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A Modelling and Computational Framework for the Assessment of the Supply Resilience of Gas Transmission Pipeline Networks

Masoud Naseri

Department of Energy, Politecnico di Milano, Italy. masoud.naseri@polimi.it

Enrico Zio

Centre de Recherche sur les Risques et les Crises (CRC), MINES Paris-PSL University, France
Department of Energy, Politecnico di Milano, Italy. enrico.zio@polimi.it

Natural gas transmission pipeline (NGTP) networks are infrastructures, whose operation is critical in view of growing global energy demand. Unexpected natural gas supply interruptions have occurred in the last decade, highlighting the critical role of reliability and resilience of NGTP networks. Graph theory, complex networks analysis, thermal-hydraulic and transient/steady-state gas flow models have been applied to assess the capacity and flow of gas pipeline networks. NGTP networks are considered as multi-component systems subject to single failure modes of a rate often assumed constant. The flow analyses are performed for the whole network without considering the priority of gas-receiving terminals and the associated different penalty schemes for gas not supplied. The present work proposes a framework for modelling and analysing of the capacity and flow of NGTP networks subject to multiple failure causes and considering repairs. Graph theory and Markov chain are used for modelling and a Monte Carlo Simulation is used for quantification. A numerical example is used to illustrate the overall modelling and computational framework. The results of the application of the modelling and computational framework here proposed work can inform operational management strategies for reducing the risk of service disruption and improving NGTP resilience.

Keywords: Gas pipeline networks, supply resilience, network flow analysis, Markov chain, network flow optimisation, Monte Carlo simulation.

1 Introduction

Global natural gas consumption is projected to reach 4,200 billion m^3 per year by 2050 (Sesini, Giarola and Hawkes, 2020). In the EU, gas supplies one-quarter of primary energy and plays a key role in coal-to-gas power generation, potentially replacing up to 50% of the EU's coal-fired power to reduce greenhouse emissions (IEA, 2019).

Considering the crucial role of gas in the EU's energy mix, ensuring a secure, reliable and cost-effective gas supply is essential (Percebois, 2008). However, gas supply disruptions remain a major concern. Over the past two decades, Europe has reported more than 388 incidents in gas transmission pipelines (Austvik, 2016; EGIG, 2020).

Then, resilience has become a key driver in Natural gas transmission pipeline (NGTP)network design and operation (Jiang *et al.*, 2023; Cimellaro, Villa and Bruneau, 2015; Dell'Isola *et al.*, 2020; Okoro, Khan and Ahmed, 2022). Monte Carlo (MC) simulation of damage and recovery of pipelines (Su *et al.*, 2018b; Su *et al.*, 2018c; Fan *et al.*, 2022; Sacco *et al.*, 2019; Compare *et al.*, 2020), coupled with hydraulic analysis of network gas flow (Jiang *et al.*, 2023), graph theory- and flow-based methods (Li *et al.*, 2021; Praks, Kopustinskas and Masera, 2015; Qiao *et al.*, 2017; Su *et al.*, 2018a; Su *et al.*, 2022) have been used for assessing the resilience of natural gas supply and suggesting operational management strategies to reduce the risk of service disruption.

These assessments often consider a single failure mode for pipeline failures. However, in practice, pipelines can have different failure modes such as corrosion-related leakage and rupture, and may fail for multiple reasons (Pettitt and Morgan, 2009). Since required maintenance tasks and network downtimes depend on the type of failure, neglecting the analysis of multiple failure modes may lead to unrealistic results.

Methods for assessing gas pipeline network resilience often rely on network flow capacity models to estimate flow under various disruption scenarios. While thermal-hydraulic models (Su *et* *al.*, 2018a) and steady-state/transient-state gas flow models (Liu, Shahidehpour and Wang, 2011; Jiang *et al.*, 2023; Su *et al.*, 2022) offer high accuracy, they require numerous parameters, such as operating temperature, gas composition, altitude changes and pipeline roughness, making them computationally expensive, especially for large transnational NGTP networks. Graph-based flow algorithms, like Floyd's algorithm (e.g., see (Su *et al.*, 2018a)), compute maximum network capacity between virtual super-sink and super-source nodes, but fail to consider priority differences among gas-receiving terminals during disruptions.

