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An integrated systemic method for supply reliability assessment of natural gas pipeline networks

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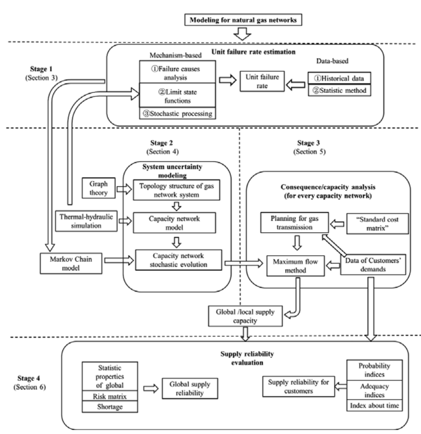
HIGHLIGHTS

- A method is developed to analyze reliability of supply of gas pipeline networks.
- Uncertainty, complexity and physical constraint are considered in the method.
- Indices are developed with respect to global system and individual customer.
- The application of the method is studied in a complex natural gas pipeline network.

GRAPHICAL ABSTRACT



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ABSTRACT

A systematic method is developed for supply reliability assessment of natural gas pipeline networks. In the developed method, the integration of stochastic processes, graph theory and thermal-hydraulic simulation is performed accounting for uncertainty and complexity. The supply capacity of a pipeline network depends on the unit states and the network structure, both of which change stochastically because of stochastic failures of the units. To describe this, in this work a capacity network stochastic model is developed, based on Markov modeling and graph theory. The model is embedded in an optimization algorithm to compute the capacities of the pipeline network under different scenarios and analyze the consequences of failures of units in the system. Indices of supply reliability and risk are developed with respect to two aspects: global system and individual customers. In the case study, a gas pipeline network is considered and the results are analyzed in detail.

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1. Introduction

Natural gas pipeline networks are important critical infrastructures connecting natural gas resources and demands. Several unexpected natural gas supply interruptions have occurred in the last decade with severe consequences on economy and society stability around the world [1]. Realizing the importance of natural gas pipeline networks for energy security, reliable and continuous supply of natural gas has become a serious and worldwide concern for economic, political and technical reasons.

Recently, reliability, risk and vulnerability perspectives have been embraced for natural gas supply security [2,3]. Reliability has been applied to engineering systems for > 60 years. The most widely accepted qualitative definition of reliability is in terms of the probability of a component, sub-system or system "to perform a required function in set conditions and for a stated period of time" [4]. However, for the supply function of natural gas pipeline networks, we take the definition of reliability for critical infrastructure systems. The supply reliability of a natural gas pipeline network is defined as the probability of successfully providing the service required to satisfy the customers' demand of gas. Supply reliability indices are, then, calculated considering both supply capacity and demands.

Many efforts have been devoted to research in the field of reliability of infrastructure networks, as above defined. System reliability analysis methods, such as logic modeling and system decomposition, have also been classically used to estimate system reliability [3,5,6]. Statistics is used to calculate the reliability indices when relevant historical data are available [7–9].

However, conventional reliability theory cannot capture the complexities (structure and dynamic) of large infrastructures extending on large geographic scales, operating under variable conditions and consisting of large number of components with heterogeneity [10,11]. Specifically for natural gas supply reliability assessment, a comprehensive model is needed to describe the uncertainty, function, operation and capacity of the system and the consequences of specific events.

Many approaches exist for modeling the stochastic properties of complex infrastructures, e.g., natural gas pipeline networks, power grids, or rail systems. Stochastic simulation methods, e.g., Monte Carlo based methods [12–16], Markov process based methods [17,18] and others [19–22], are widely used to model a complex system with uncertainties. Probabilistic dynamic modeling is applied to describe interdependences among critical infrastructures and global effects of specific scenarios [23].

Graph theory for vulnerability and reliability analysis is an effective approach that has been proposed recently to model transport infrastructure systems as graphs to analyze their connectivity properties [24,25]. In particular to analyze the vulnerability and reliability of a transmission network, there are methods based on topological properties [2,26–30], flow-based methods [31–36] and hybrid methods [13,37–39]. Further, structural-function modeling, based on graph theory and system engineering, are also used [40]. A structural-function model consists of two parts: a structure model and a function model. Physical objects in the systems are represented in terms of edges and nodes in the structure model and the system behaviors are represented in the function model. The function model can be engineering-oriented e.g. thermal-hydraulic models for natural gas networks [41], the function model for gas-grid coupling [42], or simplified and abstracted, e.g. flow-based methods [39,2,43].

Also, the importance of considering operation, function, capacity and limitation of a gas supply system is emphasized in some works, such as GEMFLOW [44] and MC-GENGERCIS [14].

The aim of this paper is to present an original methodology to evaluate supply reliability in natural gas pipeline networks. A method to describe uncertainty and complexity of pipeline network systems has been developed. The method consists of a unit analysis module, a system analysis module and a reliability calculation module. The function of the unit analysis module is to analyze complex and uncertain causal relationships between causes and failures modes. The system analysis module is developed to depict the structure and capacity of pipeline networks and simulate the response to stochastic failures. Uncertainty, system structure complexity and system dynamic complexity are considered in the model. The calculation of supply reliability in natural gas networks includes two parts: the global part and the customer part. The global part mainly aims to calculate supply capacity from the point of view of the global system. The customer part accounts for the customer demand. For a detailed assessment, indices of the customer part are divided into three aspects: probability, adequacy and time.

The developed framework integrates methods for addressing the problems from different perspectives — environmental, functional constraint, topology and dynamic. Comparing with the traditional reliability methods, it has the advantage of addressing the reliability assessment problem considering these different perspectives for holistically capturing the high complexity of the natural gas pipeline network and the related uncertainties, which cannot be easily treated with classical methods of logic modeling and system decomposition. From a practical point of view, the methodology can aid engineers and managers estimating safety margins to serve costumers reliably.

2. Methodology

For a clear illustration, the developed methodology is divided into three parts: unit failure analysis, system modeling and reliability assessment. The framework is shown in Fig. 1 and the following paper is organized as follows.

In Section 3, two methods are adopted in unit failure analysis, i.e., the failure-mechanism-based method and the historical-data-based method. Natural gas pipelines have large geographical extension and can be affected by multiple factors: then, the failure probability of pipelines changes in space and time. On the contrary, failure probabilities of the others are stable because of the limited variability of the surroundings they operate in.

To simulate the consequences of stochastic failures of units in natural gas supply systems, several methods have been developed [41,2]. In this paper, methods including stochastic processes, graph theory and thermal-hydraulic simulation are combined to simulate stochastic changes of pipeline network system (Section 4) and estimate the consequences (Section 5), accounting for uncertainty and complexity.

Then, supply reliability in natural gas pipeline networks is determined in terms of the amount of gas that the pipeline network can support and the degree to which customer demands are satisfied (Section 6).

3. Unit failure probability estimation

3.1. Pipeline failure analysis

Several factors can lead to the failure of natural gas pipelines. According to the data from European Gas Pipeline Incident Data Group (EGIG), material failure and corrosion are responsible for 30–40% of all pipeline failures; the rest is due to external factors, such as maintenance works, wrong operations and third party interference [45]. According to this, corrosion analysis is considered as a critical part in pipeline failure analysis. On account of the diverse conditions and non-linear factors affecting the structure integrity, utilizing statistical failure data can give a global estimate of pipeline reliability but may not be accurate for the specific pipelines in diverse conditions. The failure probability of a specific pipeline should be calculated with consideration of its particular factors of operation such as pipeline parameters and failure mechanisms.

