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DESIGN OPTIMIZATION OF GAS TRANSMISSION SYSTEM WITH DIFFERENTIAL EVOLUTION ALGORITHM

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ABSTRACT

Gas distribution through a pipeline network is a highly complex process and requires significant financial investment. This network system consists of a source, pipe, the compressor and sink (consumer). The source is the node where the producer has the gas pressure that will be distributed, the pipe is used to connect the producer and the consumer. Between the pipes there is a compressor which functions to increase the pressure. This network system was created at a significant cost, so it is necessary to search for minimal costs, but consumer demand is still met. This research discusses the search for an optimal gas network with minimum costs. This minimum cost depends on several parameters i.e. the length and diameter of pipe, also the pressure on the compressors entry and exit points. There are many optimization methods, but one of the simple and easy to implement methods is the Differential Evolution Algorithm, so this method is used to determine the optimal solution to this problem. Researchers used seven DE variants based on mutation strategies, namely DE/rand/1, DE/best/1, DE/rand/2, DE/best/2, DE/current-to-best/1, DE/current-to-rand/1, and DE/rand-to-best/1. The seven variants have never been used in gas distribution networks by previous researchers. Therefore, the seven variants were compared, and the minimum solution was determined. The results show that the DE/best/2 variant is the variant that produces the minimum total costs compared to the other variants. DE/best/2 achieved the lowest annual operating cost at USD 13.99 million.

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1. INTRODUCTION

Natural gas resources as one of the important energy sources to help drive world economic growth, both in developed and developing countries [1]. For nearly a century, natural gas has been transported safely, reliably, and economically using pipelines networks. Pipeline networks also provide long-term stability and security during the gas distribution process [2]. The efficient and economical design of the pipeline network involves numerous parameters, such as gas sources, delivery locations with pipeline segments, and compressors [3]. Additionally, several constraints must be met, this matter making this problem highly complex and requiring efficient optimization strategies.

Optimization is a process carried out to achieve the best results in a given situation [4]. There are two broad classes of optimization methods: deterministic and stochastic (or metaheuristic) [5]. Metaheuristic methods can solve complex optimization problems more efficiently [6]. They are designed to solve a set of problems approximately without explicitly adapting to each one[6]. In computational intelligence, evolutionary algorithms (EAs), including metaheuristic optimization with population-based, are commonly applied [7]. The mechanism of biological evolution inspired the presence of EAs. Biological properties used include mutation, reproduction, recombination, and selection. Among these, the Differential Evolution (DE) algorithm [8] has gained significant attention for its simplicity, robustness, and strong performance in continuous optimization.

DE finds the candidate solutions from population through an iterative modification process using mutation and crossover operations. DE has only three adjustable parameters i.e. total of population (*NP*), factor of mutation (*F*), and crossover probability (*CR*). In specific optimization problems, the performance of DE depends heavily on the scheme of trial vector generation and the choice of parameters [6] Many approaches have been developed to make better its performance, including a variety of mutation strategies [9]. There are several classic DE mutation factors, including DE/rand/1, DE/rand/2, DE/best/1, DE/best/2, and DE/current-to-rand/1. Each DE mutation factors has different characteristics affecting its impact on the process of solving various global optimization problems [9]. Each mutation factor also has advantages in the balance of exploration and exploitation. DE has been completely used to determine optimal solutions for various cases, for example [10] used DE to find the equipment optimal capacity of energy system. Moreover, [11] proposed to determine optimal solution of net present value on an offshore oil field. Therefore, the use of DE to determine the optimal solution in gas distribution problem through pipe network is an interesting to study.

In previous studies, the optimal gas distribution problem has been widely discussed, such as research conducted by [3], [12], [13], [14], [15], [16], [17], and [18]. [3] applied DE with a single mutation strategy to determine the optimal configuration. Building on their work, this study evaluates seven DE variants—DE/rand/1, DE/best/1, DE/rand/2, DE/best/2, DE/current-to-best/1, DE/current-to-rand/1, and DE/rand-to-best/1—to determine the optimal solution under the same problem constraints. Furthermore, this study compares the ability of several DE variants to determine the optimal pipeline networks in gas distribution network. The results of this comparison can be used to identify the best DE mutation strategy to find optimal solutions and determine the design configuration of the pipeline network to be formed. This research provides insights into determining the optimal strategy based on length and diameter pipe, as well as compressor end pressure. Furthermore, the results can be used as a reference for decision-making, which is important to improve design efficiency and reducing operational costs. This research is expected to benefit pipeline network configuration designers and gas transmission companies. It includes a demonstration of optimizing pipeline network configurations to minimize total operating costs and a comparison of optimal solutions from DE variants that employ different mutation strategies.