In fact, NGTP networks span multiple countries, and therefore, pipeline failures can disrupt gas supplies across borders affecting multiple parties. For example, Norwegian Continental Shelf pipelines supply over 25% of the EU gas market, with delivery points at Germany, Belgium, and France, from which gas is further exported to the Netherlands and Denmark (Norskpetroleum, 2025). In addition, nationally, different gas-receiving terminals may be more vulnerable to gas supply disruptions and must therefore be prioritised for protection and resilience.

Supply shortages or extended downtimes force producers to either buy extra gas downstream or pay penalties for contract violations (Rømo et al., 2009). The impact depends on alternative supply availability and the location of receiving terminals within the extensive transmission network where the supply shortage must be addressed. Therefore, optimising network flow requires node importance measures and differentiated penalty schemes in addition to the operating cost considerations, which conventional graph-based flow algorithms do not often provide.

This work introduces a modelling and computational framework that integrates node-importance-based flow optimisation and a multi-component, multi-state network Markov chain model, solved using Monte Carlo (MC) simulation. The proposed framework leverages graph theory (Gross, Yellen and Anderson, 2018) and complex network analysis to estimate the optimised network flow in a NGTP system represented as a directed graph, whose topology and functional characteristics evolve stochastically over time due to the random nature of damage and recovery processes affecting network components functionality and flow capacity.

This framework can be applied for the operational management of gas networks, for enhancing the supply resilience in response to network disruptions.

The rest of the paper is organised as follows. Section 2 introduces the proposed computational framework, detailing its key elements, including the network flow optimisation model and the network state transition simulation framework. Section 3 illustrates the application of the framework through a case study. Section 4 presents conclusions and suggestions for future work.

2 Modelling and Computational Framework

The proposed modelling and computational framework consists in two main parts: A node-importance-based flow optimisation model, and a MC simulation-based framework where network's stochastic evolution is modelled.

2.1 Network Flow Optimisation Model

Let us consider an offshore NGTP network, where gas can flow in only one direction. A directed graph $G(V, E)$ (Gross, Yellen and Anderson, 2018) is used to model the network with nodes $i \in V$, representing the receiving terminals, and production or supply facilities, and edges $(i, j) \in E$, $i, j \in V$, $i \neq j$, representing network pipelines. Further, let $V^D \subset V$ and $V^S \subset V$ denote a set of demand nodes (i.e., onshore gas delivery terminals) and offshore production facilities, respectively.

Production facility $i \in V^S$ has a maximum production capacity of s_i and gas-receiving terminal $i \in V^D$ has a desired demand d_i that needs to be satisfied by the network. Physical and functional characteristics of network components are represented by node and edge attributes. Let $L_{i,j}$, $c_{i,j}$, $f_{i,j}$ denote the length, maximum capacity and gas flow rate of pipeline (i, j), respectively. It is assumed that network nodes cannot fail and transition rates $r_{i,j}$ are used for the stochastic state transition process of network pipelines.

A (partial) failure of network pipelines can reduce the pipeline flow capacity, affecting the total network flow. This can result in a partial loss of capacity, causing the failure to meet the desired demand at gas-receiving terminals, leading to unmet demand penalties. The optimisation model aims to optimise the re-dispatch of natural gas in the network pipelines while minimizing total operating and penalty costs, and ensuring that the network's maximum capacity is utilised. The optimisation is modelled as

$$\min_{\overrightarrow{f^t}} g\left(\overrightarrow{f^t}\right)$$

where

$$g\left(\overrightarrow{f^t}\right) = \sum_{(i,j)\in E} c_{i,j}^T L_{i,j} f_{i,j}^t$$
$$+\sum_{j\in V^D} c_j^{P_D}\left(d_j^t - \sum_{i:(i,j)\in E} f_{i,j}^t\right)$$
$$+c^{P_S}\sum_{i\in V^S}\left(s_i^t - \sum_{j:(i,j)\in E} f_{i,j}^t\right) \quad (1)$$