The data source for pipelines failure analysis comes from pipeline internal detections. Number, location and geometric parameters of

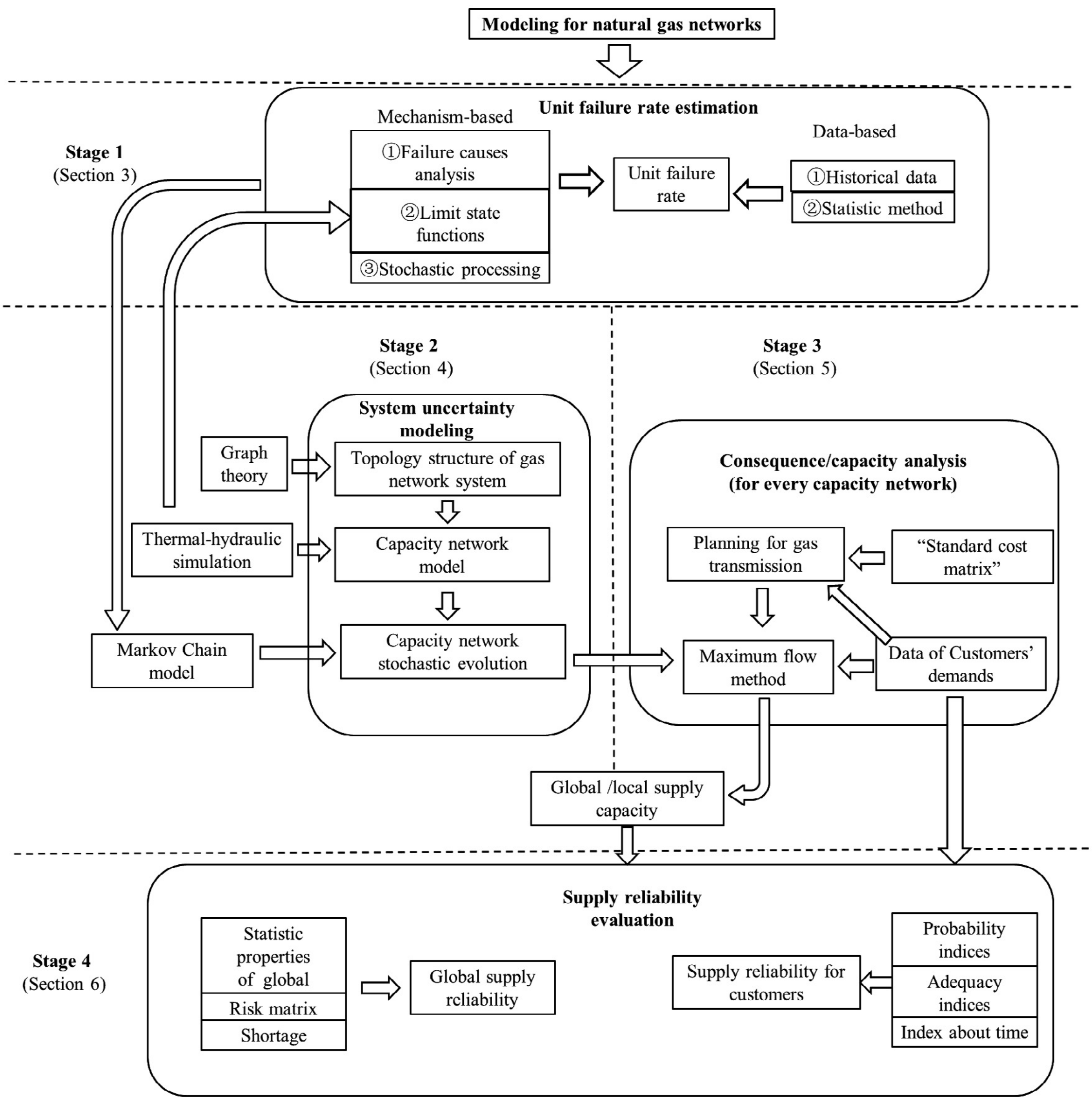

Fig. 1. The framework of the developed methodology.

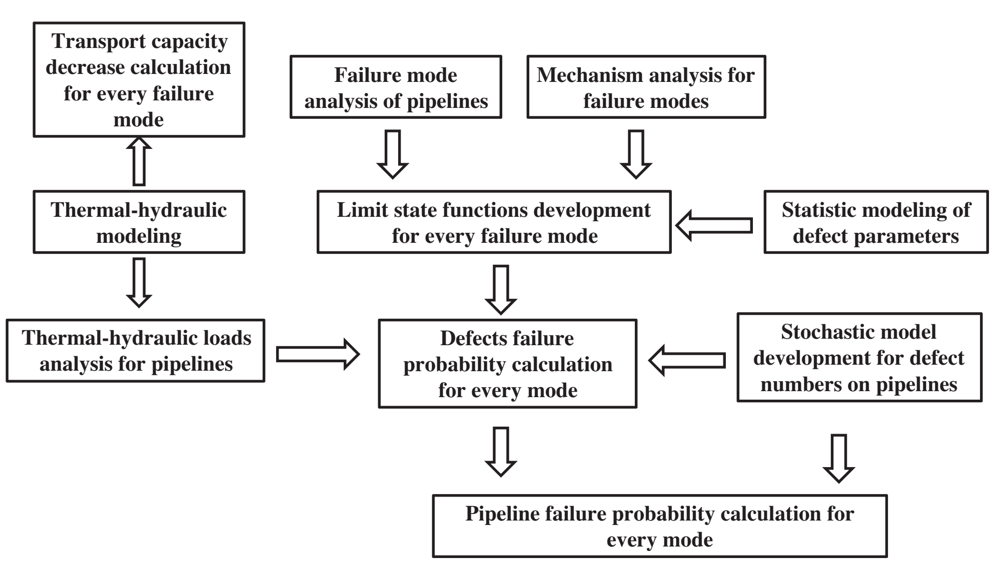

Fig. 2. Structure of the pipeline failure analysis method.

defects are recorded.

The analysis method is illustrated in Fig. 2 and explained in the following paragraphs.

A corroding natural gas pipeline with defects may fail in three modes [46] i.e., small leak, large leak and rupture, which lead to a decrease of pipeline transportation capacity to different levels. Failure mechanisms are modeled by limit state functions. The limit functions are defined as follows:

$$L_1 = 0.8w_t - depth \quad (1)$$

the limit state function L_1 represents defect penetration through the pipe wall, where w_t and *depth* represent pipe wall thickness and defect depth, respectively. Typical industrial practice, according to the literature [46] suggests that pipe wall is prone to leak once defect depth reaches $0.8w_t$;

$$L_2 = P_{burst} - P_{in} \quad (2)$$

where P_{burst} donates the burst pressure of corrosion defect under pipeline internal pressure P_{in}. This limit state function defines the limit state of pipe burst with plastic collapse due to internal pressure;

$$L_3 = P_{rupture} - P_{in} \quad (3)$$

where $P_{rupture}$ is the pipe defect rupture pressure with unstable defect extension in the axial direction.

A schematic of the three distinct failure modes is shown in Fig. 3 [47]: small leak - $(L_1 \leqslant 0) \cap (L_2 > 0)$, large leak - $(L_1 > 0) \cap (L_2 \leqslant 0) \cap (L_3 > 0)$, and rupture - $(L_1 > 0) \cap (L_2 \leqslant 0) \cap (L_3 \leqslant 0)$ on the basis of which the probability of each failure mode can be calculated by Monte Carlo simulation. To determine the internal pressure P_{in}, thermal-hydraulic models for natural gas transmission pipelines are developed in TGNET - an offline simulation software for gas transmission pipelines.

The number of defects on a pipeline is uncertain and can be modeled by stochastic processes [48]. In this paper, the number of defects per kilometer of pipeline is modeled as a Poisson process. The Poisson rate is estimated as the average of defects in one kilometer, from pipeline internal detection findings. Pipeline failure probability due to corrosion is, then, calculated by summing the failure probabilities from the defects developing on it.

Failures due to wrong operation and third-party interference are random and the probability should be estimated on the basis of historical data. Probability of failure due to maintenance works can be also predicted, considering the regularity of each activity.

Finally, pipeline failure probability is estimated by summing the failure probabilities due to the different, mutually exclusive root causes of corrosion, wrong operation, third party interference and maintenance work.

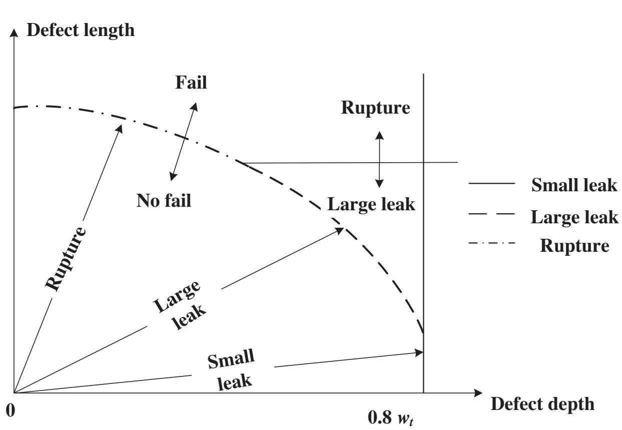

Fig. 3. The distinct pipeline failure modes.

