Pipe size sensitivity in pressure relief networks using genetic algorithms

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Abstract

This paper utilizes a stochastic optimization approach using genetic algorithms, for conducting rigorous pipe size sensitivity assessments onto the design of pressure relief networks. By sampling high performance candidates, only the finest options can survive. The pressure relief network system that was investigated in this work was previously reported in literature. The problem is constrained and involves minimizing a cost objective function that evaluates the overall network performance, in which the best pipe size combination should be selected for each segment within the network. The overall goal of this paper was to seek cost-effective designs for the pressure relief piping system by exploring different ranges of pipe diameters that are available for each segment in the network and comparing how the overall design of the system is affected, when the number of pipe size options to select from is varied.

Keywords: design; model; optimization.

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1. INTRODUCTION

Genetic algorithms are stochastic optimization techniques that can seek well-performing solutions in an evolutionary manner, by sampling regions that possess high performance probabilities where only the fittest options survive [1]. The idea of applying the principles of natural evolution as an optimization tool for engineering problems has been first introduced in the 1950s, in which for a given problem certain operators that were inspired by natural genetic variation and natural selection were found to generate populations of candidate solutions [2,3]. A decade later, Fogel and coworkers introduced an evolutionary programming technique in which candidate solutions represented as finite−state machines, were evolved by randomly mutating their state−transition diagrams, then selecting the fittest [4]. Following this, the development of evolutionary optimization strategies became a highly active research area. For instance, Rechenberg developed a methodology that utilizes an evolutionary principle to optimize real-valued systems that involve devices such as airfoils [5]. Later, Genetic Algorithms (GAs) were first introduced by Holland [6], in which he adopted an approach that was slightly different to Rechenberg's evolution strategies and Fogel's evolutionary programming techniques [4,5]. Instead of designing specific algorithms for solving particular types of problems, he introduced effective techniques for importing the mechanisms of natural adaptation into computer systems, by closely relating this natural phenomenon in biological evolution to computational behaviour [6]. His approach involved bit-string and real-valued representations to optimize systems using a genetically−inspired search methodology, in which the algorithm moves from one population of solutions to a new one, according to the laws of natural selection. Later on, evolution strategies, evolutionary programming, and genetic algorithms all began to interact to form the backbone of evolutionary computing [1]. GAs represent one of the most widely used algorithms in evolutionary computing, which in turn includes other search methods that employ population-based techniques that apply the principles of natural evolution [1]. In evolutionary computing, a representative strategy is often needed for choosing the best performing

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sets of solutions from which evolving generations can be created, in addition to computational efficiency for evaluating generations of solutions.

GAs are known to be efficient, adaptive, and capable of providing near-optimal solutions using robust search methodologies [2,3]. Moreover, they are very efficient in solving both constrained and unconstrained problems. Since the search technique of such approaches involves simultaneously operating on a set of generated solutions within a population, this reduces problems of getting trapped in local optima, and makes them suitable for parallelization [7]. Moreover, GAs can handle many types of objective and constraint functions; being continuous or discontinuous, differentiable, or non-differentiable, even black-box functions with some undefined parameters [8]. Since they can operate effectively on almost any type of functions, this makes them very suitable for solving complex problems [7]. Moreover, genetic algorithm has demonstrated great effectiveness in identifying the global optimum solutions [9]. However, if not handled properly, GAs can sometimes suffer from premature convergence, causing solution deterioration. Figure 1 compares the principal characteristics of classical deterministic algorithms against genetic algorithms.

