk (*SR*)

$$\min\left\{\sum SR_i\right\} \quad (22)$$

Objective 2: minimizing the power demand (*PD*) of the compressors

$$\min\left\{\sum \frac{Q_m H}{\eta_{is}}\right\} \quad (23)$$

The constraints are Equations 24-27 below:

Constraint 1: Flow balance at the nodes under steady state

$$\sum Q_{m,in} = \sum Q_{m,out} \quad (24)$$

Constraint 2: the limits of the compressors as Equations 8-11.

Constraint 3: the limits of the pressure variables.

$$p_j^{\min} \le p_j \le p_j^{\max} \quad (25)$$

In this work, the multi-objective optimization problem is solved by an evolutionary optimization algorithm, named as NSGA-II, which finds multiple Pareto-optimal solutions (Kuznetsova et al. 2014). The optimization process is described in the flowchart of Fig. 2:

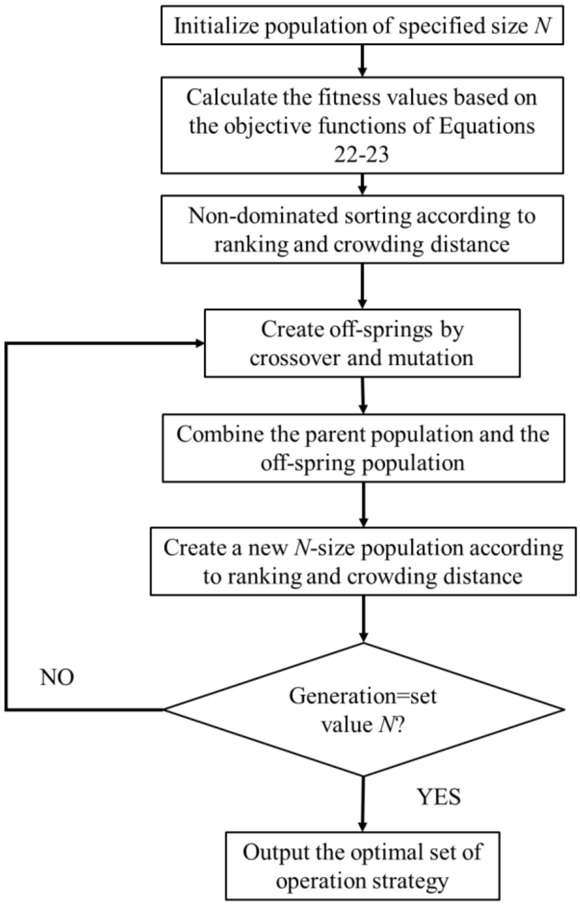

Fig. 2 Flowchart of the NSGA-II algorithm

Then, in this paper, we use the popular "max-min method" to select an optimal compromise solution from the Pareto set (Zio and Bazzo 2011). Consider a Pareto point (*PD*, *SR*) as the coordinates in the criterion space; then we can define the deviation from the best values by:

$$z_{EC} = \frac{\left|PD - PD^{\min}\right|}{\left|PD^{\max} - PD^{\min}\right|} \quad (26)$$

$$z_{SR} = \frac{\left|SR - SR^{\min}\right|}{SR^{\max} - SR^{\min}} \quad (27)$$

in which $PD^{\min}$ and $SR^{\min}$ represent the minimum values of *PC* and *RS* in the Pareto solutions. Based on that, we can obtain the compromise optimal Pareto solution by:

$$\min\left[\max\left[PD, RS\right]\right] \quad (28)$$

3. Case study

To verify the effectiveness of the operation optimization developed model, we have performed two applications on pipeline networks, i.e., a tree-topology pipeline network and a loop-topology pipeline network.

