Petroleum and Coal

Article **Open Access**

A Systematic Method for Multi Objective Design Optimization of Natural Gas Transmission

Yassmen Y. Rawash[1], Said M. Aly[1], H. A. Abdel Samad[2], Mostafa H. Hussein[2]*

[1] *Chemical and Petroleum Refining Engineering Department, Faculty of Petroleum and Mining Engineering – Suez University- Suez 41522 – Egypt*

[2] *Chemical Engineering Department, Higher Institute of Engineering – Shorouk Academy- Shorouk City 11837 – Cairo – Egypt*

Received Merch 1, 2024; Accepted June 10, 2024

Abstract

The growing demand for natural gas as a vital energy source underscores the need to optimize gas transportation networks. This optimization involves reconciling conflicting goals, such as maximizing delivery flow rate, minimizing power and fuel consumption, and optimizing line pack. To address this complexity, and introducing a novel multi-objective optimization method that builds upon the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).The study outlines the fundamental research design, which entails applying the TOPSIS-based multi-objective optimization approach to gas transportation networks. This method generates a range of Pareto optimal solutions, equipping decision-makers with multiple viable options. Key outcomes underscore the efficacy of the proposed strategy. The investigation of three case studies reveals that the TOPSIS-based multi-objective optimization technique yields more economical networks than alternative methods. This showcases its potential in augmenting the efficiency and cost-effectiveness of natural gas transmission networks. In conclusion, this study advances gas transportation network optimization by introducing an innovative multi-objective optimization technique grounded in TOPSIS. The approach offers decision-makers an array of Pareto optimal solutions, aiding their selection of the most favorable one. The results emphasize the technique's capacity to develop economical networks and its versatility across various gas transportation scenarios. Moreover, incorporating this approach into existing optimization frameworks holds the promise of overall enhancements in gas transportation network performance.

Keywords: *Multi-objective optimization; MCDM; TOPSIS; Mathematical modeling; Gas transportation; Line pack.*

1. Introduction

The significance of natural gas as a prominent energy source for future endeavors is increasingly acknowledged, primarily owing to its various advantages such as reduced greenhouse gas emissions and relatively lower capital costs. These qualities make it a compelling choice across multiple sectors, particularly in the development of new power generation facilities. The pivotal role of natural gas as a primary energy source is evident in three distinct sectors of energy consumption, namely residential/commercial, industrial, and electricity generation sectors. These sectors heavily rely on natural gas to fulfill their energy requirements, and natural gas has demonstrated its efficiency and effectiveness as a reliable energy source for these specific applications [1].

The residential and commercial sectors predominantly utilize natural gas for heating and cooking applications, while the industrial sector employs it for various processes such as chemical production and manufacturing. Natural gas has gained popularity in the electric generation sector as a fuel for power generation due to its low emissions and cost-effectiveness. Its unique properties contribute to its reliability and versatility as an energy source. For instance, natural gas can be conveniently transported through pipelines and possesses a high energy density, making it suitable for a wide range of applications. Furthermore, natural gas can be stored for extended periods, ensuring a dependable energy supply even during periods of high demand or supply disruptions.

To conclude, natural gas presents numerous benefits that make it an attractive energy option for the times ahead. Its flexibility and consistent applicability in residential, commercial, industrial, and electricity generation domains highlight its versatility and reliability. The distinctive properties of natural gas make it a convenient and cost-effective option for meeting the increasing energy demands while addressing environmental concerns.

The natural gas industry encompasses various activities including gas production, transportation, and sales. This specific investigation focuses on the transmission of gas through pipeline networks, which can be classified into two distinct categories: transmission and distribution. Transmission involves the transportation of large volumes of gas over significant distances, often at high pressures, from gas sources to distribution centers. Conversely, gas distribution entails the targeted delivery of gas to individual consumers. Both the transmission and distribution systems depend on various equipment like pipes, regulators, valves, and compressors to facilitate the gas transportation process.

In the realm of pipeline operations, operators commonly give precedence to three primary goals: guaranteeing the conveyance of natural gas, achieving economic benefits, and optimizing line pack. The effective delivery of natural gas is impacted by variables like gas production capability, consumer requirements, pipeline transmission capacity, and the presence of external gas storage options. Economic benefits encompass elements such as gas procurement expenses, revenue from sales, and operational costs related to the pipeline. Line pack pertains to the stored volume of natural gas inside the pipeline at any specific point in time [2].

The optimization of pipeline operations aims to achieve the maximum attainable natural gas delivery, line pack, economic benefit, or a combination of these objectives. This optimization process takes into account the intricate interplay of various factors inherent in pipeline operations.

The intricacies and multifaceted difficulties inherent in designing and constructing natural gas transmission pipeline networks necessitate a diverse array of engineering knowledge and skills. The planning phase of these networks involves making decisions regarding the type, location, and installation schedule of key physical components, including pipelines and compressor terminals. The aim is to reduce expenses while staying within the confines of network limitations. Historically, this matter has been treated as a conceptual design challenge rather than an optimization issue that entails selecting the optimal design choice from a variety of feasible solutions. Addressing this challenge necessitates the utilization of advanced mathematical techniques and modeling methodologies.

Usually, natural gas transmission systems consist of an arrangement of gas collection pipelines, transition pipelines, distribution pipelines, compressor stations, and distribution points [3]. Gas collection pipelines play a crucial role in gathering untreated natural gas from production wells and transporting it to purification facilities for subsequent refinement. Subsequently, transmission pipelines are tasked with transporting the purified natural gas over considerable distances, often spanning thousands of kilometers, from purification plants to urban gate stations. Ultimately, distribution pipelines are designed to distribute natural gas to end-users according to their individual requirements. The existence of these pipelines forms a crucial infrastructure that demands meticulous planning, design, and maintenance to ensure the safe and efficient transportation of natural gas to meet the requirements of consumers.