The first term of Eq. (1) represents the network transportation cost, where $L_{i,j}$ and $c_{i,j}^T$ are length and transportation cost per unit of flow-length of pipeline (i,j), and $f_{i,j}^t$ is the flow of pipeline (i,j) at time t. The second term, represents the penalty of gas undersupply at gas-receiving terminals $V^D \subset V$, where $c_j^{P_D}$ is penalty cost per unit of flow for undersupplied gas at gas-receiving terminal $j \in V^D$ indicating node importance, and d_j^t is the desired amount of gas at the respective terminal at time t. The third term expresses a dummy penalty cost to ensure that the network uses its maximum production capacity at time t, with c^{P_S} being a sufficiently large penalty factor. The optimisation problem constraints are given by Eqs. (2) and (3),

$$\sum_{j\in \mathrm{Pred}(i)} f_{j,i}^t = \sum_{k\in \mathrm{Succ}(i)} f_{i,k}^t + d_i^t,\ \ \forall i \in V\backslash V^S \quad (2)$$

$$0 \le f_{i,j}^t \le c_{i,j}^t \qquad \forall (i,j) \in E \quad (3)$$

$$\sum_{k\in \mathrm{Succ}(i)} f_{i,k}^t = s_i^t - \bar{s}_i^t,\ \ \forall i \in V^S \quad (4)$$

$$0 \le \bar{s}_i^t \le s_i^t \qquad \forall i \in V^S \quad (5)$$

where Eq. (2) ensures the conservation of flow at gas-receiving terminals and intermediate nodes, with $\mathrm{Succ}(i) = \{j|(i,j) \in E\}$ and $\mathrm{Pred}(i) = \{j|(i,j) \in E\}$ being the set of successors and predecessors of node i, respectively. d_i^t is the demand of node i at time t, which is zero for intermediate nodes and the desired demand at respective receiving terminal. Eq. (3) states that the flow of each pipeline at time t is non-negative and bounded to the pipeline's maximum capacity at time t. Eq. (4) states that conservation of flow at the production facilities with $\bar{s}_i^t$ being the amount of unproduced gas at the respective facility, and Eq. (5) states that this value is non-negative and bounded to maximum production capacity of the respective facility, s_i^t.

2.2 Monte Carlo Simulation of the Network Stochastic Process

The flow capacity of an NGTP network and its ability to meet gas demands at receiving terminals, depend on its topology and functionality that are determined by the states of the network's elements. The resulting network's state, determined by the combination of the states of the network's components, evolves over time due to stochastic transitions of the states of the states of the components. The stochastic process of transition among network states is simulated using the MC simulation technique (Zio, 2013). By solving the network flow capacity model for the stochastically evolving network's states, the optimised network flow and the amount of gas delivered to receiving terminals can be obtained.

While there are various pipeline failure modes, almost 60% of offshore oil and gas pipelines failures are corrosion-related (Revie, 2015) and can be categorised into small leakage, large leakage and rupture (Ma *et al.*, 2023). Correspondingly, we consider five different states for each pipeline, namely operational (s_O), small leakage (s_S), large leakage (s_L), rupture (s_R) and state s_C denoting all other failure modes.

The Markov Chain model, presented in Fig. 1 describes the stochastic transitions of the pipeline states. Assuming the pipelines' times of transition among states are exponentially distributed, the constant transition rates can be estimated using historical data. Eq. (6) presents the pipeline (i,j)'s constant transition rate matrix.

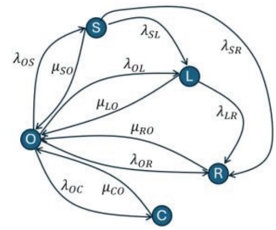

Fig. 1. Markov chain model representing the stochastic transitions of pipeline (i,j)'s states

As given by Eq. (6), small leakages may develop into large leakages with transition rate λ_{SL}, or cause a pipeline rupture with a transition rate of λ_{SR}. Similarly, a large leakage may cause a pipeline rupture with a transition rate λ_{LR}. Repair processes are described by constant repair rates, μ_{SO}, μ_{LO}, μ_{RO} and μ_{CO} which denote the rates of return to operation from small leakage, large leakage, rupture and other failures, respectively.