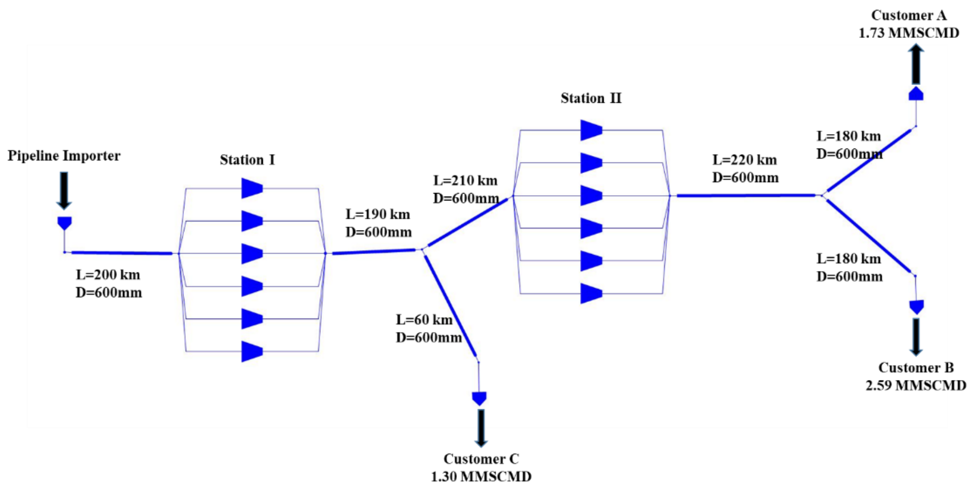

Fig. 3 The layout of the tree-topology natural gas pipeline network

In Fig. 3, the tree-topology natural gas pipeline network has two compressor stations, which are both equipped with six compressors arranged in parallel. In this pipeline network, there is a gas source supplying natural gas to three different kinds of customers at the ends of the branches. The basic parameters are presented in Fig. 3. In Fig. 4, the loop-topology pipeline system has two compressor stations, also with six parallel compressors each. It connects one pipeline importer and three customers. The import pressure is set at about 50 bar. Besides, the basic parameters of the pipeline network and the customer demands are given in Figs. 3-4. In this application, customers have the same contract minimum delivery pressure of 45 bar. The range of the compressor speed is set to 5200-9500 rpm and the pressure of the pipelines should not exceed 70 bar. We assume that the line-pack consumption impacts 10 km of the pipeline connecting to the customers and the average duration of the consumption is around half an hour. The parameters of the quadratic polynomial functions (Equations 8-9) are set by c_1=8.43270 × 10^{-7}, c_2=1.04130 × 10^{-3},

c_3=-9.03270 × 10^{-1}, c_4=1.74291 × 10, c_5=1.43376 × 10^5, c_6=-8.00511 × 10^7, respectively. The developed multi-objective optimization models are solved by the GA algorithm in MATLAB, whose basic parameters are: population size=300, crossover fraction=0.8 and maximum number of generations in the GA = 300. The adaptive mutation is used to create the mutated children. The function tolerance is used as the convergence criterion, and its value in MATLAB is determined by 1×10^{-4}.