3.2. Station failure rate estimation

Compared with pipelines, compressor stations, LNG (Liquefied Natural Gas) terminals and natural gas storages are relatively stable in their conditions of operation. Therefore, their failure probabilities are obtained from the statistics of historical data.

4. Development of the stochastic capacity network model

A stochastic capacity network model is developed to describe the stochastic evolution of running state of gas pipeline networks due to random failures of units.

The inputs of the developed model are as follows:

a. Geographical information of the pipeline network.
b. Information of the gas components.
c. Pipeline parameters: length, diameter, etc.
d. Compressor station parameters: compressor technical parameters, allocation of compressors.
e. Probability of the units of making transitions between different states of running and failure (estimated or calculated in Section 3 as failure probability).

The process of the model development, partly based on Section 3, is shown in Fig. 4。

4.1. Capacity network model

A capacity network model is here developed for the description of the system structure and the transportation capacity status. The capacity network model is a directed weighted graph. In the capacity network model, pipelines are represented as arcs of given capacity weights connecting nodes representing compressors, LNG stations, natural gas storages and demand sites. The capacity network model is directed, and the directions of gas flows are determined as explained in Section 5.1.

The capacity weights of the arcs, which represent the transportation capacity of pipelines, are calculated with the thermal-hydraulic model implemented in the Pipeline studio – TGNET (from Energy Solutions). Pipeline Studio is a pipeline management design software and engineering solution that combines reporting tools and graphical configuration with industry-proven simulation engines. It provides accurate and reliable answers to steady-state and transient analysis. Pipeline Studio can deliver accurate offline Pipeline management design, planning and hydraulic analysis for natural gas pipelines [49].

The capacity weights will change when the pipeline is in failure. The three failure modes of pipelines (small leak, large leak and rupture) are simulated by TGNET to calculate capacity degeneration of pipelines. Effects of compressor failure on pipeline capacity are also calculated by simulation.

4.2. The stochastic capacity state transition models of the natural gas pipeline network units based on Markov chains

To simulate the random changes of capacity states of the network units, Monte Carlo simulation (MCS) is adopted. In this work, we need to simulate the evolution process of the units running states, considering that each unit has multiple states and capacities in different states are different. In the evolution process, some transitions between states of units can occur bi-directionally, whereas some others are only one-way. We describe this as a Markov process, in which the states transition rates or probabilities are mathematically represented as transition rates or probability matrices, and state probabilities are eventually computed by solving a system of equations [50]. As introduced in Section 4.1, the transportation capacities of pipelines are represented as arc weights in the capacity network model. Hence, changes of units are equal to changing the weights on the network arcs.

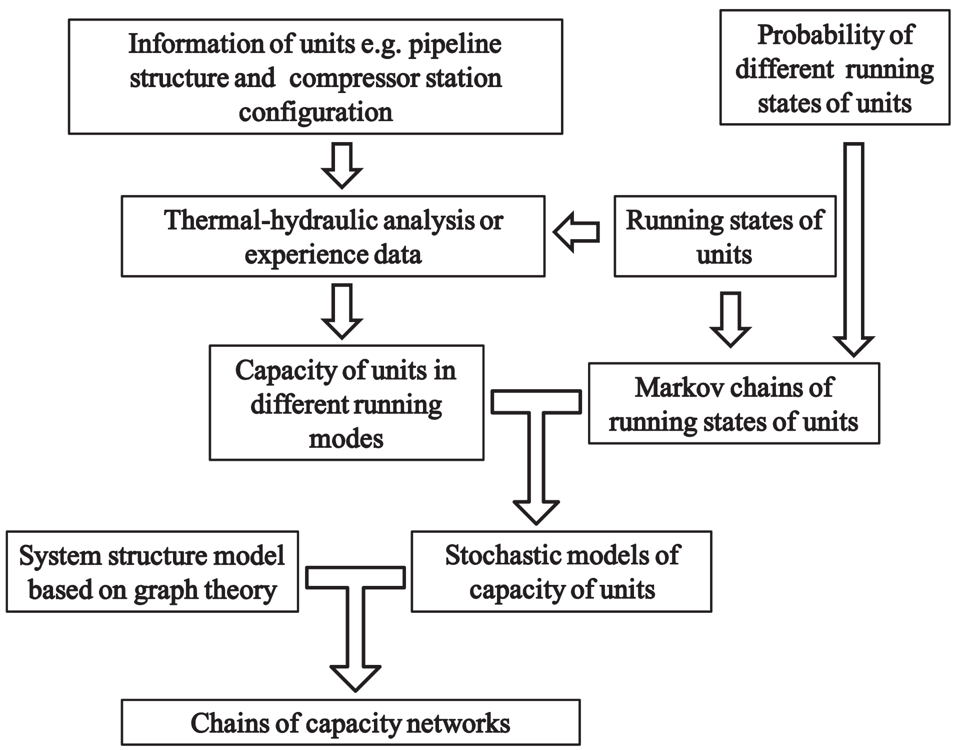

Fig. 4. Process of development of stochastic capacity network model.

In Sections 4.2.1–4.2.4, the definitions of states and transition rules are illustrated in detail.

The details of the Monte Carlo simulation of the Markov process are as follows, refer to the flowchart shown in Fig. 5:

(1) Set initial time $t = 0$, mission time $T = 1$ year and time step $\Delta t = 1$ month.
(2) The normal states of the units are set as their initial states. Based on the initial states, the capacity network model at $t = 0$ is generated.
(3) Until mission time T, Sample the units states in $t = t + \Delta t$, based on the transition probability matrices and the current states.
(4) Record the capacity network chains in this simulation year. A capacity network chain is a sequence of capacity network states occurring along the simulation time.
(5) Repeat the steps (2)–(5) for Nm times (here $Nm = 10^6$).
(6) Output the capacity network model chains.

4.2.1. Stochastic model for pipeline states transition

According to Section 3.1, there are three states of pipelines: normal, degeneration (small leak or large leak) and interruption (rupture or wrong operation), corresponding to three capacities. The normal state is able to transform bi-univocally with the other states or remain unchanged. The states of degeneration and interruption are reset to normal in the next time trial of simulation. Transition probability matrixes of pipelines are determined by failure probability (solved in Section 3.1), the relationship discussed above (shown in Fig. 6) and historical data.

4.2.2. Stochastic model for compressor station

According to practical experience, besides normal running state, two types of unexpected events may occur, which are again named in this work as degeneration, due to compressor failure, and interruption, caused by factors like total failure of the station and others. It is intuitive to understand the “compressor failure” event: only compressors fail whereas other components in the station are normal. On the other hand when degeneration occurs, the compressor station will maintain the gas transportation ability, but, the capacity of the surrounding pipelines reduces to a certain level, which can be calculated by thermal-hydraulic simulation. Finally during the interruption state, not only the ability of pressurizing but also that of transportation goes to zero. Interruption can be caused by several factors such as incorrect operation and maintenance work. The transitions among the states of compressor stations are again those of Fig. 5.

4.2.3. Stochastic model for LNG terminal

In this work, we consider three types of natural gas sources in a pipeline network: pipeline, natural gas storage and LNG terminal. Generally, upstream pipelines are stable gas sources, whereas the others are unstable because of their uncertain multiple states of supply.

Capacity of a LNG terminal is maintained within a normal range, but in a few situations, significant reduction of supply capacity, even interruption, may happen. The reasons of capacity reduction or supply interruption of LNG terminals are relevant to component performance, stability of LNG sources and rate of LNG consumption, and it is important to collect comprehensive historical data about the LNG terminal supply state [51]. The normal state can change to capacity reduction state or interruption state, and both of these can subsequently return to normal.

4.2.4. Stochastic model for natural gas storage

The supply states of natural gas storages and the transition scheme among these states are similar to those of the LNG terminals. According to experts and operators, capacity reduction and supply interruption of gas storages are mainly caused by facility failure and continuous withdrawal. The transition probabilities are estimated on the basis of historical data [51].