In research conducted by Kashani [4], a multi-objective methodology was employed to optimize three conflicting objectives: maximizing gas delivery flow, maximizing line pack, and minimizing operating costs. The proposed approach aims to concurrently optimize these objectives while considering the interdependencies and complexities associated with pipeline operations. By utilizing a multi-objective optimization approach, pipeline operators are empowered to make well-informed decisions that strike a balance between these objectives, resulting in enhanced efficiency and cost-effectiveness in pipeline operations. By considering multiple objectives, pipeline operators can gain a comprehensive understanding of the trade-offs involved in pipeline operations, enabling them to make more informed decisions. This approach offers valuable insights and guidance for the design and operation of natural gas transmission pipeline networks.

In the context of natural gas pipeline optimization, the thematic mission indicates to the object that the optimization method seeks to achieve. Typically, there are three main objective functions: (a) One of the primary objectives in natural gas pipeline optimization is to maximize the delivery of gas to a particular consumer. This objective measures the extent to which pipelines and associated infrastructure are effectively utilized to transport gas and meet the demands of the intended consumer [3-4]. (b) An additional goal within the optimization of natural gas pipelines involves maximizing line pack, representing the gas volume stored within the pipeline. This stored gas serves as a resource during high-demand periods or to counteract supply irregularities. The challenge of line packing seeks to determine the best balance between compressor power usage and the potential advantages of maintaining a greater line pack for the future. By optimizing line pack, the pipeline's peak capacity is elevated, leading to improved efficiency and dependability in gas delivery [5]. (c) An additional goal within the optimization of natural gas pipelines involves maximizing line pack, representing the gas volume stored within the pipeline. This stored gas serves as a resource during high-demand periods or to counteract supply irregularities. The challenge of line packing seeks to determine the best balance between compressor power usage and the potential advantages of maintaining a greater line pack for the future. By optimizing line pack, the pipeline's peak capacity is elevated, leading to improved efficiency and dependability in gas delivery [6].

In summary, the objective function plays a crucial role in pipeline optimization as it guides the optimization process towards achieving desired outcomes and balancing the competing objectives of gas delivery, line pack, and economic benefit.

In a study conducted by Felipe [7], a multi-objective optimization approach was employed to facilitate the process of making informed decisions of regulatory authorities in the design of natural gas transmission networks. The study addressed two conflicting objective functions: reducing transitional rent and maximizing the volume of gas transported. Mathematical models and simulation tools were utilized to evaluate different design scenarios, considering factors such as gas production, transmission capacity, and consumer demand. The study's findings offer valuable insights into the trade-offs between different design parameters, assisting in the selection of optimal solutions.

Huai Su [8] improved a multi-faceted optimization procedure that weighs the balance between precision and energy requisites in natural gas pipeline networks. This optimization methodology acknowledges uncertainties related to supply conditions and consumer consumption while factoring in the network's consistent operational characteristics. The objective is to concurrently diminish power requirements and the possibility of gas supply insufficiencies, all while accounting for constraints encompassing pipeline capacity, pressure thresholds, and temperature limitations. This proposed approach aids decision-makers in selecting the best operational strategy for natural gas pipeline networks, serving as a valuable tool for the design and planning stages.

Kai Liu [9] improved a dynamic pipeline network model to minimize compression costs in natural gas pipeline networks while considering uncertainties in demand and gas composition. The utilized model involved precise thermodynamic formulas to precisely determine the compressibility factor of the gas at any given time and location. The method introduced in this study considered unpredictability in the composition of the supplied gas and the flow rates at the demand nodes. Through iterative calculations, the algorithm converged to a robust and cost-effective solution. The model created offers decision-makers a valuable instrument to optimize natural gas pipeline networks by accounting for uncertainties, guaranteeing the attainment of the best solution while minimizing compression expenses.

Qian Chen [10] constructed is a stochastic multi-objective optimization framework designed to manage momentary peak adjustments within natural gas pipelines. This framework addresses the uncertainties associated with gas demand and fine-tunes the performance of compressors and subterranean gas storage. The framework takes the form of a comprehensive nonlinear program (NLP), integrating gas flow equations and governing operational limitations. The primary aim is to curtail operational expenses and enhance line pack by the conclusion of the time frame. This endeavor involves the application of centrifugal compressors and thermodynamic equations to account for the characteristics of natural gas, all while accommodating an array of legal and physical constraints. This methodology offers decision-makers a valuable instrument for optimizing networks of natural gas pipelines, all while navigating uncertainties in demand. It guarantees the realization of the optimal solution by minimizing operational costs and maximizing line pack.

In their study, Xiong Yin [11] developed a machine learning-based surrogate model to control flow in station-level process piping networks (SLPPN). The surrogate model employed a hybrid modeling process that combined data-driven and physics-based simulation approaches to capture flow characteristics while increasing computational speed. Using the surrogate model, an innovative two-step controller was developed as a substitute for the traditional proportional integral differential (PID) controller. This controller integrated open-loop optimal control with closed-loop feedback control. In the initial stage, genetic algorithms (GA) were applied to ascertain the optimal control strategies of the surrogate model to facilitate quick simulation. Subsequently, a subsequent PID controller was engaged in the second stage to rectify any disparities between the target value and the flow after the initial control phase.