$$r_{i,j} = \begin{bmatrix} - & \lambda_{OS}^{i,j} & \lambda_{OL}^{i,j} & \lambda_{OR}^{i,j} & \lambda_{OC}^{i,j} \\ \mu_{SO}^{i,j} & - & \lambda_{SL}^{i,j} & \lambda_{SR}^{i,j} & 0 \\ \mu_{LO}^{i,j} & 0 & - & \lambda_{LR}^{i,j} & 0 \\ \mu_{RO}^{i,j} & 0 & 0 & - & 0 \\ \mu_{CO}^{i,j} & 0 & 0 & 0 & - \end{bmatrix} \quad (6)$$

Network random walks in time are simulated using an indirect MC sampling method. This involves first sampling the time t^* of the network transition, followed by sampling the network's next configuration by identifying which pipeline has undergone a transition and its new state.

This process is repeated until the mission time is reached. For the detailed illustration of MC simulation for sampling system state transitions see (Zio, 2013).

Pipeline capacities at time t, $c_{i,j}^t$, depend on their state and are defined as a fraction of pipeline's maximum capacity, $c_{i,j}$

$$c_{i,j}^t = \delta(s_{i,j}^t) c_{i,j} \quad (7)$$

where $\delta(s_{i,j}^t)$ is a state-dependent capacity correction factor and $s_{i,j}^t \in \{s_O, s_S, s_L, s_R, s_C\}$ is the state of pipeline (i,j) at time t. Whereas ruptures and other failures result in total loss of pipeline capacity, we assume, without loss of generality, that small and large leakages lead to 10% and 50% reduction in pipeline capacity, respectively.

The flowchart presented in Fig. 2 illustrates the step-by-step procedure for simulating network stochastic transitions and optimising the network flow at each transition time given the new network configuration. First, the optimised flow of network pipelines, $\overrightarrow{f_{opt}^t}$, is computed using the flow optimisation model for the original network at time $t = 0$, assuming all pipelines are in operational state s_O. Next, the system transition time t^*, the transitioning pipeline k at time $t + t^*$ and its new $s' = s_k^{t+t^*}$ are simulated. Pipeline capacities, and consequently, the network topology are updated at time $t + t^*$. The flow optimisation model is then reapplied to the updated network configuration. This process is repeated until horizon time τ is reached, providing the network flow at each time step for each simulation run. Once a sufficiently large number of simulations have been performed, the average network flow over time is obtained by averaging the network flow values across all runs.

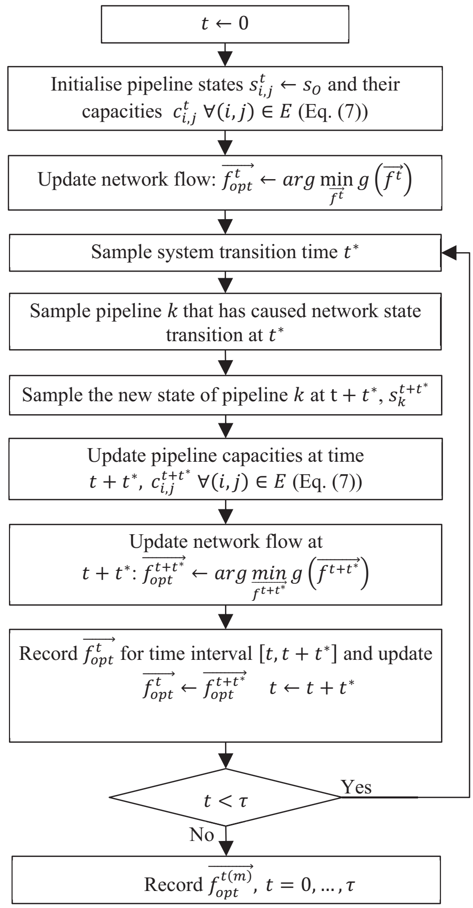

Fig. 2. Computational framework for network supply resilience of NGTP networks

3 Illustrative Example

To illustrate the proposed framework, we consider a hypothetical offshore NGTP network comprising four production platforms—nodes 0, 1, 2 and 3—with maximum production capacities of 20, 75, 80 and 25 MMCMD, respectively. The network also includes four gas-receiving terminals—nodes 12, 13, 14 and 15—with respective demands of 20, 50, 70 and 60 MMCMD. As shown in Fig. 3, the network consists of 18 pipelines, with their lengths and maximum capacities are presented as $(c_{i,j}, L_{i,j})$.