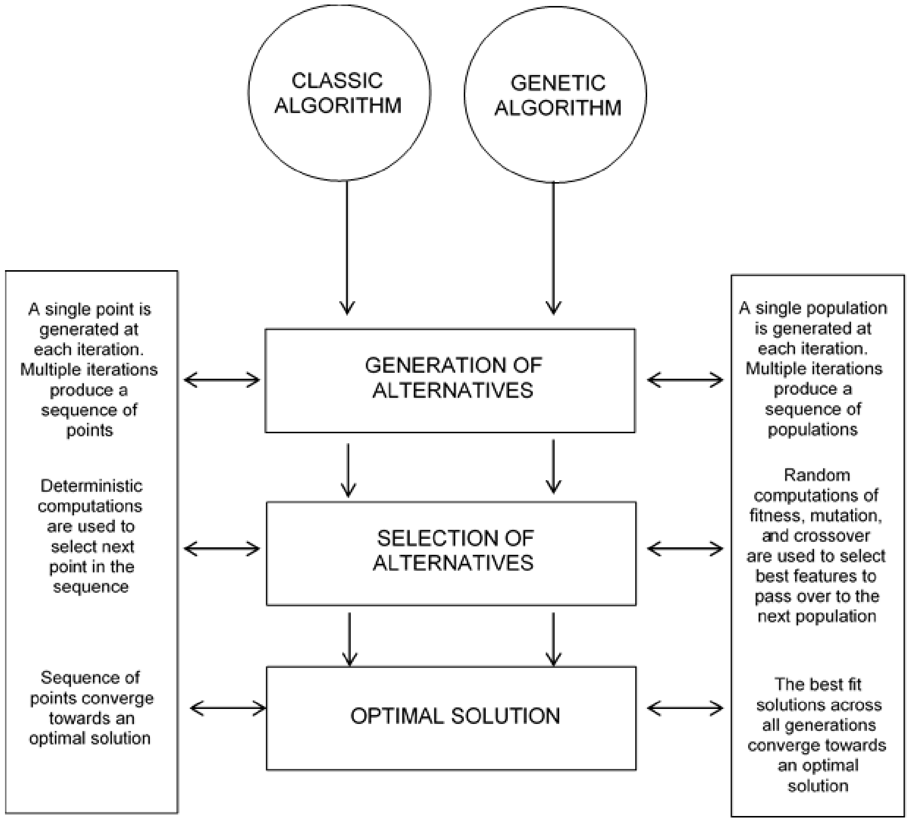

Figure 1. Comparison between classical algorithms vs. genetic algorithms

It is evident that the focal steps in both algorithms are generation, selection, and optimal solution extraction; however, each involves differences in the execution procedure. Classical algorithms manipulate a single solution in each step while genetic algorithms involve the manipulation of a generation of solutions [7]. Therefore, a successful implementation of GAs must always consider the aspects discussed above.

GAs have been proven useful in a variety of engineering design and optimization problems. For example, they have been used in problems involving reservoir and water quality management [10], extractants design [11], watershed problems [12], water networks [13,14], reservoir operation [15], reservoir characterization [16], machinery layout optimization [17], iron ore pressure optimization [18], separator pressure optimization in multistage production [19], scheduling types of problems [20] and many more. In this work, we study a pressure relief network design problem through the application of GAs. The adoption of this stochastic approach for network design types of problems comes out to be very appropriate to obtain robust, fast, and close to near-optimal solutions. The detailed model that was utilized for this problem is provided in Section 2.

2. DESIGN OF PRESSURE RELIEF NETWORKS

Pressure relief networks are important safety measures that prevent the dispersion of dangerous gases in many chemical processing plants, especially in oil refineries. The network consists of a number of pipe segments that connect process equipment to the necessary discharge zones (or flares), such that when a valve is accidently ruptured, all its contents are discharged safely, as demonstrated in Figure 2.