This study aims to optimize gas transportation networks in response to the growing demand for natural gas. It introduces a novel multi-objective optimization method based on TOPSIS, addressing conflicting goals like maximizing delivery flow rate, minimizing power and fuel consumption, and optimizing line pack. By applying this approach to real-world networks, it generates a range of Pareto optimal solutions, offering decision-makers multiple viable options. The study demonstrates the superior economic performance of the TOPSIS-based method through three case studies, highlighting its potential to enhance the efficiency and cost-effectiveness of gas transmission networks. Ultimately, this research contributes an innovative approach that can be integrated into existing optimization frameworks, promising overall improvements in gas transportation network performance.

2. Formulation model for gas pipeline network

Gas pipeline network models can be constructed using a variety of mathematical techniques, such as optimization methods like linear and nonlinear programming (LP) The methods employed include mixed-integer linear programming (MILP), nonlinear programming (NLP), and mixed-integer nonlinear programming (MINLP), as well as graph theory and simulation models for simulating gas flow behavior under various conditions. The gas pipeline network formulation form involves defining the objective function, decision variables, constraints, network topology, gas properties, and input data. Subsequently, an appropriate optimization or simulation method is applied to determine the optimal solution that satisfies the requirements of the problem. The selection of the most suitable mathematical technique and optimization or simulation method relies on the specified properties s of the gas pipeline network and the problem being addressed [1].

2.1. Gas properties

Understanding and anticipating the behavior of gases in diverse applications such as process design, combustion analysis, and gas transportation hinges on comprehending gas properties. The determination of these properties' rests on fundamental concepts in thermodynamics, fluid dynamics, and molecular theory [12]. Some properties of the gases were calculated according to the procedures published in the reference [13].

2.2. Pipeline network calculations

Pipeline volume flowrate equation

The flow equation relates the gas flow rate with gas properties, pressure, pipe diameter and equivalent length for a horizontal pipe by [14]

$$Q = 77.54\left(\frac{T_b}{P_b}\right)\left(\frac{P_1^2 - P_2^2}{G * T * Le * Z * f}\right) * D^{2.5} \tag{1}$$

Friction factor

The friction factor (f) in pipeline flow is a dimensionless quantity that characterizes the resistance to flow caused by the roughness of the pipeline surface and other factors such as turbulence and viscosity. It is an important parameter in pipeline design and operation, as it affects the pressure drop and energy losses. it can be determined using empirical equations or experimental data. The most commonly used equation for estimating the friction coefficient is the Nikuradse equation, which is an implicit equation that relates the friction factor to the roughness height of the pipeline surface (ε), and the diameter of the pipeline (D). The Nikuradse equation is given by [15].

$$\frac{1}{\sqrt{f}} = -2\log\left(\frac{\varepsilon/D}{3.7}\right) \tag{2}$$

2.3. Power demand reduction

In transition systems of natural gas, compressor stations consume a significant portion of energy. Thus, decrease their energy requirements can efficiently raise the competence of pipeline system and the operating revenue. In addition to, most of compressors run on gas. Turbine, decrease the energy requirement of the compressor stations can also improve the environment by decreasing greenhouse gas liberation. Giving this, it is not surprising that reducing the energy requirement of compressors is a major purpose to improvement of gas transition systems. Compressor stations act a critical role in operation of natural gas pipelines, by providing the necessary energy to maintain gas flow and pressure throughout the pipeline system.

The energy complemented via the compressor is estimated as head H i.e., the amount of energy supplied per unit mass of gas. The value of head can be acquired using the succeeding equation 5.

$$H = ZRT\frac{K}{K-1}\left[\left(\frac{p_d}{P_S}\right)^{\frac{(K-1)}{K}} - 1\right] \tag{3}$$

In which K is estimated via Pambour [10]

$$K = \frac{\sum C_{pi}MY_i}{\sum C_{pi}MY_i - R} \tag{4}$$

We can estimate the energy provided to the gas in the compressor by Demissie [16].

$$Power = \frac{Q.H}{\eta_{is}} \tag{5}$$

2.4. The fuel consumption of compressor

The fuel consumption of compressors is essential for ensuring energy efficiency, reducing operational costs, and promoting sustainability in various industries that rely on compression systems, including oil and gas, petrochemicals, and power generation.

$$\dot{m}_f = \frac{10^6 W}{\eta_m \eta_d LHV} \tag{6}$$

2.5. Line pack in pipeline

Line pack indicates to the amount of gas that is stored in a pipeline to maintain system pressure and meet fluctuations in demand. When natural gas is delivered through a pipeline system, the gas flow rate and pressure can vary depending on the demand from customers. For the purpose of maintaining a safe and effective operating pressure range, pipeline systems frequently utilize line pack. This involves storing surplus gas during periods of reduced demand and subsequently releasing it during periods of heightened demand.

Line pack is typically measured in terms of the amount of gas stored per unit length of pipeline, such as cubic feet per mile, or cubic meters per kilometer. The quantity of line pack necessary is contingent upon numerous factors, encompassing the dimensions and capabilities of the pipeline, the consumption trends of consumers, and attributes of the gas flow, such as pressure and temperature.
The value of line pack in MMscf is determined by using the following equation, Menon [12].

$$LP = 7.885x10^{-7}\left(\frac{T_{SC}}{P_{SC}}\right)\left(\frac{P_{avg}}{Z*T}\right)(D^2*L) \tag{7}$$

2.6. Total cost

Various elements impact the overall cost of a natural gas network, which comprises factors like the pipelines' length and diameter, the essential capacity for pressure and flow rate, and any distinct engineering prerequisites [12].

$$Total\ cost = operating\ cost + fixed\ cost \tag{8}$$

$$operating\ cost = 100000 + (Power \times 850) \tag{9}$$

$$Fixed\ cost = (1495.4 \times Ln(Yr) - 11353) \times D \times 250 \times L/1600 \tag{10}$$