4.3. The stochastic capacity network model

According to the developed stochastic models in Section 4.2, the weights of the arcs in the capacity network model (Section 4.1) are changing stochastically in time. From the systemic point of view, the stochastic flow network model integrates the units stochastic models and the capacity network model to represent the dynamics of the

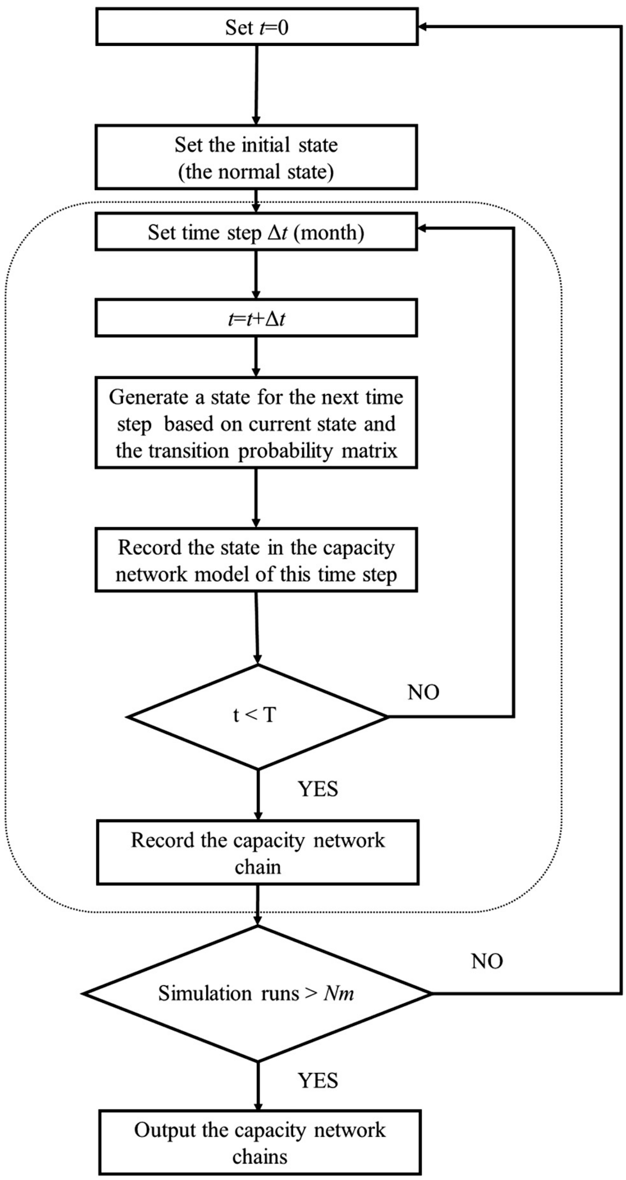

Fig. 5. The flow chart of MC simulation for the discrete Markov process evolution of one unit in the pipeline network.

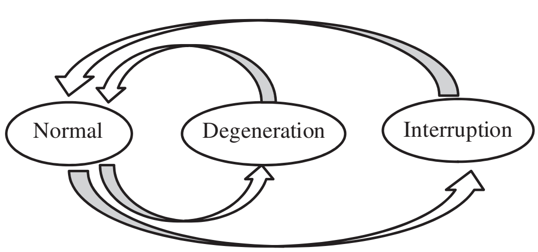

Fig. 6. States and transition rules of pipeline states.

natural gas pipeline network.

Fig. 6 presents a simple example of the capacity network model and the system stochastic evolution in time. In Fig. 7, a, b c (a′, b′, c′) are the weights of the arcs, which represent the capacities of the pipelines.

5. Development of the method for consequence/capacity analysis

When units fail stochastically, the network transmission capacity will reduce, leading to shortage of supply to customers. The consequence calculation is performed based on the capacity network model. Because the elements in the capacity network change stochastically, the calculation is repeated in every time step of the Markov chain. Transient condition is not considered here because of the relative long time step of stochastic simulation (month).

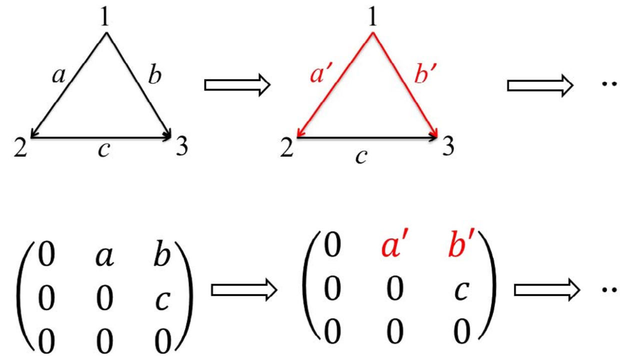

Fig. 7. Illustration about the stochastic network model.

The consequence calculation includes two steps:

a. Planning for natural gas transmission direction in the pipeline network.
b. Planning for maximum transmission capacity

To manifest the connection between stochastic analysis and consequence analysis in this research, a chart about the process of modeling of the two parts is shown in Fig. 8.

5.1. Planning for natural gas transmission direction in the network

In this paper, we consider that economical efficiency and supply distance are the most relevant attributes to gas transmission planning. Other conditions, e.g., political reasons and social impacts, are not considered in this paper. The process is as follows.

A. “Standard cost matrix” calculation

The “standard cost matrix” is an adjacent matrix based on the pipeline network structure and the “standard cost” on each arc. The so-called “standard cost” (calculated by Eq. (4) below) is determined by pipeline length and cost of transmission. The “standard cost” does not represent a real cost of transmission but a factor for optimization of transmission path. High value of “standard cost” corresponds to long distance and expensive cost of transmission. To differentiate the importance between these two factors, weights of importance of these parameters are assigned for the calculation of “standard cost”:

$$C_{ij} = \alpha L_{ij} \times \beta (Q_{ij} \times c) \tag{4}$$

where L_{ij} represents the length of the pipeline from node i to node j in the network (km); Q_{ij} represents the designed quantity of natural gas transported from i to j (MCM); c represents the cost of gas transportation ($/(km·MCM)); α and β, ranging from 0 to 1, represent the importance weights of distance and cost of transmission, respectively; C_{ij} represents the optimization factor combining cost and distance ($). Although the unit of the so-called “standard cost” is $, it is different from the actual cost.

Comparing with actual cost, the proposed “standard cost” is more suitable to present management principles under different conditions. In the real process of gas transmission planning, cost is not always the most important factor to be considered. For example, for long distance transmission with low density of customers, economical plans are preferred; whereas in the case of high density or importance of customers, transportation efficiency becomes more important than cost.

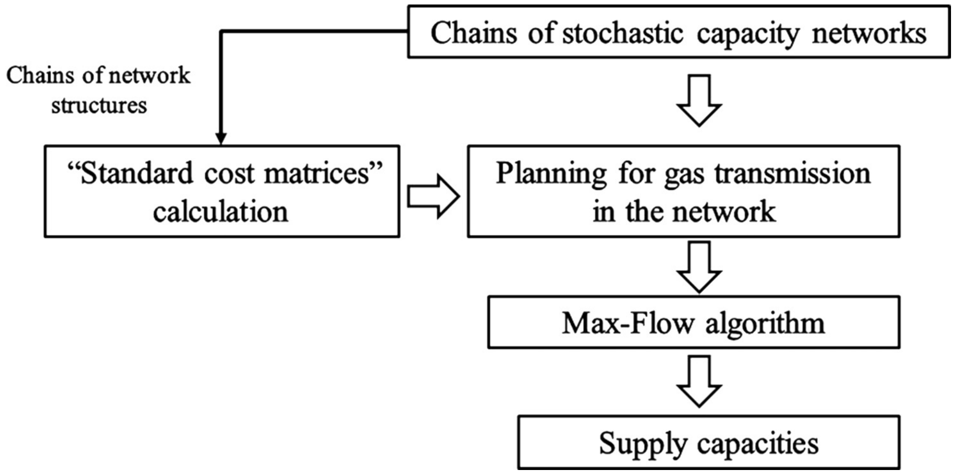

Fig. 8. Process consequence/capacity analysis of gas network system.

Considering this, we opted for using the "standard cost" as the objective of the optimization, and the different management principles are adopted by adjusting the weights in Eq. (4).

B. Gas flow direction determination

For transmission planning, the "best paths" from each gas source to every other node in the network, except other sources, are calculated with Floyd algorithm on the basis of the "standard cost matrix". Floyd algorithm is a method from graph theory, which is used to find "the shortest path" between different nodes in a graph [52], where "shortest" depends on the definition of the weights on the arcs of the graph. In our case, the "shortest path" is calculated with respect to the minimum "standard cost" and, thus, represents the "best path" considering both transmission distance and cost.