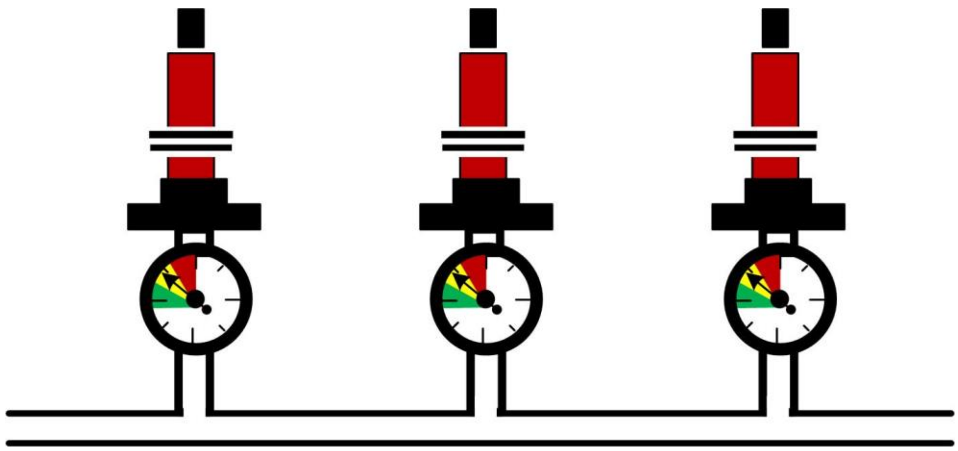

Figure 2. Illustration for a segment taken from a pressure relief network

Hence, relief networks typically consist of a piping system that connects relief valves to a sub-header as well as a main header, in addition to liquid/vapor knockout drums, and a flaring system, which in most cases serves as a disposal system for excess vapor release in a fire zone from pressure control valves during off-design operation [20]. The relief and flare system designs should accommodate the maximum relief loads, during emergency and operational scenarios.

Pressure relief networks must therefore be designed to transport gaseous fluids very quickly, which requires maintaining a sonic velocity in all discharge valves for a certain transitory period. Backpressure values for all valve-flare paths along the network must therefore be kept below a certain limit. This can be achieved by establishing upper bounds on the pressure drops for all paths available for flow control, which are usually determined according to the process conditions and valve specifications. The network design problem therefore consists of selecting an optimal set of diameters that minimizes the total cost of the network, while satisfying the pressure drop constraints imposed on the system. The pressure relief network that was considered in this work is provided in Figure 3.

The network structure consists of 34 source nodes, and 79 fixed length pipe segments. The respective node properties for this pressure relief network example have been obtained from Murtagh [22], and the respective branch lengths for each segment in the pressure relief network have been obtained from Dolan *el al.* [23].

The design of this network has first been attempted by Murtagh [22], in which he utilized a nonlinear programming (NLP) formulation in order to determine continuous values of the respective diameters associated with each of the 79 segments. Cheng and Mah [24] then employed a dynamic programming approach, referred to as the discrete merge method, which selects the diameter values according to a provided list of commercial diameters. Later on, Dolan el al. [23] proposed a stochastic method to solve the same problem, using a canonical form of simulated annealing. This involved conducting successive evaluations of design alternatives whereby new design configurations were obtained either by increasing or decreasing the diameters of the pipe segments of the current configuration. The diameters were selected according to the same list that was provided by Dolan *el al.* [23]. Soon after, Cardoso *et al.* [24] employed a non-equilibrium simulated annealing algorithm, in which they used a simple stopping criterion to control the algorithm's convergence. Costa *et al.* [26] then proposed a linear programming (LP) formulation of the same problem in which the decision variables were also the individual pipe segment diameters.