3. Multiple criteria decision making (MCDM)

Multiple criteria decision making (MCDM) is a decision-making framework that is used to evaluate and select alternatives based on multiple criteria or objectives. MCDM is a useful tool in situations where there are multiple and competing objectives that need to be considered when making decisions. The MCDM process involves identifying the decision problem and the available alternatives, determining the criteria or objectives that are relevant to the problem, determining the relative significant of the criteria, evaluating the alternatives based on the criteria, this can be done using various techniques, such as scoring or ranking the alternatives based on their performance on each criterion. Once the alternatives have been evaluated, the decision-maker needs to determine the trade-offs between the different criteria or objectives. This involves balancing the relative significant of each criterion against the performing of each alternative on that criterion, and finally making the decision based on the overall evaluation. MCDM has a wide range of uses in fields such as finance, engineering, environmental management, and healthcare. However, it is important to note that MCDM can be challenging due to the subjective nature of the evaluation process, the difficulty in assigning weights to criteria, and the potential for information overload. Therefore, it is important to use a rigorous and transparent decision-making process that involves multiple stakeholders and to continually review and update the criteria and weights as new information becomes available [18].

$$\varphi = \begin{array}{c} \\ \gamma_1 \\ \gamma_2 \\ \vdots \\ \\ \gamma_m \end{array} \begin{array}{c} \begin{array}{ccccc} \beta_1 & \beta_2 & .. & .. & \beta_n \end{array} \\ \begin{bmatrix} \lambda_{11} & \lambda_{12} & .. & .. & \lambda_{1n} \\ \lambda_{21} & \lambda_{22} & .. & .. & \lambda_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \lambda_{m1} & \lambda_{m2} & .. & .. & \lambda_{mm} \end{bmatrix} \end{array} \tag{11}$$

where, γ_i, $(i = 1,2, \dots \dots, m)$ are alternative β_j, $(j = 1,2 \dots \dots, n)$ are criteria, for a clear view of this method.

TOPSIS method consists of a series of sequential steps that are presented next.

Step1: The most common normalization method is;

1- for max, we have

$$\eta_{ij} = \frac{\lambda_{ij} - min(\lambda_{ij})}{max\ (\lambda_{ij}) - min(\lambda_{ij})}\ ,(i \in m \quad, j \in n) \tag{12}$$

2- for min, we have

$$\eta_{ij} = \frac{max(\lambda_{ij}) - \lambda_{ij}}{\max(\lambda_{ij}) - \min(\lambda_{ij})} \quad , \qquad (i \in m \quad , \qquad j \in n) \tag{13}$$

As a result, a standardized decision matrix M is acquired indicating the relative performing of the substitutions as:

$$\mu = \begin{bmatrix} \eta_{11} & \eta_{12} & .. & .. & \eta_{1n} \\ \eta_{21} & \eta_{22} & .. & .. & \eta_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \eta_{m1} & \eta_{m2} & .. & .. & \eta_{mn} \end{bmatrix} \tag{14}$$

Step2: The standard deflection method estimates the weights of purposes thru:

$\tau_i = \frac{\sigma_i}{\sum_k^m \sigma_k}$, where, (15)

$$\sigma_i = \sqrt{\frac{\sum_{i=1}^{m}(\lambda_i - \lambda^{\sim})^2}{n-1}} \tag{16}$$

and, $\lambda^{\sim}$ = mean variable

$$\lambda^{\sim} = \sum_{i=1}^{m} \lambda_i / n \tag{17}$$

Step3: A set of weights *(τ_1, τ_2..............τ_n)* and $\sum_i^n \tau_i = 1$, where $\tau_i > 0$, *(i = 1, 2… n)* is given to the corresponding criterion λ_i, where *(i = 1,2,…, n)*.
The matrix $\varepsilon = \tau_i \eta_{ij}$ is calculated by multiplying the elements at each column of the matrix μ by their associated weights τ_i, *(i = 1,…, n)*.

$$\varepsilon = \begin{bmatrix} \tau_1\eta_{11} & \tau_2\eta_{12} & .. & .. & \tau_n\eta_{1n} \\ \tau_1\eta_{21} & \tau\eta_{22} & .. & .. & \tau_n\eta_{2n} \\ .... & .... & .. & .. & .... \\ .... & .... & .. & .. & .... \\ \tau_1\eta_{m1} & \tau_2\eta_{m2} & .. & .. & \tau_n\eta_{mn} \end{bmatrix} \tag{18}$$

Step4: Calculate the separation measures (α_i^+ *and* α_i^-) between alternatives using the distance MinkowskiLp Metric as follow:

$$\alpha_i^+ = \sqrt{\sum_{j=1}^{m}(\varepsilon_{ij} - \varepsilon_j^+)}^{2}, \ (i = 1, \dots\dots\dots, n) \tag{19}$$

$$\alpha_i^- = \sqrt{\sum_{j=1}^{m}(\varepsilon_{ij} - \varepsilon_j^-)}^{2}, (i = 1, \dots\dots\dots, n) \tag{20}$$

Step5: In terms of performance evaluation of alternatives, the higher value, the better performance. Optimum alternative is selected according to the greater relative closeness [19].