2. RESEARCH METHODS

2.1 Problem Formulation

Initially, natural gas was regarded as a secondary product of coal or crude oil production, which caused it to be underutilized. After the introduction of the concept of pipelines acting as a transport system, natural gas became, and has remained, one of the main sources of energy [19]. Pipelines were the one way to distribute natural gas from the production site to the demand site until the development of liquefied natural gas (LNG) [19]. Gas distribution through pipelines is an effective and efficient way to connect producers with consumers.

With the increasing demand for natural gas as an energy source, it is crucial to optimize gas transmission systems. The problem of optimal operation of a gas distribution pipeline network is generally formulated as minimizing the total cost of the pipeline network while still meeting the consumer demand at different distribution points [20]. If possible, compressors are utilized and installed to supply more gas to the pipeline network and increase gas pressure, compensating for the pressure loss caused by the hydraulic friction of the pipeline [20]. The optimization of pipelines for natural gas transmission involves several variables, such as pipe diameter, pipe length, pressure, temperature, distance between compressor stations, delivery pressure, and demand pressure [1]. Each of these parameters influences the overall cost of operation and construction, so proper selection is required. Eq. (2) is the objective function used in this study. This function accommodates the parameters that influence the cost of constructing a gas pipeline network.

Edgar and Himmelblau [21] simplified this problem by identifying every factor in the design of a pipeline configuration, including the number of compressor positions, the length of the pipeline segment among compressor positions, the diameter of the pipe segments, and the suction and discharge pressure at each compressor. To minimize the total annual operating cost including the capital expense in the objective function, optimization of these parameters is required [3].

The pipeline configuration studied in this work is the same as Edgar and Himmelblau's original scenario [21]. Each node represents a compressor station, and each straight line is a pipeline segment. The compressor is used to increase the pressure and the pressure is assumed to decrease along the pipeline [3]. This scenario is a simple illustrative example of a gas transmission system; for complex networks, some scheme branches and loops can be accommodated at the expense of additional execution time [3].

2.2 Pipeline Network Configuration Problem

In each pipeline configuration, each pipeline segment and node are labelled separately. Let N represent the total number of compressors. The number of suction pressures is $N-1$, the number of discharge pressures is N, and both the diameters and lengths of the pipeline segments total $N+1$ [3]. Each pipeline segment is characterized by its initial pressure, flow rate, outlet pressure, length, and diameter [3].

The following assumptions are made [3].

1. Each of the compressors loses 0.5 % of the gas transmitted. The mass flow rate is constant and for each pipeline segment four variables are obtained.
2. In inlet of the compressor have the temperature equal to that of the surroundings. Because each compressor functions adiabatically.
3. Each pipeline is long. It has returned to the ambient temperature.
4. For each pipeline segment, the pipe diameter and length affect the annualized capital costs. The annualized capital costs are taken as \$870 per meter per year [22].
5. For one compressor, work is estimated using the following equation:

$$W = 0.08531Q\frac{k}{k-1}T_i\left[\left(\frac{p_d}{p_s}\right)^{\frac{z(k-1)}{k}} - 1\right], \tag{1}$$

where $k = \frac{c_p}{c_v} = 1.26$ for gas at suction conditions [14]. For w, Q, T_i, p_d, p_s, z are rate of work, flow rate into the compressor, suction temperature, discharge pressure, suction pressure, compressibility factor of gas at suction conditions, respectively.

2.3 Objective Function

The objective of this study is to minimize the total cost of the gas distribution network. The objective function is built from operational and maintenance costs of the gas distribution network which are calculated using a formula [3]:

$$\boldsymbol{f = \sum_{i=1}^{n}(C_o + C_c)W + \sum_{J=1}^{m} C_s L_j D_j}\,, \tag{2}$$

where $n, m,\ C_o,\ C_c, C_s,\ L_j, D_j$ are number of compressors, number of pipeline segments, annual operating cost, compressor capital cost, pipe capital cost, length of pipeline j, and diameter of pipeline j, respectively.