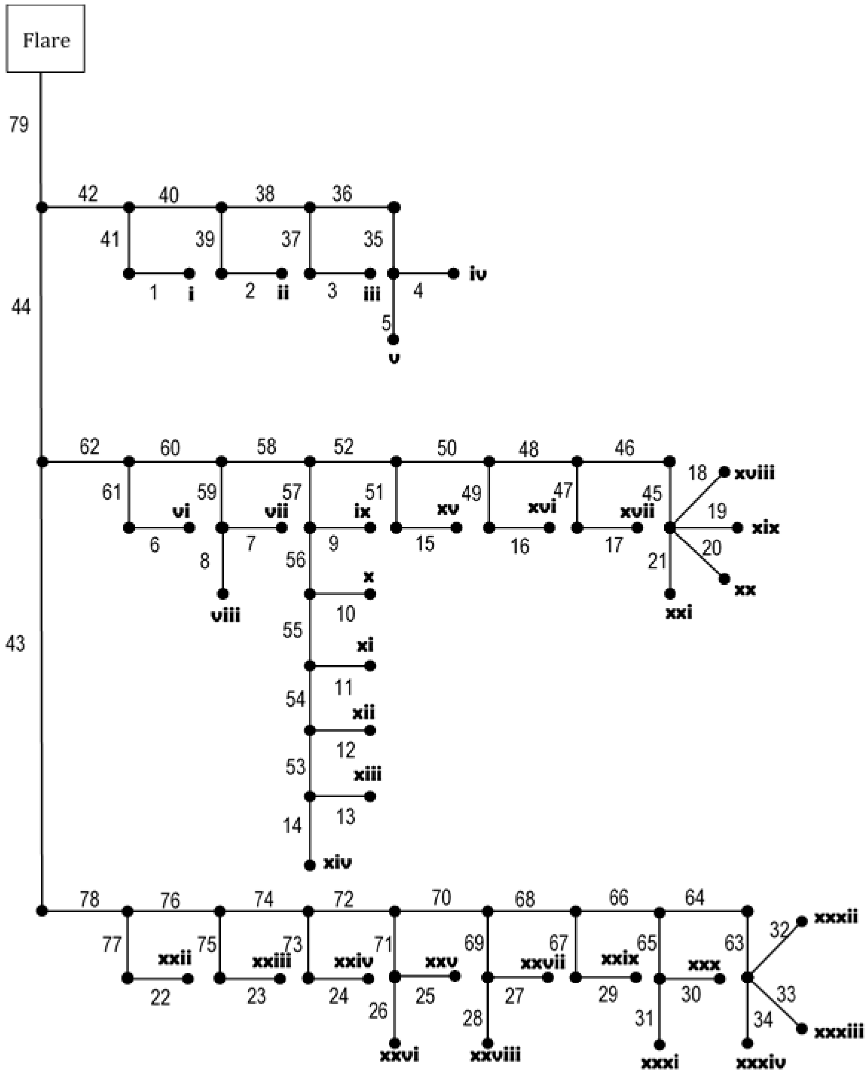

Figure 3. Pressure relief header network

3. OPTIMIZATION MODEL

The difference between the upstream and downstream pressure, $P_{A,i}$ and $P_{B,i}$ for each segment in the network i has been found according to the equation [22]:

$$P_{A.i}^{\;2} - P_{B.i}^{\;2} = \frac{0.3697 f_i \left(l_{s,i} + l_{eq,i}\right) W_i^2 R T_i}{\pi^2 g_c M_i d_i^5} \left[1 + \frac{4.61 di}{4 f_i l_i} log\left(\frac{P_{A.i}}{P_{B.i}}\right)\right] \quad \forall i \in < I \tag{1}$$

It has been reported that the term [1 + (4.61d_i / 4$f_i l_i$) log ($P_{A,i}$ / $P_{B,i}$] is very close to unity [22,23] therefore, the pressure drop can be approximated by the equation:

$$P_{A.i}^{\;2} - P_{B.i}^{\;2} = \frac{K_i}{d_i^{4.814}} \quad \forall i \in < I \tag{2}$$

The parameter K_i was computed by using the equation [23]:

$$K_i = \frac{0.001109\, \mu^{0.186}\, W_i^{1.814}\, R T_i \left(l_{s,i} + l_{eq,i}\right)}{\pi^2 M_i} \quad \forall i \in < I \tag{3}$$

The expression for calculating K_i utilizes a fanning friction factor f_i determined according to the equation [26]

$$f_i = 0.0475\left(2.8186\times10^6\,\frac{w_i}{\mu d_i}\right)^{0.186} \tag{4}$$