$\theta_i = \frac{\alpha_i^-}{\alpha_i^- + \alpha_i^+}$, where $0 \le \theta_i \le 1$ (21

4. Case studies

4.1. Case 1 (Tree)

The gas pipeline network under investigation adopts a tree-topology configuration, comprising of two compressor stations featuring a parallel arrangement of six compressors each studied by Su *et al.* [20]. Within this network, a gas source is responsible for supplying natural gas to three distinct customer types located at the extremities of the network branches. The fundamental parameters outlining this configuration can be found in Figure 1. The internal diameter of all pipes is 24 inches, and the friction factor is set to 0.009. The base temperature and pressure conditions are specified as 520°R and 14.5 psia, respectively. The compressors are arranged in two pairs, namely (S1, S2) and (S4, S5), with each compressor station consisting of six centrifugal units operating in parallel. The physical properties of the gas mixture used in the network can be found in Table 1.

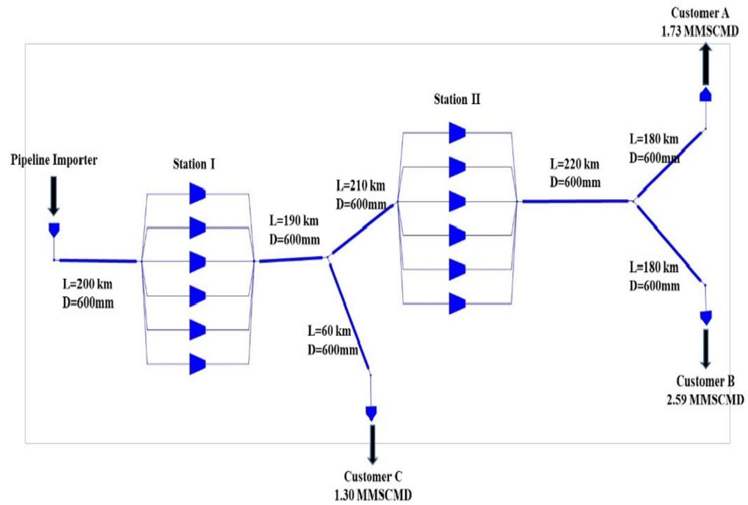

Figure 1. Pipeline network for Case 1 [20].

Table 1. Physical properties of gas mixture for both Cases.

Gas component	C1	C2	C3
Mole fraction Y_i	0.700	0.250	0.050
Molecular mass($\mathrm{gmole^{-1}}$)	16.040	30.070	44.100
Lower heating value at 15°C and 1 bar ($\mathrm{MJm^{-3}}$)	37.706	66.067	93.936
Critical pressure (bar)	46.000	48.800	42.500
Critical temperature (K)	190.60	305.400	369.800
Heat capacity at constant pressure ($\mathrm{J.mol^{-1}.K}$)	35.663	52.848	74.916

4.2. Case 2 (branched-cyclic)

The second case study, which pertains to network characteristics, was sourced from the real-world data provided by the French Company GdF Suez [21]. The presented transmission network is depicted in Figure 2 in a schematic manner, reflecting its multi-supply and multi-delivery nature. This case study exhibits a more intricate combinatorial aspect compared to case study 1 due to the presence of three loops and seven compressor stations. The transmission network comprises a total of 19 delivery points, denoted by small empty circles, from which gas is extracted. Gas supply can be obtained from six different points, represented by hexagons. Additionally, the network considers 20 intermediate nodes that facilitate interconnections and, in certain instances, explicitly specify modifications in design parameters. In entirety, the network comprises 45 nodes and 30 pipe segments. Additionally, there are seven compressors deliberately situated within the network to counteract pressure drops. The initial temperature and pressure conditions are defined as 520°R and 14.5 psia correspondingly. The length, inside diameter, and roughness of each pipe are shown in Table 2.

Table 2. Length and outside diameter data for Case 2.

Pipe arc	O.D (in)	L (mile)	Roughness (m)	Pipe Arc	O.D (in)	L (mile)	Roughness (m)
0000	30	40.06	0.00002	0260	30	59.81	0.00001
0010	28	63.50	0.00002	0280	30	74.82	0.00001
0020	28	50.25	0.00001	0290	36	03.06	0.00001
0030	26	16.94	0.00001	0300	48	19.31	0.00001
0051	48	107.94	0.00001	0310	36	33.38	0.00001
0060	48	03.06	0.00001	0321	36	34.06	0.00001
0080	48	76.38	0.00001	0331	36	48.13	0.00001

Pipe arc	O.D (in)	L (mile)	Roughness (m)	Pipe Arc	O.D (in)	L (mile)	Roughness (m)
0090	36	50.81	0.00001	0340	32	55.63	0.00001
0100	48	26.00	0.00001	0390	20	39.94	0.00002
0110	42	17.75	0.00001	0880	42	40.06	0.00001
0150	36	13.50	0.00001	0900	42	127.81	0.00001
0160	42	8.88	0.00001	0910	42	22.63	0.00001
0170	42	27.06	0.00001	0920	36	78.63	0.00001
0200	24	29.25	0.00001	0930	36	42.31	0.00001
0240	24	17.44	0.00001	1050	42	0.0006	0.00001