In 2023, the Norwegian Continental Shelf (NCS) gas pipeline network, consisting of 27 pipelines over 8,800 km, exported 116 billion m³ of natural gas, generating NOK 628 billion in revenue, with an OPEX of NOK 7.223 billion (GASSCO, 2023). Based on this, the transportation unit cost, $c_{i,j}^{T}$, is estimated as 40 €/MMCM-km for all pipelines and the export gas price, $c_i^{P_D}$, at 474,062 €/MMCM. The unmet demand penalty cost is obtained by scaling the gas price value by a vector of node importance factor of [1.5, 1.1, 1.8, 1.0] for gas-receiving nodes 12, 13, 14 and 15, respectively.

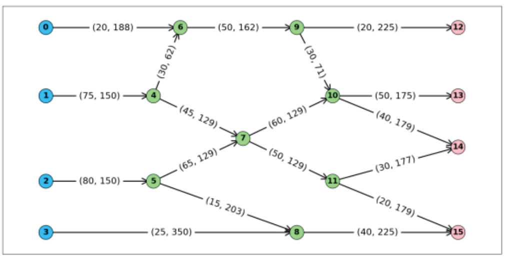

Fig. 3. Illustration of the hypothetical network

For offshore gas pipelines, corrosion accounts for 65% of failures (Revie, 2015) (assuming 35% small leaks, 20% large leaks, 10% ruptures), whereas other failures make up 35%. Small leaks may further escalate into large leaks or ruptures with a 10% probability each, and 10% of large leaks may lead to ruptures. Using such information, and assuming exponentially distributed failure and repair times, and assuming mean-time-to-repairs of 2, 5, 6 and 6 weeks for small leakages, large leakages, ruptures and other failures, respectively, and a pipeline transition rate of 0.48 failures per 1000 km-year, the pipeline transition rates are derived as presented in Table 1.

Table 1. Pipeline transition rates

$s \rightarrow s'$	(# failures/h)	$s \rightarrow s'$	(# failures/h)
$\lambda_{OS}^{i,j}$	1.9250E-08$L_{i,j}$	λ_{SL}	3.7202E-04
$\lambda_{OL}^{i,j}$	1.1000E-08$L_{i,j}$	λ_{SR}	3.7202E-04
$\lambda_{OR}^{i,j}$	5.500E-08$L_{i,j}$	λ_{LR}	1.3228E-04
$\lambda_{OC}^{i,j}$	1.9250E-08$L_{i,j}$	μ_{SO}	2.9762E-3
μ_{LO}	1.1905E-3	μ_{RO}	9.9206E-4
μ_{CO}	9.9206E-4		

3.1 Results and Discussion

Fig. 4 shows the network flow over five years using 5E4 simulation runs. The maximum capacity of the network in fully operational state is 200 MMCMD. The average network flow, which is the total gas received at receiving terminals, collectively, is 196.11374 (±0.06302) MMCMD, with transportation and penalty costs of 4.61104 (±0.00149) and 2.11986 (±0.03313) € million, respectively (see Figs. 5 and 6).

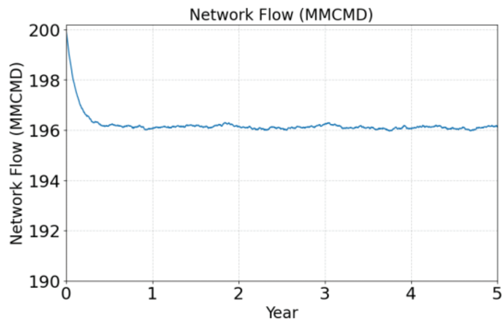

Fig. 4. Total network flow in million cubic metres per day (MMCMD)