2.4 Constraints

Each gas compressor has restrictions that have been set to maintain the performance of the gas transmission system so that it operates successfully and can supply the total gas pressure needed at the minimum possible cost. The constraints consist of two i.e., inequality and equality constraints. The following is an explanation of each of these constraints.

2.4.1 Inequality Constraints

Each compressor has a discharge pressure that must be greater than or equal to its suction pressure, and the compression ratio must not exceed a specified maximum K [3][23]:

$$\frac{p_{di}}{p_{si}} \geq 1, i = 1,2,3, \dots, n, \tag{3}$$

$$\frac{p_{di}}{p_{si}} \leq K_i, i = 1,2,3, \dots, n. \tag{4}$$

In addition, each pipeline variable must remain within allowable bounds [3]:

$$p_{di}^{min} \leq p_{di} \leq p_{di}^{max}, \tag{5}$$

$$p_{si}^{min} \leq p_{si} \leq p_{si}^{max}, \tag{6}$$

$$L_i^{min} \leq L_i \leq L_i^{max}, \tag{7}$$

$$D_i^{min} \leq D_i \leq D_i^{max}. \tag{8}$$

2.4.2 Equality Constraints

For the gas distribution network problem from [21], there is an equality constraint according to the total of demand branches; that is, the length of the system is fixed for each demand branch. There are two constraints for the two demand branches for the selected gas transmission network, as follows [3]:

$$\sum_{i=1}^{N_1-1} L_j + \sum_{j=N_1}^{N_1+N_2} L_j = L_1^*, \tag{9}$$

$$\sum_{i=1}^{N_1-1} L_j + \sum_{j=N_1+N_2+1}^{N_1+N_2+N_3+1} L_j = L_2^*. \tag{10}$$

where N_1, N_2, N_3 are number of compressors on branch one, branch two, branch three, respectively and L_j^* total length of demand pipe for branch j.

In addition, each pipeline must fulfill the flow equation Eq. (11) [3]:

$$Q_j = 871 D_j^{\frac{8}{3}} \left[\frac{p_d^2 - p_s^2}{L_j}\right]^{\frac{1}{2}}, \tag{11}$$

where Q_j has a fixed value, and p_d is discarge pressure, and p_s is the suction pressure [3].

2.5 Differential Evolution

Differential Evolution (DE) is a practical and easy-to-implement population-search-based stochastic evolution optimization algorithm. It was first developed by Rainer Storn and Kenneth Price [24] and can be employed to solve problems with multidimensional real-valued objective functions [6]. The algorithm searches the possible solutions from some population through a specific process [6]. The possible solution with the best objective value is retained for comparison with the new candidate solution in the next iteration. This process repeats until the stopping criterion is met.

DE has similarities with EAs in general, in which two main processes are used to evolve new solutions during the perturbation process, namely mutation and crossover. This is done to ensure both exploration and exploitation during the selection process [25]. The DE optimization procedure consists of four main steps:

1. Population initialization.
   In this process, the initial population and the control parameters are formed. This population consists of *NP* solutions, with each solution having *D* variables [9]. Thus, N_p and *D* are the population size and the dimension of the search space, respectively. The initial population at generation *G* is described by [9]

$$X_i^G = \left(X_{i,1}^G, X_{i,2}^G, \dots, X_{i,D}^G\right), i = 1,2,\dots,N_p \tag{12}$$

2. Mutation.
   A mutation strategy is used in DE. Process is applied to create a mutation vector for each individual in each generation *G* [9]. There are seven usually used DE mutation strategies listed in Table 1.

Table 1. Differential Evolution Mutation Strategy

DE Variant	**Mutation Strategy**
Rand/1	$V_{i,G} = X_{r1,G} + F(X_{r2,G} - X_{r3,G})$
Best/1	$V_{i,G} = X_{best,G} + F(X_{r2,G} - X_{r3,G})$
Rand/2	$V_{i,G} = X_{r1,G} + F(X_{r2,G} - X_{r3,G} + X_{r4,G} - X_{r5,G})$
Best/2	$V_{i,G} = X_{best,G} + F(X_{r2,G} - X_{r3,G} + X_{r4,G} - X_{r5,G})$
Current-to-rand/1	$V_{i,G} = X_{i,G} + F(X_{r3,G} - X_{i,G}) + F(X_{r1,G} - X_{r2,G})$
Current-to-best/1	$V_{i,G} = X_{i,G} + F(X_{best,G} - X_{i,G}) + F(X_{r1,G} - X_{r2,G})$
Rand-to-best/1	$V_{i,G} = X_{r3,G} + F(X_{best,G} - X_{r3,G}) + F(X_{r1,G} - X_{r2,G})$

   in which $r_j \in [1, N_p]$, r_j are random numbers with *j* = 1, 2, 3, 4, 5 and $r_j \neq i$. In addition, X_{best} is the individual with the best objective value in generation *G*, and *F* is a scale factor used to control the scale of mutation, which is bounded in the range (0, 1].