On the basis of "the best paths" from the gas sources to all other nodes in the network, all the nodes (except the gas sources) are ranked from low to high standard cost. Then, for each gas sources, an ordered node sequence is determined as best gas flow direction from low to high standard cost nodes.

C. Gas transmission planning

The range of customers that a gas source can supply is determined in this part. According to step B, a source will give priority to the nearby demand sites with highest economic efficiency. Then, the algorithm will check whether the capacity of the source is exhausted: If there are residual capacity and unsatisfied customers, the algorithm will search for the next unsatisfied demand site in the sequence found at step B. This process continues until the residual capacity of the source is zero or all customers are satisfied.

D. Adjustment for different conditions

As the capacity network evolves stochastically with time, the "standard cost matrix" will change together. Hence, the gas transmission planning in the network should be adjusted after occurrence of unexpected events. Because these events occur randomly in time, the steps from A to C are performed at every time step, for adjustment to the current network condition.

5.2. Transmission capacity calculation

For large scale and complex network structures, the difficulty to find the optimized distribution plan increases significantly. Operational research [53–56] and game-theory [57,58] methods are often used for resource distribution. And, considering the need of computational efficiency for large scale, complex networks, graph theory has emerged as a valuable alternate [2,59].

The calculation of supply capacity in both normal and unexpected conditions is converted to a maximum flow problem in graph theory. The aim of a maximum flow problem is to calculate the maximum transmission capacity between two nodes in a transportation network (source and sink). Several approaches have been put forward as solutions of the maximum flow problem in graph theory, e.g., Ford-Fulkerson algorithm, Dinic algorithm and so on. In this part, Ford-Fulkerson algorithm is carried out in two steps [60]:

- Search paths connecting the source and the sink with available capacity on the edges.
- Repeat the search process until no additional flow can be added to the path.

In the search, two constraints should be respected:

- The sum of the flow entering a node must be equal to the sum of the flow exiting the node (except for the source and the sink).
- The flow in the edges is non-negative and within the allocated capacities.

In general, there are multiple sources and sinks in a gas network and the flow from any source can be sent to any sink. This is known as a Multiple Sources and Sinks problem in graph theory, which can be converted into a one-sink and one-source problem by assuming a "super source" and a "super sink" connecting with all the sources and sinks by edges of unlimited capacities.

By so doing, supply capacity of a natural gas pipeline network in different scenarios, gas amount served to every demand site and actual gas flow in the pipeline are obtained for supply reliability assessment.

6. Supply reliability assessment of natural gas pipeline networks

Evaluation of supply reliability in a natural gas network consists of two aspects: global and individual. The global aspect represents the functional integrity of the network system; the individual aspect reflects the ability of the network system to satisfy the customers' demands. The latter is more important for evaluating supply reliability. Statistical characteristics of the capacity of gas networks, which represent the ability of the pipeline network to serve the customers stably and continuously, are calculated from a global point of view. However considering the differences among individual gas demand sites e.g. spatial location and amount of gas demands, the gas network may not be able to satisfy all customers under all conditions. In other words, satisfied demand of customers-a relevant aspect for supply security- can vary

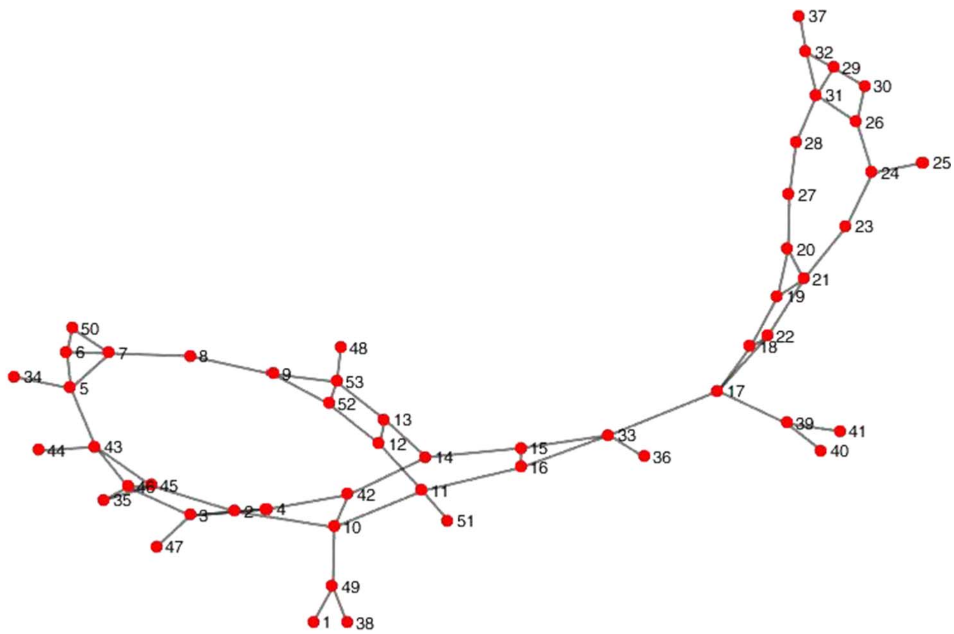

Fig. 9. Layout of the natural gas transmission network.

among customers. Hence, it is necessary to perform also an analysis for each individual customer served by the natural gas pipeline network.

For a comprehensive assessment of each customer, indices are developed from three aspects similar to what is done for power grids [61]: probability, adequacy and time. Indices reporting probability (calculated by Eqs. (5) and (6) below) are used to estimate the frequency of dissatisfaction of every customer and predict the ability that the gas network can satisfy each customer under the occurrence of unexpected events. Adequacy is used to capture the consequences of unexpected events on system and every customer. Time of supply shortage or interruption further reflects the severity of consequences, as a 1 h interruption and a 24 h interruption obviously cause different effects. Although the forms of the defined indices are novel, the concepts behind them are already frequently used in routine operation and management. The aim of the developed indices is helping to quantify the (abstract) management concepts of supply security. The purposes and the application of these developed indices will be illustrated in detail in the case study.

6.1. Indices of probability

Reliability can be calculated varying with different customers in pipeline supply networks. For simplicity, the reliability of supply at a demand site is here illustrated by an exponential estimation of Eq. (5), in which Rate of shortage (*ROS*) is equivalent to conventional (system/component) failure rate. *ROS* is estimated by Eq. (6).

$$Reliability = e^{-ROS\cdot t} \tag{5}$$

$$ROS = \frac{Number\ of\ customer\ shortages}{number\ of\ months} \tag{6}$$

6.2. Indices of adequacy

$$Global\ average\ natural\ gas\ shortage = \frac{sum\ of\ all\ global\ natural\ gas\ shortages}{number\ of\ \ months} \tag{7}$$

In Eq. (7), *Global average natural gas shortage means* total probable shortage of natural gas supplied by the gas pipeline network system in one month. *Sum of all global natural gas shortages* means the summation of the amount of gas shortages occurred in the simulations.

$$Average\ number\ of\ unsatisfied\ customers = \frac{sum\ of\ unsatisfied\ customers}{number\ of\ months} \tag{8}$$

In Eq. (8), ***Average number of unsatisfied customers*** means the average number (per month) of customers (or demand nodes) whose demands are not 100% satisfied by the pipeline network. *Sum of unsatisfied customers* means the summation of the number of unsatisfied customers (or nodes) during all simulations.

$$Average\ natural\ gas\ shortage\ of\ a\ customer = \frac{sum\ of\ natural\ gas\ shortage\ of\ a\ customer}{number\ of\ months} \tag{9}$$

In Eq. (9), ***Average natural gas shortage*** of a customer means the average amount of natural gas shortage of one customer per month. *Sum of natural gas shortage of a customer* means the summation of amount of natural gas shortage of one customer during the simulations.

6.3. Index of duration of shortage

$$Average\ shortage\ duration = \frac{\sum_{times\ of\ shortage\ of\ the\ customer} duration\ of\ each\ shortage\ event}{number\ of\ months} \tag{10}$$

In Eq. (10), the duration time of shortage event is sampled randomly [27]. *Average shortage duration* means the average duration of shortage events of one customer per month.

7. Case study

The application of the developed method has been performed on a fictitious natural gas network, assuming reasonable and coherent information and data of pipeline network, including pipeline parameters, customer demands, gas source capacity and compressor station parameters. The network is shown in Fig. 9. Assumptions about locations, types and capacities of the gas sources are reported in Table 1, whereas the demands of customers are listed in Table 2.

The unit — MCM/d is the acronym of “million cubic meters per day”.