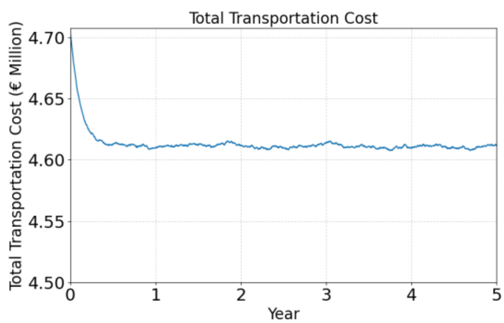

Fig. 5. Gas transportation cost in million euros

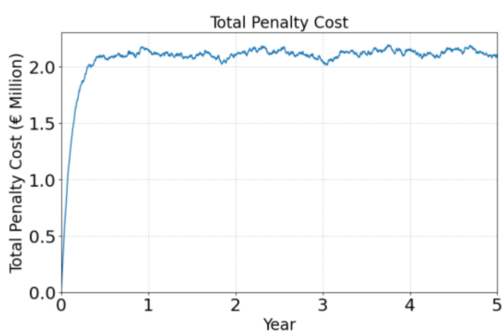

Fig. 6. Total penalty cost over time for undersupplied gas at receiving terminals, in million euros

Fig. 7 shows the amount of gas received at individual terminals, which is lower than the respective desired amounts due to the stochastic transitions of gas network pipeline states. As these transitions affect pipeline flow capacities, some gas shortages occur at the receiving terminals (see Fig. 8). The reduction in network capacity must be adjusted by production platforms while considering the relative importance of supply to gas-receiving terminals. Such production deficits are illustrated in Fig. 9 for individual production platforms. However, adjusting production flow rates may be constrained by physical characteristics of production platforms and reservoir behaviours. In such cases, the dummy penalty cost factor c^{Ps} (see Eq. (1)) may be adjusted to account for these constraints.

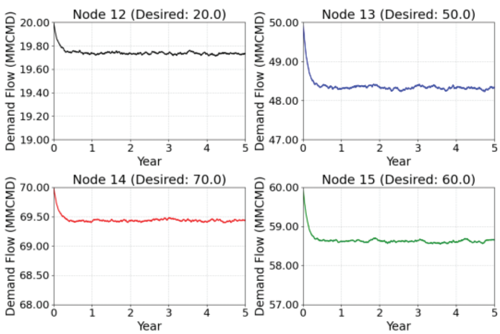

Fig. 7. Flow (in MMCMD) at gas-receiving terminals

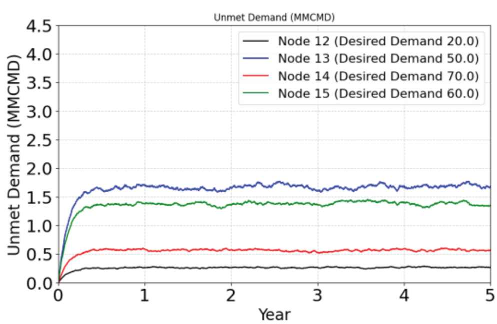

Fig. 8. The amount of unmet demand at gas-receiving terminals (in MMCMD) (Scenario 1 with node importance factors of [1.5, 1.1, 1.8, 1.0])

The results presented above correspond to node importance factors of [1.5, 1.1, 1.8, 1.0] (Scenario 1), clearly demonstrating that the gas supply optimisation framework prioritises nodes 12 and 14 over nodes 13 and 15 (Figs. 7 and 8) when re-dispatching flow through the network.

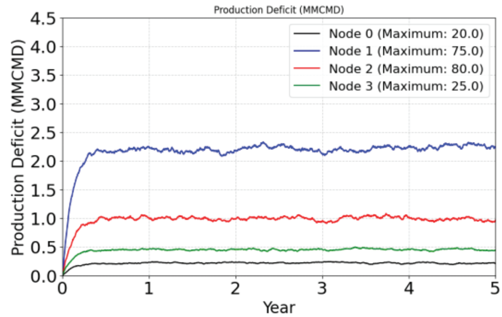

Fig. 9. Flow deficits at production platforms to adjust the maximum allowable flow through the network

To further illustrate this, Scenario 2 is considered with node importance factors of [1.0, 1.2, 1.0, 1.5]. Under this scenario, gas supply is prioritised for nodes 13 and 15 (see Fig. 10). Table 2 compares transportation and penalty costs, network flow rate, as well as production and demand deficits for both scenarios.