3. Crossover.
   After the mutation process, a trial vector $U_i^G = \left(U_{i,1}^G, U_{i,2}^G, \dots, U_{i,D}^G\right)$ is formed for each individual crossover scheme operator (binomial and exponential) on X_i^G and V_i^G [9]:

$$U_{i,j}^G = \begin{cases} V_{i,j}^G, & if\ \left(rand_{i,j}(0,1) \le Cr\ or\ j == j_{rand}\right) \\ X_{i,j}^G, & \text{otherwise} \end{cases}, \tag{13}$$

   where $j_{rand} \in [0,1]$ is a uniformly distributed random variable. *Cr* is the probability of crossover, which is bounded in the range (0, 1].

4. Selection.
   The selection stage determines whether the target vector or trial vector will be retained and continued to the next generation based on the objective value [9]. For minimization problems, the vector with the lowest objective value will be selected for the next generation [9]:

$$X_i^{G+j} = \begin{cases} U_i^G, & if\ \left(fit\left(U_i^G\right) \le fit\left(X_i^G\right)\right) \\ X_i^G, & \text{otherwise} \end{cases} \tag{14}$$

   Applying different strategies to the perturbation process leads to several variants of DE that can be used to obtain a solution.

2.6 Method

In this research, a quantitative approach is employed to optimize the pipeline network configuration in gas distribution networks. The data and scenarios used in the study are obtained from scientific journals [3] and are processed and analysed by applying seven DE variants. The research uses the DE algorithm, including a comparison of several DE variants with different mutation strategies, to solve the optimization problem. Following the literature review, data are collected on parameters and scenarios used in the calculation of operation costs for pipeline networks. These parameters and scenarios are obtained from various references.

The first initial scenario studied involves ten compressors and eleven pipeline segments forming three branches for two demands. From this scenario, the data to be generated include $\boldsymbol{p_d}, \boldsymbol{p_s}$, *L*, *D*, and the flow rate *Q*, which is calculated using the objective function to obtain the total operation cost. The last step of the research involves comparing the optimal solutions generated by different DE variants and forming the pipeline network configuration based on these solutions. The implementation of differential evolution algorithm in this study case is shown in Fig. 1.