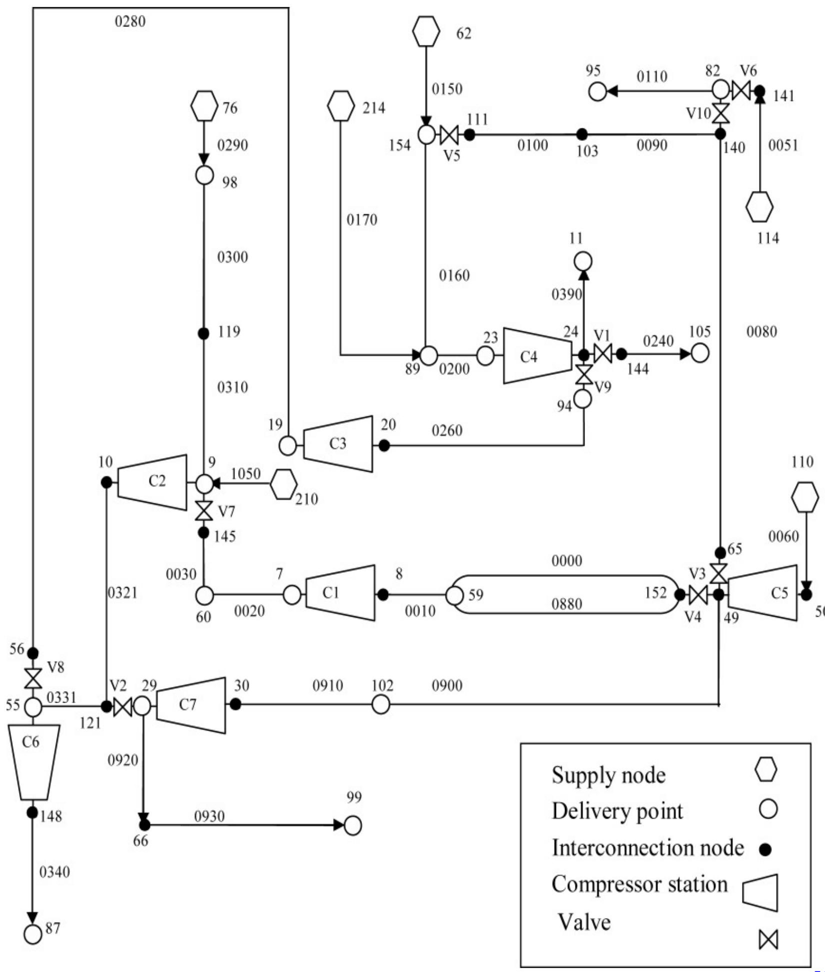

Figure 2. Pipeline network for Case 2 (by courtesy of Gaz de France) [21].

5. Results and discussion

The outcomes of this investigation underscore the efficacy of employing the TOPSIS method for multi-objective optimization in the context of natural gas transmission networks. Across all two examined cases, the TOPSIS method consistently identified the optimal configuration, signifying its robustness in reconciling conflicting objectives. This outcome supports the contention that TOPSIS is a highly effective approach for addressing the complexities inherent in optimizing gas transportation networks. This assessment provides valuable insights into the potential advantages of employing TOPSIS as a primary optimization methodology in this domain [22-23]. Table 3 displays data specifications for different scenarios including flowrate, power, and line pack for case 1. The normalized decision matrix results by using equations (12 & 13) are shown in Table 4.

Table 3. Data specifications for Case 1.

Scenario	Pmin (psi)	Pmax (psi)	Flowrate (MMscf)	Power (hp)	Line pack (MMscf)	Fuel consumption (klb/sec)
1	653	1016	261.41	5,720	104.244	277.064
2	700	1000	262.44	5,046	106.839	244.449
3	750	950	234.35	4,010	111.070	194.240
4	800	1000	321.57	4,103	118.460	198.736
5	850	1000	284.44	2,506	122.718	121.395

Table 4. The normalized decision matrix for Case 1.

Scenario	Flowrate	Power	Line pack	Fuel consumption
1	0.31031	0.00000	0.00000	0.00000
2	0.32210	0.20951	0.14044	0.20951
3	0.00000	0.53205	0.36946	0.53205
4	1.00000	0.50317	0.76941	0.50317
5	0.57436	1.00000	1.00000	1.00000

By using TOPSIS method which presented previously, the results of calculation of the standard deviation (σ_i) and the objective weight($\boldsymbol{\tau_i}$) using equations (15 & 16) are presented in Table 5. The next step is calculating the weighted normalized $\boldsymbol{\mu}$ matrix. The results are presented in Table 6 for each scenario.

Table 5. Standard deviation (σ_i) and objective weight (τ_i) results for Case 1.

Standard deviation (σ_i)	0.37281	0.37828	0.42106	0.37828
Objective weight (τ_i)	0.24046	0.24398	0.27157	0.24398

Table 6. The weighted normalized decision matrix for Case 1.

Scenario	Flowrate	Power	Line pack	Fuel consumption
1	0.07462	0.00000	0.00000	0.00000
2	0.07745	0.05112	0.03814	0.05112
3	0.00000	0.12981	0.10034	0.12981
4	0.24046	0.12277	0.20895	0.12277
5	0.13811	0.24398	0.27157	0.24398

In the next step, calculate the total cost and separation measures ($\boldsymbol{\alpha_i^+}$ ***and*** $\boldsymbol{\alpha_i^-}$) by using equations (8, 19 & 20), the outcomes are exhibited in Table 7 where the optimum scenario is scenario 5 when pressure range (580:1000 psi)

Table 8 displays data specifications for different scenarios including flowrate, power, and line pack for case 2. The normalized decision matrix results are shown in Table 9. The standard deviation (σ_i) and the objective weight($\boldsymbol{\tau_i}$) results are presented in Table 10. The weighted normalized decision $\boldsymbol{\mu}$ matrix results are presented in Table 11 for each scenario.

The relative closeness and total cost results are exhibited in Table 12. The optimum scenario is scenario 1 when pressure range (668:1089 psi).

Table 7. The relative closeness and total cost results of each scenario for Case 1.

Scenario	α_i^+	α_i^-	$\theta_i = \alpha_i^- / (\alpha_i^- + \alpha_i^+)$	Total cost (MM$/Yr)
1	0.40098	0.07462	0.15689	8.52
2	0.34389	0.10033	0.22586	7.95
3	0.31651	0.16407	0.34140	7.07
4	0.13644	0.34140	0.71446	7.15
5	0.10235	0.39033	0.79226	5.79

Table 8. Data specifications for Case 2.