The respective temperatures (T_i) and molecular weights (M_i) that are attained as a result of mixing between some of the streams for each segment i were also required, and thus were obtained by applying a simple mixing rule as shown in Equations (5) and (6) [23]:

$$T_i = \frac{\sum_i W_i T_i}{\sum_i W_i} \quad \forall i \in < I \tag{5}$$

$$M_i = \frac{\sum_i W_i M_i}{\sum_i W_i} \quad \forall i \in < I \tag{6}$$

The total cost of the pressure relief network (C^{PRN}) was computed by using the capital costs of the individual pipe segments. A linear function that relates the cost of each segment to its respective diameter was used. Summing up all the segment costs gives the total cost of the network, according to the equation [23]

$$C^{PRN} = \sum_{i=1}^{n}\left(\alpha + \beta d_i\right) l_{s,i} \tag{7}$$

where *n* represents the total number of pipe segments.

Moreover, the objective of the problem consists of a linear function. However, the pressure drop constrains that need to be imposed on the system introduce non-linearity into the problem [24], according to the equation:

$$b_i \geq (P_{A,i}^2 - P_{B,i}^2)\ \forall i \in < I \tag{8}$$

Hence, main parts of the overall model may be summarized using Eqs (2), (7) and (8) as follows:

$$\min\left(C^{PRN}\right) = \sum_{i=1}^{n}\left(\alpha + \beta d_i\right) l_{s,i} \tag{9}$$

s.t.

$$b_i \geq (P_{A,i}^2 - P_{B,i}^2)\ \forall i \in < I \tag{10}$$

$$P_{A,i}^{\ 2} - P_{B,i}^{\ 2} - \frac{K_i}{d_i^{4.914}} = 0 \quad \forall i \in < I \tag{11}$$

It should be noted that since different sets of diameter sizes will be investigated, the diameters were taken as multiples of a custom step size (γ). In order to account for this aspect, Eqs (12) – (17) have been added into the original model, so as to ensure that all diameter sizes to be obtained are all multiples within a set size range. The diameter size selected for each segment must be able to accommodate the required gas flowrate, at an appropriate pressure drop and gas velocity, for each of the respective pipe segments within the network. Hence, all diameter values will be rounded up to the next nearest size, whenever appropriate. Therefore, a calculated diameter value that is based on a rounded value z_i is first obtained for each segment, according to Eq. (12). Likewise, a calculated diameter value that is based on a non-rounded value w_i is also obtained for each segment, according to Eq. (13). The difference between those 2 extra calculated diameter values must be checked, as the difference between them has to be very small (in the order of 10^{-14}), according to Eqs (12)-(17). This aspect ensures that all attained d_i values are appropriate values that lie within the size range that is respectively specified.

$$z_i = \mathrm{round}(d_i/Y)\ \forall i \in < I \tag{12}$$

$$w_i = (d_i/Y)\ \forall i \in < I \tag{13}$$

$$C_i^1 = z_i - w_i\ \forall i \in < I \tag{14}$$

$$C_i = C_i^1 - 10^{-14}\ \forall i \in < I \tag{15}$$

$$C_i^2 = z_i - w_i\ \forall i \in < I \tag{16}$$

$$C_i = C_i^2 - 10^{-14}\ \forall i \in < I \tag{17}$$

4. MODEL IMPLEMENTATION AND ALGORITHM EXECUTION

Based on the survival-of-the-fittest principle, GAs keep hold of hereditary information from generation to generate-on [1]. The basic implementation procedure involves starting from an initial, randomly created set of solutions, and then generating new sets of solutions from already existing ones. The algorithm is programmed to examine the set of solutions attained at each generation (often referred to as the number of algorithm iterations), in a simultaneous manner. The set of generated solutions is referred to as the population of the n^{th} generation. The fittest solutions within each population are retained for carrying out a new cycle of genetic operations, in which subsequent sets of solutions are generated. Each solution is associated with a string of symbols called "chromosomes". The GA execution process allows the finest characteristics of the solutions to be identified, by employing a suitable function to assess the respective fitness of any solution.