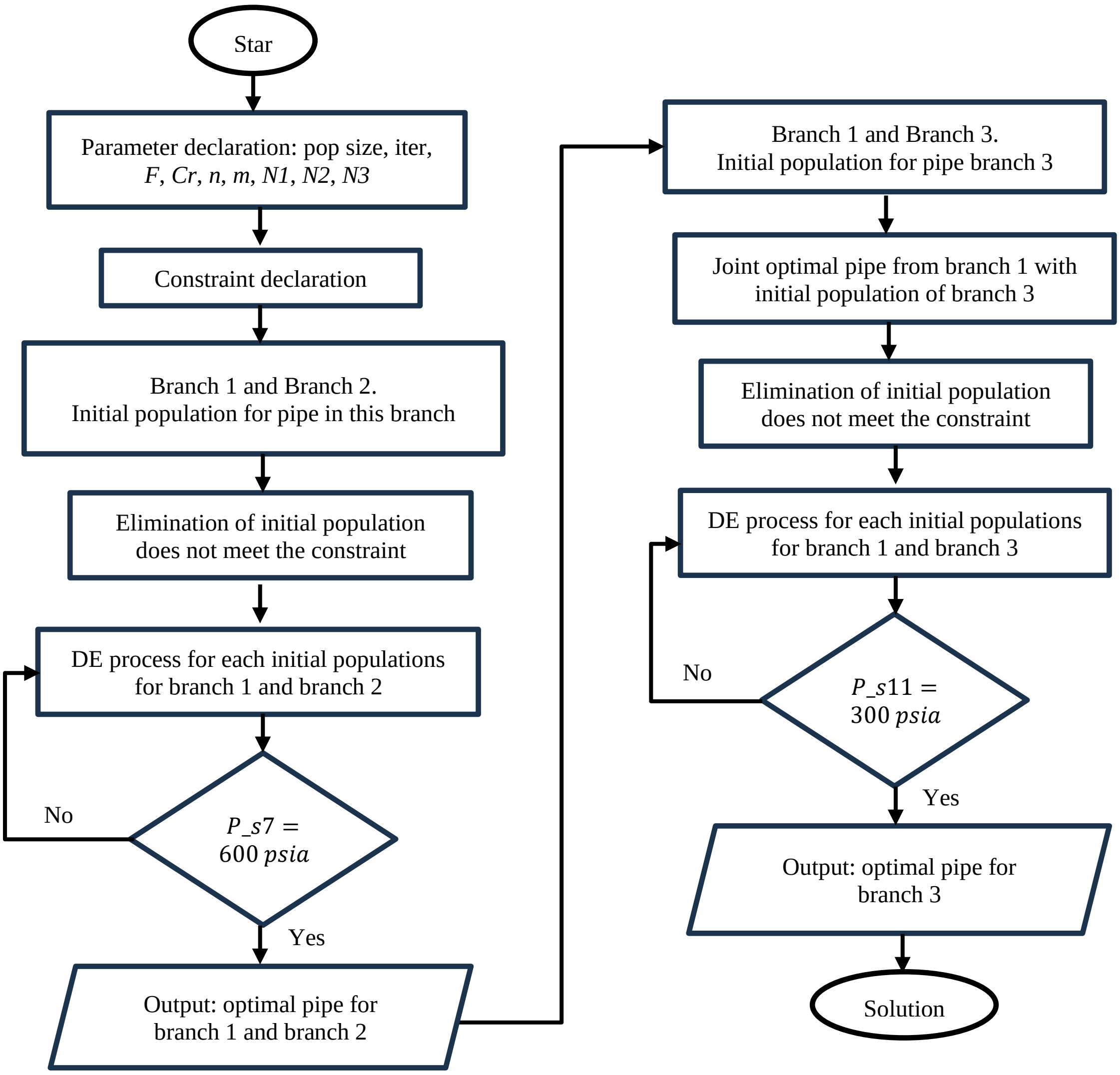

Figure 1. Diagram For Implementing the Problem of Pipeline Network with Differential Evolution.

The Fig. 1 is a diagram used to obtain the optimal solution of pipeline network. Starts by defining some DE parameters and constraint. In this study, a pipeline network has three branches, so the calculation is divided into two parts. The first part is branches one and two, while branches one and three are the second. In each of these parts are applied DE algorithm to obtain optimal solution. In this study, the algorithm was implemented in the python programming language [26].

3. RESULTS AND DISCUSSION

This study aims to determine the configuration of a pipe network that has the minimum total operating cost. The DE optimization method is used with seven mutation strategies, namely DE/rand/1, DE/best/1, DE/rand/2, DE/best/2, DE/current-to-best/1, DE/current-to-rand/1, and DE/rand-to-best/1. The DE algorithm is executed five times for each mutation strategy with the same initial scenario and control parameters.

In previous research by Edgar and Himmelblau [21] on optimizing the design of pipe network configurations using the branch-and-bound algorithm, including deterministic methods, the optimization problem was successfully solved but with a high computational complexity. Similar research conducted by Babu [23] using the DE algorithm with a common mutation strategy, namely DE/rand/1, demonstrated that DE is well suited to complex optimization problems. This research focuses on determining the DE variant that obtains the minimum result, applying the initial scenario and constraints from the previous research.

The Fig. 2 below shows the initial scenario with the pipe network configuration designed by Babu [3] to be used in determining the optimal solution using DE.