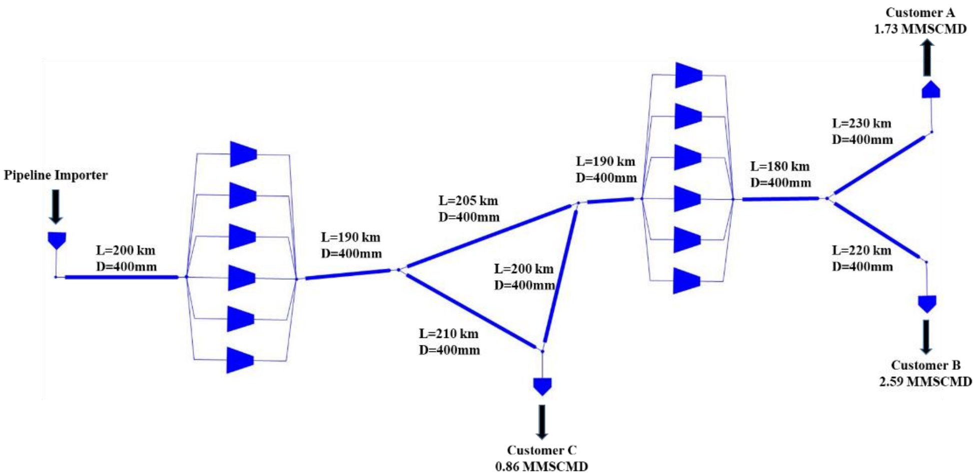

Fig. 4 The layout of the loop-topology natural gas pipeline network

Fig. 5 presents the Pareto fronts trading-off power demand of the compressor stations and probabilities of supply interruption to customers. In the case study, we separate the results from the summation curve to individual ones of each customer, for better presenting the solution sets for the customers and identifying the impact of each customer to the solutions. Utilities are used for the multi-objective optimization process to better distinguish the importance of the different customers, but for the illustration of the results, we use the probability of interruption for more intuition. In the assumed natural gas pipeline network in Fig. 4, Demand Sides A and B (Customers 1 and 2) are neighbors whose pressures and supply shortage risks (by Eqs. 18-21) are nearly the same based on Eqs. 1-6. And, because of the differences of topology locations and physical conditions between Demand Side C and Demand Sides A-B, the results of risk calculation at Demand Side C can be very different from the others. This means that, based on the representation of the risk objective function in the summation form, the GA put more “weights” on Demand Sides A-B to find the Pareto front from the system perspective. This affects the ability of the GA to give good results on Demand Side C.

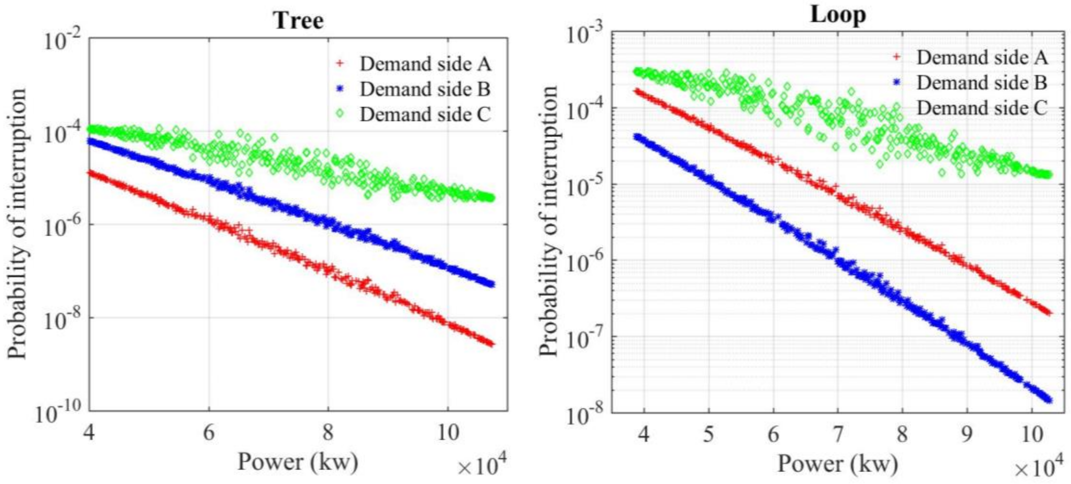

Fig. 5 Left and the right Figures, respectively, present the Pareto fronts of the Tree-topology pipeline network and the Loop-topology pipeline network

Considering that in this work, the operation strategy is adjusted by controlling the speed of the compressors equipped in the stations, the Pareto fronts are also presented in the form of trade-off between the interruption probability and the compressor speeds, as in Fig 6. Compressor speed I denotes the speed of the compressors located in Station I and Compressor speed I represents those in Station II.

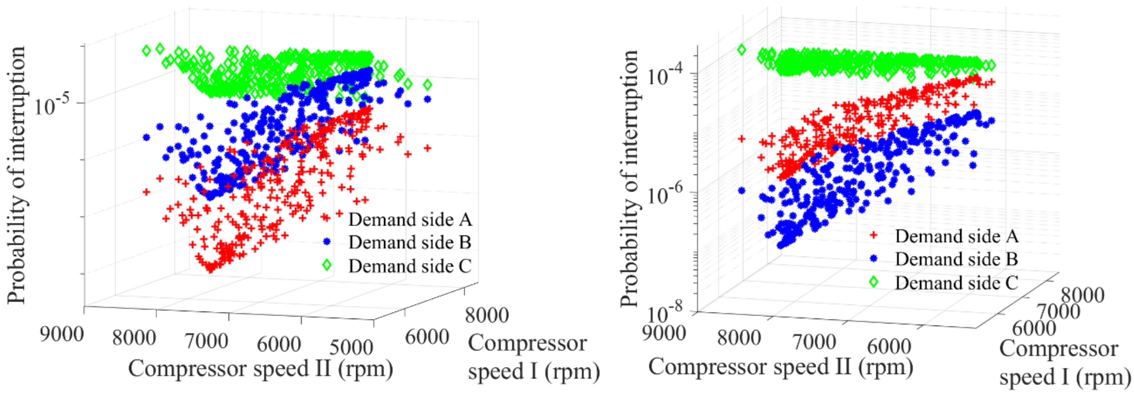

Fig. 6 Left and the right Figures, respectively, present the Pareto fronts of the Tree-topology pipeline network and the Loop-topology pipeline network

We, then, use the “max-min” method introduced in Section 2.3 to select a compromise solution, assuming several acceptable values of interruption probability and power demand.