Therefore, the algorithm execution has been set up in the following order (and is illustrated using the flowchart provided in Figure 4):

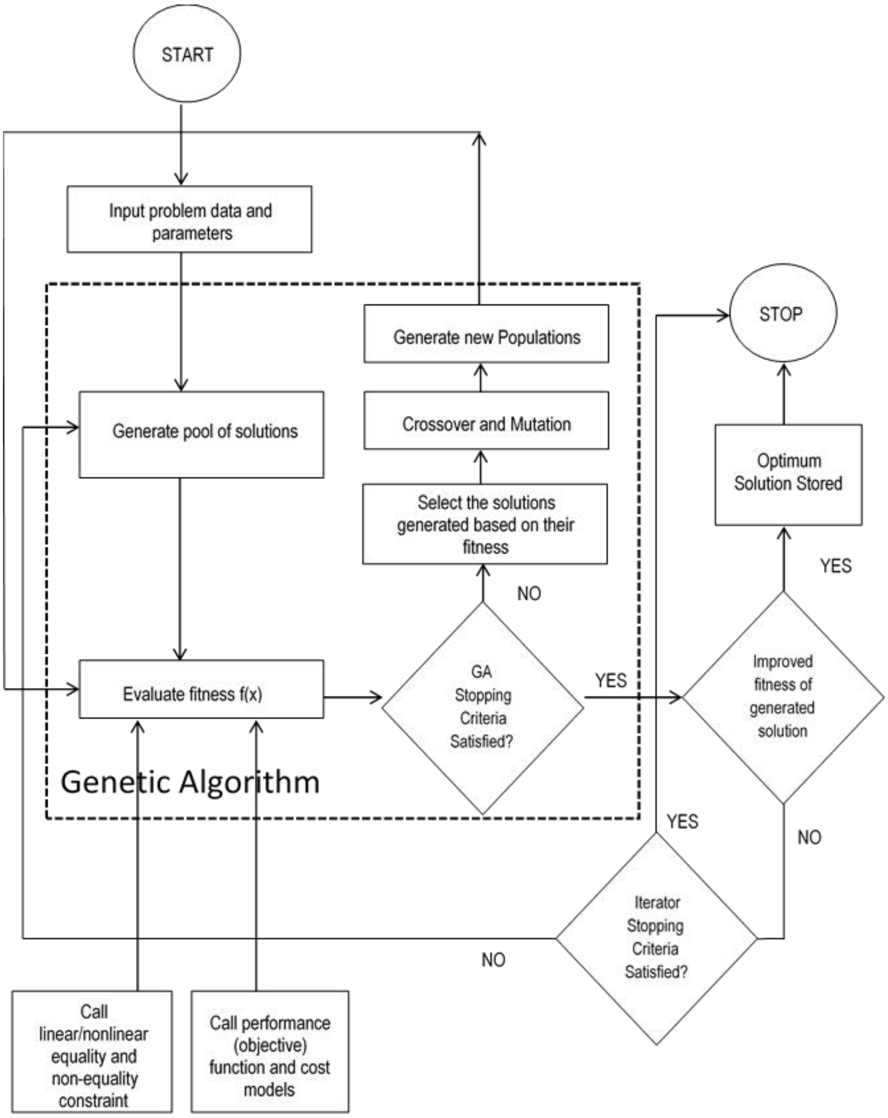

Figure 4. Flowchart illustration for the Genetic Algorithm execution

1) Create a randomly generated population of n chromosomes that represent candidate solutions.
2) Evaluate the fitness of each chromosome in the population using a fitness function $f(x)$.