Table 1
Properties of the gas sources of the gas network.

Location	Type	Limit (MCM/d)
9	Storage	4
10	Pipeline	31
15	LNG terminal	10
18	Pipeline	25
50	LNG terminal	7.1

Table 2
Demands of customers of the gas network.

Location	Demand (MCM/d)	Location	Demand (MCM/d)
4	1.43	31	0.80
5	1.57	34	0.80
7	1.66	35	1.10
12	1.46	37	0.90
16	4.40	38	1.74
17	1.54	40	1.30
20	0.50	41	2.00
24	1.50	42	1.80
25	1.60	43	1.40
26	1.80	46	0.50
28	2.50	49	1.20
29	2.00	51	0.98

The actual operation of the natural gas storage is considered by monitoring the operating point (withdrawal/injection rate – working gas inventory) and ensuring this point lies within the storage envelope. However, the operating region of LNG terminal is limited by the LNG working inventory and regasification capacity.

Transportation capacities of pipelines in normal and unexpected conditions were estimated by thermal-hydraulic simulation. Internal pressure distributions in pipelines were also simulated, for pipeline failure analysis in the next step. The thermal-hydraulic models for each pipeline were developed by the professional software-TGNET with the assumed data, and the recommended data in TGNET (e.g. constituents of natural gas, compressor parameters and pipe roughness).

Information about structure defects can be obtained through pipeline internal detection. Generally, defect properties of pipelines in different environments are varied. Because of lack of data, the diversity of defect properties is ignored in this paper, but this is not a drawback of the method and can be easily incorporated. The defect statistic properties considered are given in Table 3.

Failure probability of a pipeline is calculated as the sum of the failure probabilities of all defects present on it. Number of defects per kilometer pipeline is estimated by Poisson process. Defect failure probability is estimated by the method mentioned in Section 3.1. Burst pressure and rupture pressure in the limit functions are estimated by PCORRC model [62] (Eqs. (11) and (12) below) and Kiefner model [63] (Eq. (13)), respectively.

$$P_{rupture} = \frac{2\sigma_f W_t}{MD} \tag{11}$$

$$M = \begin{cases} \sqrt{1 + 0.6275\frac{L^2}{DW_t} - 0.003375\left(\frac{L^2}{DW_t}\right)^2} & L \leqslant \sqrt{50W_t} \\ 3.3 + 0.032\frac{L^2}{DW_t} & L > \sqrt{50W_t} \end{cases} \tag{12}$$

$$P_{burst} = \xi\frac{2\sigma_u w_t}{D}\left[1 - \frac{d}{w_t}\left(1 - \exp\left(\frac{-0.157L}{\sqrt{\frac{D(w_t-d)}{2}}}\right)\right)\right] \tag{13}$$

where the notations in the equations are: M - the Folias factor that accounts for bulging of the pipe before failure; σ_f - the flow stress, (MPa), the material property corresponding to yield strength; L - length of defects, (mm); D - pipe diameter, (mm); W_t - pipe wall thickness, (mm); $P_{rupture}$ - failure pressure of rupture, (MPa); P_{burst} - failure pressure of burst, (MPa); σ_u - pipe ultimate tensile strength (MPa); ξ - multiplicative model error term.

Internal pressures of pipelines are calculated by thermal-hydraulic analysis based on TGNET. We sample space locations randomly for every defect in order to distribute an operation pressure for each of them.

According to the historical data and empirical evaluation from engineers, failure probability of different modes can be are estimated for LNG terminal and natural gas storage.

Based on the results of the unit failure analysis and the results of capacity calculations, the stochastic capacity network model for the considered natural gas pipeline network was developed. The development procedure is illustrated in details in Sections 4.

The supply reliability is assessed under three scenarios.

A. All natural gas sources are supplying normally. This is the baseline case.
B. LNG terminal A at node 50 with an upper limit capacity of 7.1 MCM/d, is removed from the system.
C. LNG terminal B at node 15 with an upper limit capacity of 10 MCM/d, is removed from the system.
D. The UGS at node 9 with an upper limit capacity of 4 MCM/d, is removed from the system.
E. The pipeline connecting node 10 and node 2 is removed from the system.

In these scenarios, states or supply capacities of the units (including pipelines, compressor stations, natural gas storage and LNG terminals) might change randomly, as modeled by the Markov chains presented in Section 4.2. According to the operator of a natural gas pipeline company, it is estimated that the probabilities of function degeneration of compressor station, LNG terminal and UGS (Underground Gas Storage) are 0.020, 0.015 and 0.015 (per month), respectively. The probabilities of function interruption of compressor station, LNG terminal and UGS are assumed as 0.001 (per month).

One million Markov chains simulations were generated for each scenario, and for each of them the state of supply-demand condition was estimated through the method developed in Section 5. The simulations were performed on a monthly basis, while the data of gas flow, supply and demand were presented at a daily scale.

The cumulative distribution functions of global capacity for the three scenarios are shown in Fig. 10.

The statistics of the supply capacities in the different scenarios, including maximum, minimum, mean, standard deviation and variation coefficient are reported in Table 4.

According to the results, the pipeline network considered has a robust ability to maintain the global supply capacity at the level of 41.21

Table 3
Statistical properties of pipeline structure and defects.

No.	Parameters	Average dimension	Coefficient variation	Distribution type
1	Yield strength (MPa)	353	0.06	Normal
2	Pipe wall thickness (mm)	7	0.05	Normal
3	Defect depth (mm)	2.5	0.1	Lognormal
4	Defect length (mm)	300	0.05	Lognormal
5	Corrosion rate in depth (mm)	0.125	0.2	Normal
6	Corrosion rate in length (mm)	0.15	0.2	Normal
7	Defect number on pipeline (per kilometer)	3	–	Poisson

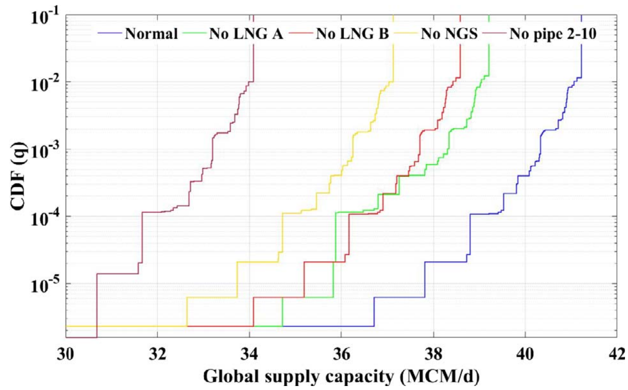

Fig. 10. Supply reliability in global system perspective expressed by CDF of global supply capacity.

Table 4
Statistics of global capacity of supply.

Scenario	Max (MCM/d)	Min (MCM/d)	Mean (MCM/d)	std
A	41.21	34.08	41.20	0.061
B	39.21	30.42	39.20	0.072
C	38.58	31.45	38.56	0.061
D	37.13	30.00	37.12	0.059
E	34.08	29.58	34.07	0.056

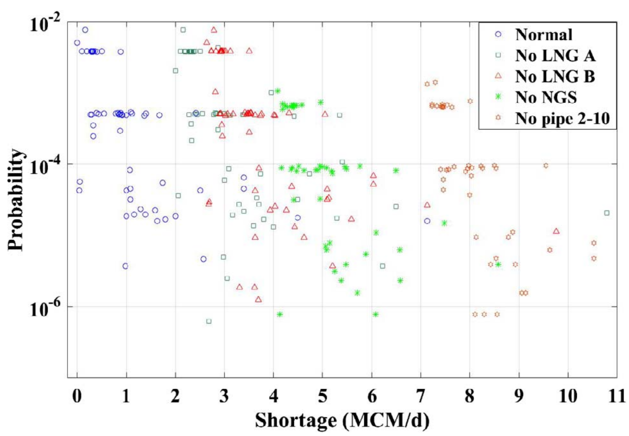

Fig. 11. Consequence/probability plot for reliability/risk analysis of gas supply.

Table 5
Results of global system supply reliability.