In Tables 1-2, we give the selected operation strategies for the two pipeline networks, based on the Pareto sets of Figs. 5-6. Because of the limitation of the page space, we only present the critical parameters, i.e., the delivery pressures at the customers and the compressor speeds. From these results, we can observe that, for different acceptable values of power demand, the method selects different operation strategies to satisfy the requirements of supply reliability. This is, to some extent, a concession of reliability on efficiency, which puts an important impact on the risk exposure management of the gas supply system. Besides, we see that, in the Pareto set, there is no possibility for the Loop-topology network to keep the interruption probabilities for all customers under 10^{-5}. This indicates that this system maybe suffers from problem of design, which cannot be fixed by only optimizing the operation strategy.

Table 1 Compromise solutions selected by the “max-min” method in the Tree-topology network

Acceptable level of interruption probability	Acceptable Power demand (kW)	Optimal operation parameters				
		Delivery pressure (bar)			Compressor speed (rpm)	
		P_A	P_B	P_C	ω_I	ω_{II}

<10^{-5}	10.5×10^4	54.77	54.78	52.33	8386	8471
	8.5×10^4	53.92	53.92	52.04	7726	7288
	6.5×10^4	N.F.S				
<10^{-4}	10.5×10^4	53.19	53.18	51.00	5218	8064
	8.5×10^4	53.19	53.18	51.00	5218	8064
	6.5×10^4	52.93	52.91	51.26	5890	6850

Table 2 Compromise solutions selected by the "max-min" method in the Loop-topology network

Acceptable level of interruption probability	Acceptable Power demand (kW)	Optimal operation parameters				
		Delivery pressure (bar)			Compressor speed (rpm)	
		P_A	P_B	P_C	ω_I	ω_{II}
<10^{-5}	10.5×10^4	N.F.S				
	8.5×10^4	N.F.S				
	6.5×10^4	N.F.S				
<10^{-4}	10.5×10^4	52.41	54.92	54.92	8529	8935
	8.5×10^4	54.02	54.01	52.05	7763	7797
	6.5×10^4	53.05	53.04	51.52	6557	6799

Uncertain levels of customer demands can impact the operation strategy optimization significantly. To analyze the sensitivity of the optimization results of this factor, a crude sensitivity analysis is conducted on the Loop-topology network, which also includes a Tree-topology part. This sensitivity analysis is performed on the pipeline network with the loop topology, which is the most complex one contains the other two topologies of one pipeline and tree-topology. This can help to uncover the impact of uncertain levels of demands on supply reliability and help engineers to notice the importance of input data pre-processing before the optimization. The analysis results are shown in Figs 7-9. By performing the multi-objective optimization for different values of the variances, we can observe the influences of their changes on the Pareto solutions of the operation optimization. Also, the impacts of the demand uncertainties are reflected on the performances of the optimized operation strategies, which are presented in Table 4.

In the sensitivity analysis, the values of the demands are assumed distributed as normal distribution and the variances of Customers A, B and C are respectively set to five different values, as in Table 3. In the optimization process, the variances of the customers are introduced in terms of the standard deviations of their demands, which are represented as σ_{Li} in Eq. 19. In the sensitivity analysis, we increase the values of σ_{Li} of the customers to analyze the impacts of the uncertainties on the optimization results. The level of uncertainties in the demands, e.g., the values of σ_{Li}, are set according to the experiences of natural gas pipeline operators and amounts of demands. But, in the real applications, these values should be calculated based on the historical data of natural gas demands.