3) A pair of parent chromosomes are then selected from the solutions generated. The probability of a chromosome being selected (P_s) is a function of fitness. The more fit the chromosome is, the more likely it will be selected.
4) Generate offspring for the new population. The goal is to optimize the fitness function by exploring the binary search space that minimizes the function, using steps (a) and (b):
   a) Crossover the pair of parent chromosomes using a crossover probability (P_c). If $P_c = 0$, no crossover takes place.
   b) To introduce randomness and variation into the solutions, a mutation probability (P_m) is used. This increases the likelihood of generating individuals with better fitness values. If $P_m = 0$, no mutation takes place.
5) Replaces the current population of solutions with the new generation of solutions.
6) Repeat steps (2)-(4). Each iteration results in a new generation of solutions. Therefore, the algorithm repeatedly modifies the population of individual solutions over successive generations, in order to identify an optimal. The desired solution will eventually have the best fitness value and is found after several iterations.

This work employs MATLAB for the GA execution, on a desktop PC with a 64-bit Operating System (2.7 GHz, 8.00 GB RAM), and an Intel® Core™ i7-2620M. Table 1 below summarizes the values of key items that were used throughout algorithm execution.

Table 1. GA configuration specified for algorithm execution

Parameter	Value in Problem 2
Population Size	50
Maximum Generation	100
Fitness Limit	Inf
Elite Count	2
Crossover Fraction	0.8

The population size sets the amount of solutions produced in each generation, and the number of generations specifies the maximum number of algorithm iterations to be performed before it terminates. The fitness limit also causes the algorithm to stop, if the fitness function attains the limit value specified. The elite count represents the number of solutions with the best fitness values in the current generation, which are guaranteed to survive to the next generation. When the elite count is at least 1, the best fitness value can only decrease from one generation to the next. MATLAB sets the default value of the elite count to 2, to enable the minimization of the fitness function. Setting the elite count to a high value causes the fittest individuals to dominate the population, which can make the search less effective. The crossover fraction also affects the performance of the genetic algorithm, since it represents the fraction of individuals produced in each generation, other than the elite solutions. It should also be noted that linear constraints and bounds are handled differently from nonlinear constraints. For instance, it is usually desirable for all linear constraints and bounds to be satisfied throughout the optimization, even if the nonlinear constraints are not satisfied at every generation. For this, the mutation and crossover functions must only generate points that are feasible with respect to the linear and bound constraints. However, when the algorithm eventually reports an optimal solution, all the nonlinear constraints must be satisfied. Therefore, two different conditions have been carried out for the mutation and crossover functions: (1) generating new individuals at every generation that do not necessarily satisfy all linear constraints, and (2) generating new individuals at every generation that satisfy all the linear constraints/bounds of the problem. In both cases, all linear/nonlinear constraints must eventually be satisfied for any optimal solution reported.

5. RESULTS AND DISCUSSION

As it has been discussed in Section 2 above, the same pressure relief header network problem was first introduced by Murtagh *et al* [22]. Soon after, Cheng and Mah [24] attempted to solve the problem by applying a discrete merging technique that generates pipe sections using serial and parallel merging. In doing so, the cost of the resulting pipe relief pressure network was reported to be $200,851. Dolan *et al.* [23] also solved the same problem, by applying a canonical form of simulated annealing, and reports a total of $165,075 in terms of total cost of the network. It should be noted that Cheng and Mah [24] as well as Dolan *et al.* [23] employ British units for the problem. Cardoso *et al.* [25] have reported a re-derived form for all equations using the International System (SI) of units when solving the same problem using the conditions utilized by Dolan *et al.* [23] and have reported solutions around $165,000 and higher. Cardoso *et al.* [24] also points out that the physical length of branch 40 in the network that was utilized by Cheng and Mah [23], is slightly different than the value reported by Dolan *et al.* [23], which may be one of the factors that could have contributed to the differences in solutions reported. Costa *et al.* [26] has formulated the same problem using a Linear Programming approach and have applied an alternative set of decision variables. The corresponding total cost of the network that has been reported by Costa *et al.* [26] was found to be $162,798.