Scenario	Pmin (psi)	Pmax (psi)	Flowrate (MMscf)	Power (hp)	Line pack (MMscf)	Fuel consumption (klb/sec)
1	668	1089	216510.8	7,916	11608	766.78
2	668	1147	66563.84	4,158	12681	402.78
3	668	1176	67718.16	3,465	13123	167.80
4	675	1118	65397.79	3,525	12219	341.44
5	668	1060	162506.2	6,897	11348	668.12

Table 9. The normalized decision matrix for Case2.

Scenario	Flowrate	Power	Line pack	Fuel consumption
1	1.00000	0.00000	0.14649	0.00000
2	0.00772	0.84421	0.75122	0.60770
3	0.01536	1.00000	1.00000	1.00000
4	0.00000	0.98648	0.49080	0.71012
5	0.64262	0.22883	0.00000	0.16472

Table 10. Standard deviation (σ_i) and objective weight (τ_i) results for Case2.

Standard deviation (σ_i)	0.46324	0.46531	0.41403	0.40869
Objective weight (τ_i)	0.26452	0.26570	0.23642	0.23337

Table 11. The weighted normalized decision matrix for Case 2.

Scenario	Flowrate	Power	Line pack	Fuel consumption
1	0.00406	0.26570	0.23642	0.23337
2	0.00204	0.22431	0.17760	0.14182
3	0.00000	0.26211	0.11603	0.16572
4	0.26452	0.00000	0.03463	0.00000
5	0.16998	0.06080	0.00000	0.03844

Table 12. The relative closeness and total cost results of each scenario for Case 2.

Scenario	α_i^+	α_i^-	$\theta_i = \alpha_i^- / (\alpha_i^- + \alpha_i^+)$	Total cost (MM$/Yr)
1	0.26045	0.40717	0.60988	11.65
2	0.27215	0.35386	0.56526	12.24
3	0.29064	0.36026	0.55348	12.51
4	0.33364	0.35274	0.51392	15.43
5	0.32682	0.29707	0.47615	14.57

Drawing upon prior research within related domains, this study introduces a pioneering multi-objective optimization model meticulously crafted to address the intricate challenges associated with conflicting objectives in the context of a multi-criteria decision-making framework. In stark contrast to antecedent studies that predominantly fixated upon singular objectives such as flow rate, power consumption, or fuel cost, this investigation distinguishes itself by concurrently embracing multiple objectives, thereby affording a comprehensive and holistic approach to the optimization of gas transmission networks. It is worth noting that this research strategically employs the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, marking a deliberate departure from previous methodologies, including the VIKOR method and weighted sum methods. The inherent attributes of the TOPSIS method, characterized by its simplicity and adaptability in the management of diverse criteria and the resolution of conflicting goals, serve to fortify its pragmatic utility. In essence, this study offers a novel vantage point in the realm of gas transmission network optimization, proffering perceptive implications and prospective advantages to both the wider gas industry and its cognate sectors.

The research findings substantiate the scalability and efficacy of the proposed model in navigating larger and more intricate gas transmission networks, adeptly discerning optimal solutions across an expansive spectrum of input parameters through the judicious application of the TOPSIS method.

By seamlessly incorporating multiple objectives and adroitly addressing the conflicts that may arise among them, this multi-objective optimization model bequeaths invaluable insights into the allocation of resources and the attainment of cost-effective operational strategies. Nevertheless, it is incumbent upon us to acknowledge that, akin to any analytical approach, the TOPSIS method is not devoid of certain limitations and potential pitfalls. Specifically, its sensitivity to the normalization procedure, presumption of uniform significance among all criteria, and its exclusion of considerations related to uncertainty and risk factors may impact its practical applicability. The assurance of robust findings necessitates the meticulous validation of the results derived from the TOPSIS method with empirical data and their critical comparison with outcomes engendered by alternative optimization methodologies.

6. Conclusion

This study introduces a novel multi-objective optimization model tailored for natural gas transmission networks. The model integrates pipeline operational factors using a multi-criteria decision-making framework. The primary aim is to:

- Simultaneously enhance delivery flow rate, minimize power and fuel consumption, and maximize line pack.
- Despite inherent goal conflicts, the model's effectiveness is demonstrated through applications on distinct network topologies.
- The TOPSIS method is employed for selecting optimal network configurations based on multi-objective optimization results.
- The approach successfully balances competing objectives, yielding efficient and operationally sound network designs.
- This methodology brings significant advantages by addressing multiple objectives simultaneously, it facilitates the creation of more efficient, reliable, and economically viable gas transmission networks.

Incorporating a multi-criteria decision-making framework enhances decision-making by analyzing trade-offs between objectives. This approach can be expanded to address various gas pipeline network optimization challenges involving conflicting objectives. Its integration with established techniques can further improve optimization processes for robust network designs.

Future research directions should explore alternative optimization techniques and consider factors like environmental impact and safety. Assessing scalability to larger and more complex networks is vital for real-world applicability. This study contributes an innovative multi-objective optimization model for gas transmission networks, highlighting its capability to concurrently optimize conflicting objectives. Advancements in this area promise efficient and sustainable gas networks to meet rising demand.