Table 3 Uncertain levels of the demands of the three customers, represented by different variances (MMSCMD)

	Level 1	Level 2	Level 3	Level 4	Level 5
Customer A	0.2592	0.3024	0.3546	0.3889	0.4320
Customer B	0.3110	0.3542	0.3974	0.4406	0.4838
Customer C	0.2592	0.3024	0.3546	0.3889	0.4320

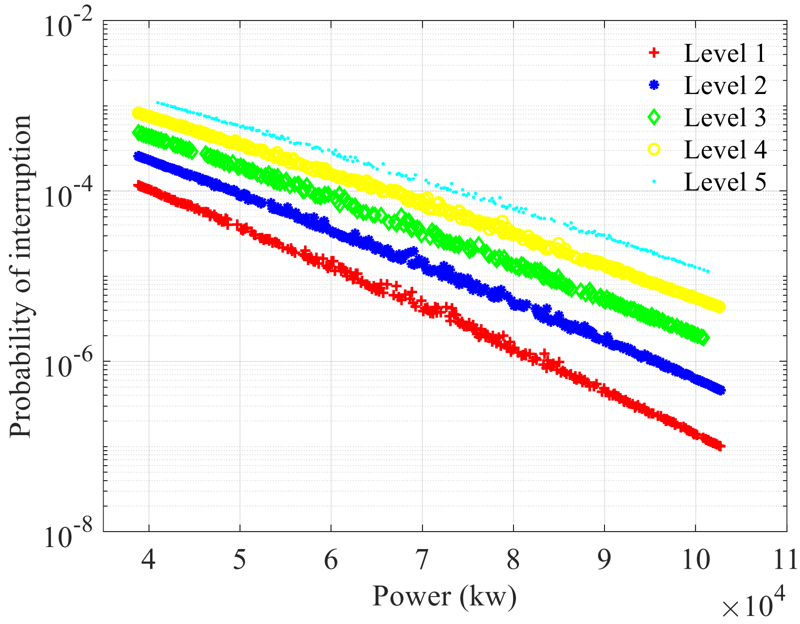

Fig. 7 Impact of the demand uncertainty of Customer A on the Pareto solutions

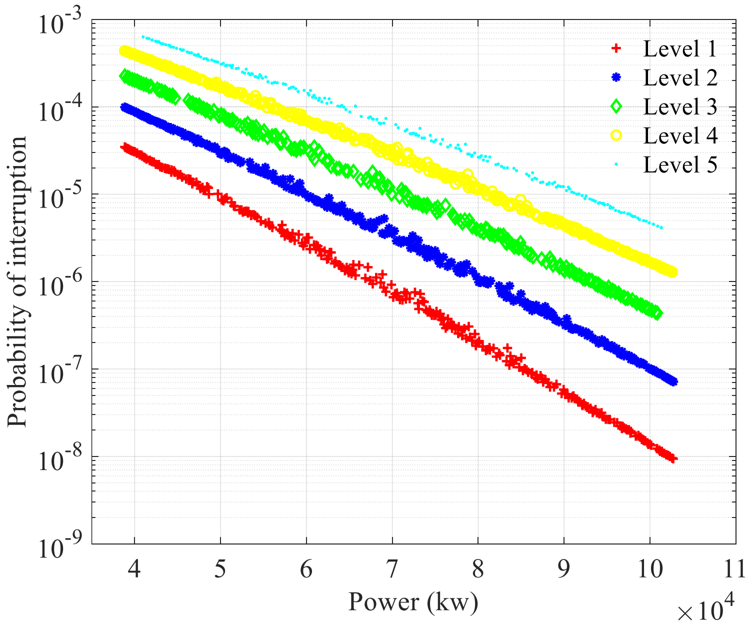

Fig. 8 Impact of the demand uncertainty of Customer B on the Pareto solutions

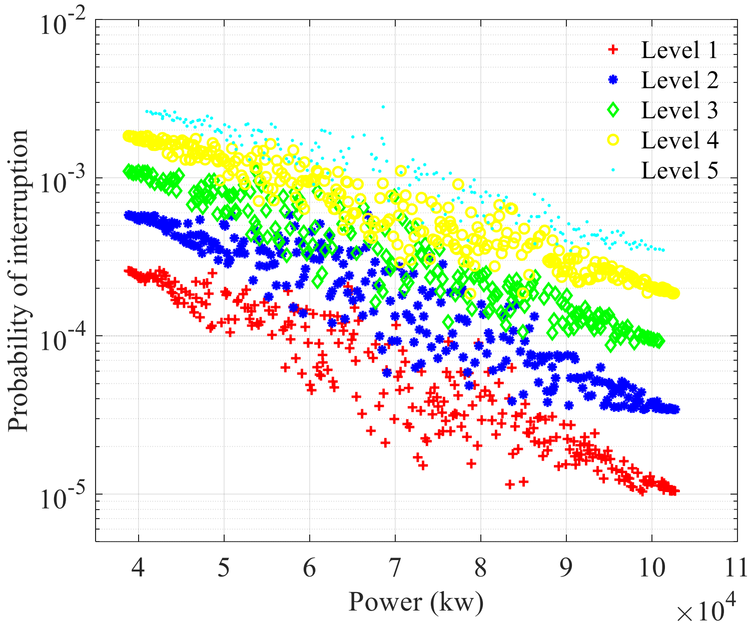

Fig. 9 Impact of the demand uncertainty of Customer C on the Pareto solutions

Table 4 Performances of the optimized operation strategies under different uncertainties of demands, under the requirements of different acceptable power demands and on acceptable level of interruption probability of 10^{-4}

Acceptable Power demand (kW)	Variance level	Optimizations performance			
		Probability of interruption under optimized operation strategy ($\times10^{-4}$)			Power ($\times10^4$ kw)
		Customer A	Customer B	Customer C	
10.5×10^4	1	0.0011	0.0001	0.1122	10.19
	2	0.0047	0.0007	0.3429	10.25
	3	0.0348	0.0087	0.8748	9.52
	4	N.F.S			
	5	N.F.S			
8.5×10^4	1	0.0123	0.0017	0.1150	8.34
	2	0.0663	0.0152	0.5886	7.85
	3	N.F.S			
	4	N.F.S			
	5	N.F.S			

From Figs 7-9, we can observe that the uncertainties of the demands can significantly affect the operation optimization results. For example, if we increase the variance of the demand of

Customer B from Level 1 to Level 2, the lowest interruption probability within the Pareto set degenerates from about 10^{-8} to 10^{-7}. If the uncertain level is directly increased to Level 5, the interruption probability within the solution set degenerates about 2-3 orders of magnitude, which is a relatively large value. Hence, in real applications, the accuracy of the measurements of the demand variances is very important for the quality of the optimization results. Besides, the results in Table 4 indicate that with the increase of the uncertainties in the demands, the performances of the optimized operation strategies, under the given constraints of power demands, severely degenerate. The reason is that higher level of uncertainty of demands makes it more difficult for the supply system to deal with the potential abnormal peaks of natural gas consumptions with the current design. In the Levels 4-5, the system is even unable to find the operation point to satisfy the constraints of supply reliability, which means that it has to be expanded by supplementing more compressors, to overcome the uncertainties of demands.

4. Conclusion and discussion