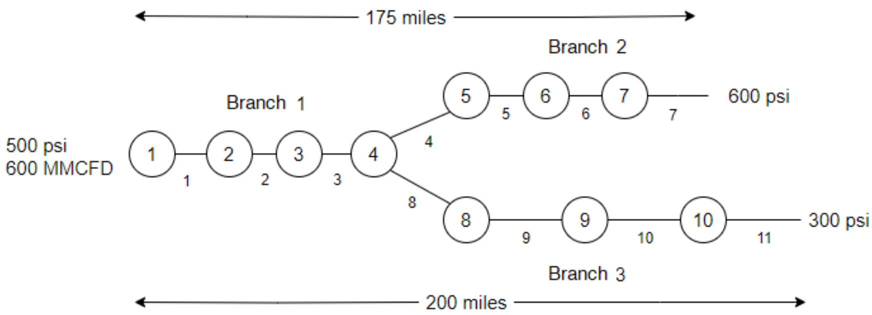

Figure 2. Initial Scenario Of Pipeline Network Configuration [3]

Each pipeline segment has some variables i.e., discharge pressure, suction pressure, length and diameter of pipe. The variables have lower bound and upper bound. Moreover, to obtain the best pipe network with minimum operating cost with differential evolution, differential evolution control parameters are needed which will be applied to the simulation process. The parameters are number of population (N_p), mutation factor (F), and crossover (Cr). No strict rules were used to determine the value. To expand the search space for solutions, in this research, the population size is selected i.e., N_p = 2000. Based on [6] $F \in [0,2]$ and $Cr \in [0,1]$, so that in this study it was chosen F = 0.02 and Cr = 0.8.

In this initial scenario, the numbers of compressor stations on branches 1, 2, and 3 are 4, 3, and 3, respectively, for a total of 10 compressor stations and 11 pipeline segments. The initial input pressure is fixed at 500 psia with a flow rate of 600 MMCFD, and the required output pressures on branches 2 and 3 are 600 and 300 psia, respectively. The combined length of branches 1 and 2 is limited to 175 m, while the combined length of branches 1 and 3 is limited to 200 m.

After determining the initial scenario, constraints, and control parameters, the process continues with the optimization of the pipeline network configuration using the DE algorithm. Experiments for each DE variant are carried out for two workflows, namely from demand 1 to demand 2 and from demand 2 to demand 1, to find out whether there is a minimum operating cost when using a different workflow. Tables 2 and 3 present a statistical analysis of five runs for each of the seven DE variants with workflows from demand 1 to demand 2 and demand 2 to demand 1.

Table 2. Statistical Analysis of Workflow from Demand 1 to Demand 2

DE Variant	Min. (USD/year)	Max. (USD/year)	SD(USD/year)	Mean (USD/year)
Rand/1	1.69E+07	2.19E+07	1.78E+06	2.03E+07
Best/1	1.74E+07	2.45E+07	2.40E+06	2.08E+07
Rand/2	1.64E+07	2.39E+07	2.63E+06	2.01E+07
Best/2	**1.42E+07**	2.41E+07	3.55E+06	2.03E+07
Current-to-rand/1	2.20E+07	2.69E+07	1.66E+06	2.39E+07
Current-to-best/1	1.82E+07	2.05E+07	8.74E+05	1.95E+07
Rand-to-best/1	1.87E+07	2.38E+07	1.91E+06	2.24E+07

Table 3. Statistical Analysis of Workflow from Demand 2 to Demand 1

DE Variant	Min. (USD/year)	Max. (USD/year)	SD(USD/year)	Mean (USD/year)
Rand/1	1.85E+07	2.70E+07	3.17E+06	2.47E+07
Best/1	2.27E+07	2.33E+07	2.17E+05	2.29E+07
Rand/2	1.71E+07	1.90E+07	7.37E+05	1.76E+07
Best/2	**1.40E+07**	2.01E+07	2.19E+06	1.59E+07
Current-to-rand/1	1.96E+07	2.22E+07	1.02E+06	2.09E+07
Current-to-best/1	2.30E+07	2.50E+07	7.19E+05	2.41E+07
Rand-to-best/1	2.42E+07	2.62E+07	6.69E+05	2.51E+07

From the optimization results obtained with the seven DE variants for both workflows, the minimum total operating cost of $13,988,681.79 per year is achieved by DE/best/2. All DE variants find a minimum operating cost between $13 and 26 million per year; this is also affected by the determination of constant values in the objective function and the DE control parameters. However, the standard deviation values are quite high in some DE variations.