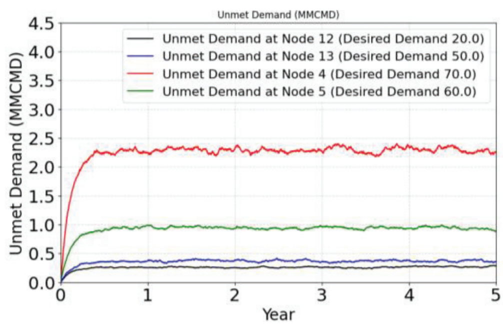

Fig. 10. The amount of unmet demand at gas-receiving terminals (in MMCMD) (Scenario 1 with node importance factors of [1.5, 1.1, 1.8, 1.0])

As presented, the undersupply of gas exhibits considerable variability across receiving terminals, corresponding to their importance factor. For instance, under Scenario 1, gas-receiving terminals 12 and 14 are more important than terminals 13 and 15, and consequently, the undersupplied gas at these terminals accounts for only 6.8% and 14.6% of the total network flow loss, respectively, whereas under Scenario 2, the undersupplied gas at these terminals accounts for 6.8% and 60.2% of the total network loss, respectively.

Gas-receiving terminal 12 in both scenarios has a similar unmet demand share, which is attributed to the network structure. In other words, there is limited possibility for the network to re-dispatch the flow that arrives at intermediate 9, whereas, for instance, intermediate nodes [4, 5, 7, 10, 11] provide more flexibility for the network flow from production platforms 1 and 2 to gas-receiving terminals 13 and 14.

Table 2. Statistics of network flow and costs for Scenarios 1 and 2 with node importance factors of [1.5, 1., 1.8, 1.] and [1.0, 1.2, 1., 1.5], respectively

	Scenario 1		Scenario 2	
Total Network Flow*	**Mean**	**STD**	**Mean**	**STD**
	196.1137	0.0630	196.1306	0.0552
Transportation Cost**	**Mean**	**STD**	**Mean**	**STD**
	4.61104	0.0015	4.6113	0.0013
Penalty Cost**	**Mean**	**STD**	**Mean**	**STD**
	2.11986	0.0331	2.0932	0.0293
Node	**Unmet Demand**		**Unmet Demand**	
	Mean	**STD**	**Mean**	**STD**
12	0.2646	0.0085	0.2622	0.0109
13	1.6723	0.0396	0.3719	0.0157
14	0.5664	0.0167	2.2920	0.0437
15	1.383	0.0319	0.9433	0.0197
Node	**Production Deficit**		**Production Deficit**	
	Mean	**STD**	**Mean**	**STD**
0	0.2206	0.0104	0.2185	0.00806
1	2.2175	0.0490	2.2108	0.0376
2	0.9943	0.0323	0.9835	0.0297
3	0.4539	0.0143	0.4565	0.0115
* MMCMD	** € Million			

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4 Conclusions and Suggestions for Future Work

We have proposed a modelling and computational framework for estimating the supply of a NGTP network, considering the relative importance of supply at different gas-receiving terminals while minimizing the total gas transportation and penalty costs. The framework integrates methods like graph theory and flow optimisation within a multi-component multi-state Markov chain model of the NGTP network. An indirect MC sampling approach is used to simulate different failure modes and repair processes of the network pipelines, and their flow capacities and stochastic evolution of network configurations.

The case study demonstrated the framework's effectiveness in re-dispatching network flow to reduce total transportation and undersupply penalties while prioritising gas-receiving terminals based on their relative importance.

Future work will focus on refining the framework by incorporating a more detailed analysis of corrosion processes and their associated failures, as well as considering stochastic gas flow characteristics such as pipeline pressure profiles and the inclusion of compressor stations to compensate for pressure drops along the pipelines. Additionally, we will explore strategies for optimising operation and maintenance decisions to enhance network capacity and overall gas supply resilience.

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