Scenario	Average global shortage (MCM/month)	Average amount of unsatisfied customers (per month)
A	0.0049	0.0118
B	0.0365	1.0128
C	0.0479	2.0118
D	0.0743	3.0103
E	0.1285	0.9907

MCM/d (with probability higher than 99%). Jumps in the CDF correspond to the effects of unexpected, stochastic events on global supply capacity. In the range of probability values from 10^{-4} to 10^{-2}, most of the "CDF jumps" are small, whereas visible "jumps" are concentrated in the range of probability values from 10^{-6} to 10^{-4}. We can conclude that the natural gas pipeline network considered can reliably supply gas to the customers, even under unexpected, stochastic failures of its units. Hence, the results provide a comprehensive picture of Comparing scenario B and scenario C, we observe that LNG terminals at different

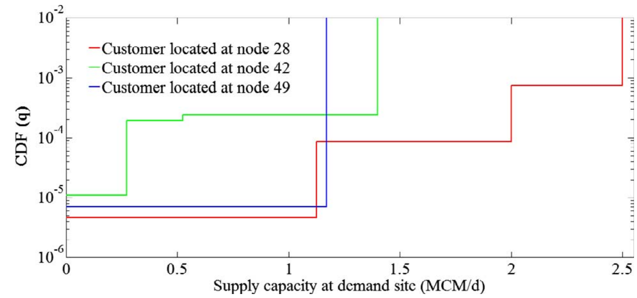

Fig. 12. Supply capacity at different demand sites in scenario A.

Table 6
Some results of supply capacity statistics at demand sites in different scenarios.

Scenario	Customer	max (MCM/d)	min (MCM/d)	mean (MCM/d)	cv%	std
A	4	1.430	0.644	1.4290	0.7370	0.0105
	5	1.660	0.747	1.6597	0.7266	0.0121
	34	0.800	0.360	0.7998	0.6830	0.0059
B	4	1.430	0.644	1.4290	0.7370	0.0105
	5	1.660	0	1.6595	1.2161	0.0202
	34	0.800	0.360	0.7998	1.7489	0.0059
C	4	1.430	0.644	1.4290	0.7361	0.0105
	5	1.660	0.747	1.6597	0.7266	0.0121
	34	0.800	0.360	0.7998	0.6830	0.0059
D	4	1.430	1.425	1.4290	0.7361	0.0105
	5	1.660	0.747	1.6597	0.7266	0.0121
	34	0.800	0.360	0.7999	0.6830	0.0059
E	4	1.430	0	1.4297	0.7953	0.0113
	5	1.660	0	1.6597	0.7664	0.0127
	34	0.800	0.360	0.7998	0.7504	0.0060

Table 7
Results of *ROS* at all demand sites in different scenarios (10^{-4} time/month).

No.	Scenario A		Scenario B		Scenario E	
	Rate of slight shortage	Rate of severe shortage	Rate of slight shortage	Rate of severe shortage	Rate of slight shortage	Rate of severe shortage
4	7.5000	0.9268	7.5000	0.9268	7.5779	1.1293
5	7.3910	0.9502	7.3910	0.9502	7.3910	0.9502
6	7.0171	0.9424	9.9065	2.8972	7.2118	0.8489
12	7.4455	0.9579	7.4455	0.9579	7.2741	0.8255
16	7.0794	0.8956	7.0794	0.8956	7.7804	0.8956
17	7.1963	0.8489	7.1963	0.8489	7.5623	0.9268
20	7.2975	0.8567	7.2975	0.8567	7.1651	0.7477
24	7.2741	1.0981	7.2741	1.0981	7.1262	1.0592
25	0.1402	0.1402	0.1402	0.1402	0.1402	0.1402
27	7.4299	0.8645	7.4299	0.8665	7.5000	0.7788
29	7.4533	0.9112	7.4533	0.9112	7.1340	0.9034
32	7.3442	0.8956	7.3442	0.8956	7.9206	0.9190
33	7.5667	0.9034	7.5764	0.9034	7.3988	0.9346
34	1.8925	0.9735	9.2134	2.8271	1.8925	0.9735
35	0.0078	0.0078	0.0079	0.0079	9906.5421	9906.5421
36	1.6044	0.1246	1.6044	0.1246	1.5888	0.0779
37	0.0857	0.0623	0.0857	0.0623	0.0857	0.0545
38	8.3022	2.0717	8.3022	2.0717	8.6215	2.1651
40	0.0700	0.0700	0.0701	0.0701	0.0467	0.0467
41	2.4143	2.4143	2.4143	2.4143	2.3598	2.3598
42	7.3209	0.7943	7.3209	0.7944	7.1417	0.9657
44	0.9657	0.9268	0.9658	0.9268	0.9658	0.9268
46	7.0327	0.8100	7.0327	0.8100	9906.5421	9906.5421
47	0.0078	0.0078	0.0078	0.0078	9906.5421	9906.5421
48	0.0701	0.0701	0.0701	0.0701	0.0156	0.0156
51	0.0156	0.0156	0.0156	0.0156	0.0078	0.0078

location play different roles in system supply capacity and have different impacts on different customers.

Consequence and probabilities are combined in Fig. 11, for a

Table 8
Results of reliability of supply at all demand sites in different scenarios.

No. of customers	Scenario A		Scenario B		Scenario E	
	Normal reliability	Urgency reliability	Normal reliability	Urgency reliability	Normal reliability	Urgency reliability
4	0.99926	0.999907	0.99926	0.999907	0.99924	0.999887
5	0.99926	0.999905	0.99927	0.999904	0.99927	0.999904
6	0.99930	0.999906	0.99901	0.999710	0.99928	0.999915
12	0.99926	0.999904	0.99925	0.999904	0.99927	0.999917
16	0.99929	0.999910	0.99929	0.999910	0.99922	0.999910
17	0.99928	0.999915	0.99928	0.999915	0.99924	0.999907
20	0.99927	0.999914	0.99927	0.999914	0.99928	0.999925
24	0.99927	0.999890	0.99927	0.999890	0.99929	0.999894
25	0.99999	0.999986	0.99998	0.999985	0.99999	0.999986
27	0.99926	0.999914	0.99926	0.999914	0.99925	0.999922
29	0.99925	0.999909	0.99925	0.999910	0.99929	0.999910
32	0.99927	0.999910	0.99927	0.999910	0.99921	0.999908
33	0.99927	0.999910	0.99927	0.999914	0.99926	0.999907
34	0.99981	0.999903	0.99924	0.999717	0.99979	0.999987
35	0.99999	0.999999	0.99999	0.999999	0.37133	0.371334
36	0.99984	0.999986	0.99984	0.999986	0.99984	0.999992
37	0.99999	0.999994	0.99999	0.999993	0.99999	0.999995
38	0.99917	0.999793	0.99917	0.999793	0.99914	0.999784
40	0.99999	0.999992	0.99999	0.999992	0.99999	0.999995
41	0.99976	0.999759	0.99976	0.999759	0.99976	0.999764
42	0.99927	0.999921	0.99927	0.999921	0.99929	0.999903
44	0.99990	0.999907	0.99990	0.999907	0.99990	0.999907
46	0.99930	0.999919	0.99930	0.999919	0.37133	0.371334
47	0.99999	0.999999	0.99999	0.999999	0.37133	0.371334
48	0.99999	0.999993	0.99999	0.999993	0.99999	0.999998
51	0.99999	0.999998	0.99999	0.999998	0.99999	0.999999

Table 9
Average shortage in a month ($\times 10^{-4}$ MCM).

NO.	Scenario A	Scenario B	Scenario C	Scenario D	Scenario E
4	0.0473	2.6089	2.6089	2.6089	2.7575
5	0.0447	2.8539	2.8539	2.8539	2.8539
6	0.0469	5.1881	2.8772	2.8772	2.9632
12	0.0422	8.0273	8.0273	8.1396	7.6726
16	0.0441	2.6632	2.6632	2.6632	2.8791
17	0.0423	0.8682	0.8682	0.8682	0.9184
20	0.0455	2.6390	2.6390	2.6390	2.5421
24	0.0010	3.0212	3.0212	3.0212	2.9632
25	0.0448	0.2523	0.2523	0.2523	0.2523
27	0.0445	4.5239	4.5239	4.5239	4.4665
29	0.0452	3.6192	3.6192	3.6192	3.4860
32	0.0452	1.4259	1.4259	1.4259	1.5246
33	0.0484	1.4604	1.4604	1.4304	1.4455
34	0.0118	4.0405	0.8705	0.8705	9906.6217
35	1.9155×10^{-5}	0.0079	0.0079	0.0078	0.0079
36	0.0100	0.8256	0.8256	0.8256	0.7588
37	0.0005	0.0802	0.0802	0.0802	0.0678
38	0.0510	2.2080	2.2080	2.2080	2.3251
40	0.0004	0.1402	0.1402	0.1402	0.0935
41	0.0149	2.6319	2.6319	2.6319	2.5754
42	0.0443	0.8764	0.8764	0.8764	0.8902
44	0.0055	0.9945	0.9945	0.9945	0.9945
46	0.0425	3.0822	3.0822	3.0822	18029.9065
47	4.885×10^{-5}	0.0053	0.0053	0.0053	6736.4486
48	61.5480	0.0821	0.0821	0.0820	0.0182
51	9.8730×10^{-5}	0.0153	0.0153	0.2567	0.0076

comprehensive analysis of reliability and risk of supply.