Nomenclature

SLPPN	Station-level process piping network
PID	Proportional integral differential
GA	Genetic algorithms
LP	Linear programming
NLP	Non-linear programming
TOPSIS	Technique for order preference by similarity to ideal solution
MILP	Mixed-integer linear programming
MINLP	Mixed-integer nonlinear programming
σ_i	Standard deviation of performance rating factor $(P_{1j}, P_{2j}, \dots \dots \dots P_{Mj})$ In R matrix.
τ_i	Objective weight
P_d	Discharge pressure of gas, psia
P_s	Suction pressure of gas, psia
P_b	Base pressure, psia,
T_b	Base temperature, ◦r
P_1	Upstream Pressure, psia
P_2	Downstream Pressure, psia
G	Gas gravity (air = 1.00)
T	Average gas flow temperature, ◦r,
L_e	Equivalent length of pipe, miles
Z	Gas compressibility factor, dimensionless
D	Pipe inside diameter, in

Acknowledgment

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors

References

[1] Wu X, Li C, He Y, Jia W. Operation optimization of natural gas transmission pipelines based on stochastic optimization algorithms: a review. Math Probl Eng., 2018; 2018.

[2] Li CJ, Jia WL, Liu E Bin, Wu X. A Multi-Hierarchy Grey Relational Analysis Model for Natural Gas Pipeline Operation Schemes Comprehensive Evaluation. International Journal of Industrial Engineering, 2012; 19.

[3] Mokhatab S, Poe WA, Mak JY. Handbook of natural gas transmission and processing: principles and practices. Gulf Professional Publishing; 2018.

[4] Kashani AHA, Molaei R. Techno-economical and environmental optimization of natural gas network operation. Chemical Engineering Research and Design., 2014; 92: 2106–22.

[5] Wu X, Li C, Jia W, He Y. Optimal operation of trunk natural gas pipelines via an inertia-adaptive particle swarm optimization algorithm. J Nat Gas Sci Eng., 2014; 21: 10–8

[6] Üster H, Dilaveroğlu Ş. Optimization for design and operation of natural gas transmission networks. Appl Energy, 2014; 133: 56–69.

[7] Da Silva Alves F, De Souza JNM, & Costa ALH. Multi-objective design optimization of natural gas transmission networks. Computers & Chemical Engineering, 2016; 93: 212-220.

[8] Su H, Zio E, Zhang J, Li X, Chi L, Fan L, Zhang Z. A method for the multi-objective optimization of the operation of natural gas pipeline networks considering supply reliability and operation efficiency. Computers & Chemical Engineering, 2019; 131: 106584.

[9] Liu K, Biegler L, Zhang B, Chen Q. Dynamic optimization of natural gas pipeline networks with demand and composition uncertainty. Chemical Engineering Sciences, 2020; 215, 115449.

[10] Chen Q, Wu C, Zuo L, Mehrtash M, Wang Y, Bu Y, Sadiq R, Cao Y. Multi-objective transient peak shaving optimization of a gas pipeline system under demand uncertainty. Computers & Chemical Engineering, 2020; 147, 107260.

[11] Yin X, Wen K, Wu Y, Han X, Mukhtar Y, Gong J. A machine learning-based surrogate model for the rapid control of piping flow: Application to a natural gas flowmeter calibration system. Journal of Natural Gas Science Engineering 2022; 98: 104384.

[12] Shashi Menon E. Gas pipeline hydraulics. Online Course. 2005.

[13] Ibrahim AH, Awad ME, Aly SM, Hussein MH. Synthesis and Design of Natural Gas Transmission Networks through Fuzzy Analogical Gates. Petroleum & Coal, 2024; 66(2): 665-675.

[14] Mohitpour M, Golshan H, Murray MA. Pipeline design & construction: a practical approach. Amer Society of Mechanical; 2003.

[15] Pambour KA, Bolado-Lavin R, Dijkema GPJ. An integrated transient model for simulating the operation of natural gas transport systems. J Nat Gas Sci Eng., 2016; 28: 672–90.

[16] Demissie A, Zhu W, Belachew CT. A multi-objective optimization model for gas pipeline operations. Comput Chem Eng. 2017; 100: 94–103.

[17] Edgar TF, Himmelblau DM, Lasdon LS. Optimization of chemical processes. 2001.

[18] Hwang C-L, Yoon K. Multiple attribute decision making: a state of the art survey. Lecture Notes in Economics and Mathematical Systems. 1981; 186.

[19] Hwang C-L, Yoon K, Hwang C-L, Yoon K. Methods for multiple attribute decision making. Multiple Attribute Decision Making: Methods and Applications a State-of-the-Art Survey. 1981:58–191.

[20] Su H, Zio E, Zhang J, Li X, Chi L, Fan L, Zhang Z. A method for the multi-objective optimization of the operation of natural gas pipeline networks considering supply reliability and operation efficiency. Comput Chem Eng, 2019; 131: 106584.

[21] Tabkhi F, Pibouleau L, Hernandez-Rodriguez G, Azzaro-Pantel C, Domenech S. Improving the performance of natural gas pipeline networks fuel consumption minimization problems. AIChE Journal, 2010; 56: 946–64.

[22] Mohamed MHH, Gawad HAA. Pioneering Heat Exchanger Network Synthesis: A TOPSIS Driven Paradigm for Optimal Solutions. Decision Making: Applications in Management and Engineering. 2024; 7: 420–41.

[23] El Gawad MSA, Aly SM, Atwa AM, Hussein MH. Multi-Objective Optimization for Synthesis Heat Exchanger Network Using TOPSIS Method. Petroleum & Coal, 2023; 65 (4): 1323-1330.

To whom correspondence should be addressed: Dr. Mostafa. H. Hussein, Chemical Engineering Department, Higher Institute of Engineering – Shorouk Academy- Shorouk City 11837 – Cairo – Egypt, E-mail: theproftifa@gmail.com