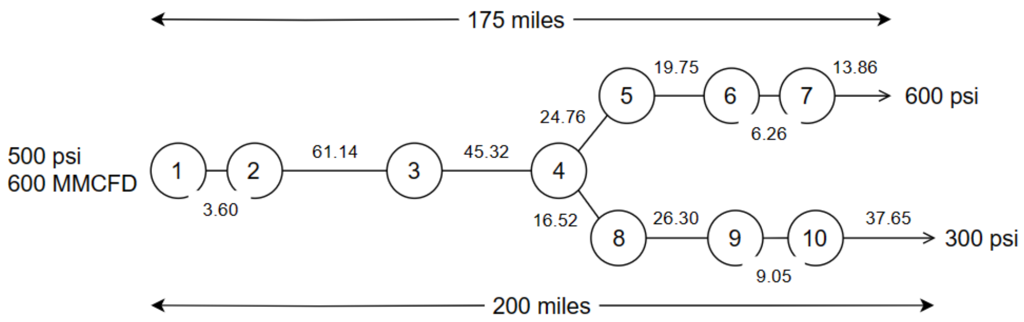

Figure 3. Optimal Pipeline Network Configuration Design Using DE/best/2

The Fig. 3 shows the optimal network configuration design. It shows 10 compressors and 2 consumers. Furthermore, between the compressors is pipe whose length is calculated to minimize costs while still meeting consumer demand. For example, between compressors 1 and 2, the pipe length is 3.6 miles (5,79 km).

Table 4. Values of Operating Variables the Optimal Network Configuration Using DE/best/2

j	$p_d(psia)$	$p_s(psia)$	$L_j(km)$	$D_i(m)$	$Q_i(MMCFD)$
1	792.46	757.38	5.78924	0.28	62.96
2	806.74	799.35	98.36603	0.18	2.15
3	818.52	806.38	72.88489	0.12	1.11
4	891.29	786.06	39.80610	0.10	2.97
5	973.09	320.45	31.76135	0.18	35.84
6	718.81	631.62	10.07029	0.15	12.73
7	663.17	599.68	22.30998	0.15	7.53
8	759.66	732.05	26.56428	0.19	8.74
9	773.40	336.15	42.32719	0.12	7.92
10	635.25	579.07	14.56896	0.34	76.07
11	994.24	299.82	60.57310	0.12	8.57
$f = 13988681.79$					

Table 5. Compression Ratio Using DE/BEST/2

Compressor Station	Compressor Ratio	Capital Cost ($/$a$)
1	1.5849	70
2	1.0652	70
3	1.0240	70
4	1.1053	70
5	1.2379	70
6	2.2431	70
7	1.0500	70
8	1.2668	70
9	1.0565	70
10	1.8898	70

The design and configuration of the optimal pipeline network found using the DE/best/2 variant are shown in Fig. 3 and Table 4.

In this case, the number of compressors is still 10, as in the initial scenario. This shows that each compressor in the pipeline network has a high compressor ratio, playing a significant role in increasing the gas pressure. The total optimal operating cost of a pipeline network is also influenced by the length and diameter of the pipes.

4. CONCLUSION

On the basis of simulation results for seven variants of the DE algorithm with different mutation strategies, namely DE/rand/1, DE/best/1, DE/rand/2, DE/best/2, DE/current-to-best/1, DE/current-to-rand/1, and DE/rand-to-best/1, in solving pipeline network configuration problems in a gas transmission system, it can be concluded that in the workflow from demand 1 to demand 2, the lowest total operating cost per year is obtained using the DE/best/2 variant while maintaining the required pressure levels and meeting the constraints set. Likewise, in the workflow from demand 2 to demand 1, the lowest total operating is achieved with the same variant. DE/best/2 uses the best individuals early in the mutation process, thus naturally increasing the intensity of exploitation. Additionally, DE/best/2 uses two vector differences simultaneously, making this variant more exploratory. The simulation results show that the DE/best/2 variant provides the most optimal solutions to the pipeline network configuration problem in the gas transmission system with the annual cost of USD 13.99 million. This research can still be developed further. Future work could explore the sensitivity analysis of optimization method parameters, the development of hybrid optimization methods, or case studies can be applied to larger networks. In addition, in this study, the metric to compare the method only uses mean, max, min, and standard deviation. Therefore, in the future, ANOVA tests can be added.

Author Contributions

Ahmad Afdhal: Data curation, Formal analysis, Methodology, Software, Validation, Writing - Original Draft. Tasmi Tasmi: Conceptualization, Funding Acquisition, Investigation, Writing - Review and Editing. Ariana Yunita: Funding Acquisition, Investigation, Project Administration. Rangga Ganzar Noegraha: Funding Acquisition, Investigation, Project Administration. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no competing interest.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

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