In the normal scenario, the highest consequence is the gas shortage of about 7.2 MCM/d with probability of around 10^{-6}. Most of the consequences are concentrated within the range of 0 MCM/d to 2 MCM/d, and the probability of more than half of the consequence is lower than 10^{-4}. The consequences under scenarios B and C move towards large values of loss of service. To quantify the loss of service, the average of global shortage and the average of unsatisfied customers are calculated according to Section 5. The results are shown in Table 5.

From the results in Table 5, the possible loss under the given condition is measured, which can be further applied by operators and managers to decide whether a system or development is necessary. Besides, by comparing the results of scenarios A, D and E, one can find that the different impacts of different types of unit failure: removing the UGS results in a relatively wide-scale consequence with low severity; removing a pipeline results in a local, but more severe consequence. This result means that the gas pipeline network has good global robustness because of its flexibility; however, some customers are vulnerable because of the critical pipelines connecting them and the sources. Hence, managers should pay much attention to these vulnerable points and improve their information of reliability of both the global system and the local customers in different parts.

The results above provide a comprehensive picture about the ability of the global system to supply the customers stably under given conditions, i.e. environment, component capacities, system structure, etc. The contributions of different units to supply reliability can be figured out by comparing the results under different scenarios. The results of the developed method give the managers and operators the quantified, specific knowledge about the characteristics of supply security of the target system, rather than just estimating abstract probability by traditional methods. This knowledge can help to develop and operate a more reliable system and to make more reasonable decisions.

However, the ability to supply all customers reliably does not mean high reliability of supply for every customer because of their differences of demand, location and other properties (Fig. 12). It is, then, necessary to perform specific evaluations for every demand site, in order to get a more comprehensive result.

On the basis of the simulation results and the data about demand of every customer, the statistic properties of unsatisfied demand at each demand site are calculated. Some results are reported in the following Table 6.

For the analysis, we define two levels of shortage: slight shortage (0.75 demand < supply capacity < demand) and severe shortage (supply capacity < 0.75 demand). Correspondingly, there are two levels of supply reliability at each demand site: urgency reliability and normal reliability, calculated by rate of severe shortage and slight

Table 10
Average duration of shortage in a month (h).

NO.	Scenario A	Scenario B	Scenario C	Scenario D	Scenario E
4	0.0180	0.0478	0.0473	0.0468	0.0182
5	0.0177	0.0453	0.0447	0.0465	0.0572
6	0.0168	0.0596	0.0469	0.0435	0.0173
12	0.0181	0.0455	0.0422	0.0458	0.0175
16	0.0437	0.0439	0.0441	0.0445	0.0187
17	0.0173	0.0424	0.0423	0.0470	0.0181
20	0.0175	0.0450	0.0455	0.0437	0.0172
24	0.0175	0.0456	0.0010	0.0434	0.0171
25	0.0003	0.0008	0.0448	0.0001	0.0003
27	0.0178	0.0448	0.0445	0.0448	0.0180
29	0.0179	0.0462	0.0452	0.0463	0.0171
32	0.0176	0.0446	0.0452	0.0453	0.0190
33	0.0463	0.0464	0.0484	0.0463	0.0178
34	0.0045	0.0554	0.0118	0.0113	0.0120
35	1.8762×10^{-5}	1.4444×10^{-6}	1.9155×10^{-5}	8.2610×10^{-6}	39.7859
36	0.0105	0.0098	0.0100	0.0105	0.0038
37	0.0002	0.0004	0.0005	0.0005	0.0002
38	0.0199	0.0515	0.0510	0.0510	0.0207
40	0.0002	0.0005	0.0004	0.0002	0.0001
41	0.0058	0.0143	0.0149	0.0155	0.0057
42	0.0176	0.0449	0.0443	0.0459	0.0171
44	0.0023	0.0049	0.0055	0.0061	0.0063
46	0.0169	0.0425	0.0425	0.0419	44.0543
47	1.8692×10^{-5}	9.5978×10^{-5}	4.885×10^{-5}	1.5361×10^{-5}	42.0746
48	0.0002	0.0003	61.5480	0.0004	3.7383×10^{-5}
51	0.0027	5.2087×10^{-5}	9.8730×10^{-5}	5.0741×10^{-5}	1.8692×10^{-5}

shortage, respectively. The rate of shortages are calculated by Eq. (5) and reported in Table 7. The monthly reliability of supply calculated by Eq. (6) is listed in Table 8. To present a clear layout, the results of three representative scenarios (normal, one gas source failure and one pipeline failure) are selected to be listed in this table.

The adequacy of gas supply to a customer is calculated by Eq. (9) (Table 9) and the average duration of shortage in a month is calculated by Eq. (10) (Table 10). According to the information in [64], duration of each shortage follows a lognormal distribution with standard deviation (58.96 h) and mean (47.53 h).

The results obtained in the case study have illustrated the roles of the probability indices, the adequacy indices and the time index in the supply reliability assessment, and the complementing among them. For example, in scenario A, by comparing the probability indices at node 34 and node 42, we find that customers at node 42 suffer from a much higher frequency of shortage than those at node 34. However, the results of adequacy show that the severities of the gas shortage are nearly the same. Hence, instead of focusing on high probability of shortage at node 42, managers should pay more attention to node 34 because of the high consequence of a disturbance. Besides, comparing scenario B and scenario C, we observe that LNG terminals at different locations play different roles in global supply capacity (Table 5), and have different impacts on different customers. For example, results in Table 9 and Table 10 show that removing the LNG terminal at node 51 results to the dropping of supply at node 7 and node 34, and removing the LNG terminal at node 15 results to decrease of supply at node 48.

The reliability results from customers' viewpoint perform a more detailed and comprehensive assessment of the system ability to serve every customer reliably. Besides probability results, quantified losses considering amount of gas and duration of negative impacts are also provided for every customer, which helps to uncover the problems, such as those discussed in the last paragraph, difficult to be found from a global perspective.

8. Conclusions and future work

We have developed a method and proposed quantitative indices for supply reliability assessment in natural gas pipeline networks. In the developed method, methods including stochastic processes, graph theory and thermal-hydraulic simulation are integrated considering uncertainty and complexity in natural gas pipeline network systems. The results of the application of the method on a test case have been presented and discussed thoroughly. The assessment proceeds in three stages: unit failure analysis, system analysis and reliability evaluation.

For the unit failure analysis of pipelines, methods of structure reliability analysis are used to analyze the complicated relationship between diverse influencing factors and failure modes. The data for limit state functions can be obtained from the results of internal inspection. The failure analysis of compressor stations, LNG terminals and natural gas storages, failure analysis is performed on the basis of historical data.

Internal pressure and pipeline capacity under different running conditions are obtained by the simulation of the thermal-hydraulic model considering the structure properties of pipelines, configuration of compressor stations and natural gas constituents. To simulate the complex physical process of natural gas transmission in pipelines, TGNET is used to compute the thermal-hydraulic models for every pipeline in the network.

For the analysis of network capacity and supply service consequence, a stochastic simulation model for the network system is developed on the basis of stochastic process and graph theory. Graph theory is used for the system description, planning and consequence analysis. The stochastic Markov process modeling is used to simulate the random evolution of the system in time, due to the stochastic transitions of the states of its units.

Reliability modeling and concepts derived from power system reliability assessment are used for the supply reliability assessment with respect to two aspects: global system and individual customers. Global supply reliability is estimated with the statistical properties of system capacity; supply reliability analysis of individual customers is performed on the basis of consequence analysis and demands data.

The developed method will be supplemented and improved in several aspects in the future, especially analyzing network capacities and consequences of unit failures considering the transient physical processes and operations, for example, capturing the pressure off-limit in short periods. Besides, the probabilistic demand of loads will also be included in the modeling framework.

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