In this work, we have developed a method for the multi-objective optimization of the operation of natural gas pipeline networks. In this method, both supply shortage risk minimization and power demand minimization are considered as the objectives. The optimization method is developed on steady hydraulic conditions of the pipeline networks. To quantify the supply reliability, a novel limit state function is established, which can provide a novel, easier way to consider supply issues besides the classical thermal-hydraulic simulation methods. The multi-objective optimization problem is here solved by the NSGA-II algorithm and the max-min method is used here to select compromise solutions from the obtained Pareto set.

The method has been applied to a Tree-topology and a Loop-topology pipeline network, and the optimization results have been discussed in detail. A sensitivity analysis, reporting the impact of demand uncertainty on the optimization results has been carried out. This work introduces supply reliability of natural gas as an important consideration for optimizing the operation strategies of natural gas pipeline networks. The results of the case studies present the good ability of the developed model to find the compromise between power demands and supply reliability requirements. The optimization results can help to make more reasonable decisions for gas pipeline operators. And this method can also help to find the potential problems for pipelines with different structures. For example, by comparing Tables 1 and 2, we can see that the pipeline system with loop-topology suffers more risk of shortage than the tree-structured system, within the same power demand. Besides, the results of the sensitivity analysis indicate that the level of uncertainties of natural gas demands can significantly impact the optimization performances, which means that the demand uncertainty should also be considered as a critical issue from the perspective of design and operation of natural gas pipeline networks.

Future research will analyze the robustness of natural gas supply capacity for a more comprehensive optimization framework, considering supply reliability, operation cost and greenhouse emission. Dynamic properties will also be included in the future work. Besides, to enhance the effectiveness of this method, we will develop better representations of the objectives, develop methods for hyper-parameter optimization and explore other algorithms, to find improved solutions. Finally, the developed model will be used to solve the real optimization problems, based on real pipeline network systems and historical data of natural gas demands.

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