In this paper, the effect of imposing different ranges of pipe diameter values for pressure relief piping networks has been carried out, using varying sets of diameter size options. The main goal was to determine whether having more sizing options would provide any enhancement to the design. Attaining optimal pipe diameter values for each segment in the network is considered crucial in the design of any piping system, especially if all segments are interconnected into one merged piping scheme [13,14,26]. The overall goal was to identify how the extraction of cost-effective designs for a pressure relief piping network would vary according to different ranges of pipe diameter selections being available for each segment in the network. A total of 8 different sets of pipe diameter ranges have been investigated. The respective pipe sizes that have been made available for selection in each case have been summarized in Table 2. The most inclusive pipe size range that was considered involves a total of 18 different diameters values, while the least inclusive pipe size range involves a single pipe size only. The rest of the diameter sets that have been considered all lie somewhere in between the most inclusive range (Set 1), and the least inclusive (Set 8). Table 2 lists the smallest to the largest pipe size available for each of the Sets 1 through 8. It should be noted that Murtagh *et al.* [22] had obtained continuous diameter values for the pressure relief network, while Cheng and Mah [24], Dolan *et al.* [23], Costa *et al.* [26], and Cardoso *et al.* [25] have all utilized Set 3 (with γ = 0.0508 m), for conducting their diameter selection.

Table 2. Commercial pipe diameter sizes used used for optimization

Pipe diameter sizes, m							
Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8
γ / m							
0.0254	0.0381	0.0508	0.0762	0.1016	0.1524	0.2032	0.4064
Pipe diameter sizes, m							
0.0254	0.0381	0.0508	0.0762	0.1016	0.1524	0.2032	0.4064
0.0254	0.0381	0.0508	0.0762	0.1016	0.1524	0.2032	0.4064
0.0508	0.0762	0.1016	0.1524	0.2032	0.3048	0.4064	
0.0762	0.1143	0.1524	0.2286	0.3048	0.4572		
0.1016	0.1524	0.2032	0.3048	0.4064			
0.1270	0.1905	0.254	0.381				
0.1524	0.2286	0.3048	0.4572				
0.1778	0.2667	0.3556					
0.2032	0.3048	0.4064					
0.2286	0.3429	0.4572					
0.254	0.381						
0.2794	0.4191						
0.3048	0.4572						
0.3302							
0.3556							
0.381							
0.4064							
0.4318							
0.4572							

This work mainly aims at identifying the best combination of pipe size diameters to be used for each of the 79 segments in the network that would ultimately minimize the cost of the system, whilst satisfying all other operational constraints that are required for this pressure relief setup. Exploring the effect of having increased or decreased diameter sizes was found imperative, in order to provide more insight into how the overall design of the system would change if the sizing choices increase or decrease. Table 3 summarizes the costs of the networks attained for each of the cases that have been investigated. It should be noted that two different conditions have been carried out for the mutation and crossover functions throughout the genetic algorithm execution. The average computational time for each run was between 60 to 120 s, for all 16 cases reported. Cases (1a)-(8a) involve generating new individuals at every generation that do not necessarily satisfy all linear constraints, while Cases (1b)-(8b) involve generating new individuals at every generation that satisfy all the linear constraints/bounds of the problem. In both situations, all linear/nonlinear constraints are eventually satisfied for all optimal solution which have reported.

Table 3. Summary of network costs obtained for each case

Set - γ / m	Case	Cost, $*	Case	Cost, $*
Set 1 - 0.0254	**1a**	135,130	**1b**	101,900
Set 2 - 0.0381	**2a**	108,400	**2b**	106,260
Set 3 - 0.0508	**3a**	100,970	**3b**	130,380
Set 4 - 0.0762	**4a**	82,022	**4b**	92,545
Set 5 - 0.1016	**5a**	84,362	**5b**	84,648
Set 6 - 0.1524	**6a**	129,160	**C6b**	123,140
Set 7 - 0.2032	**7a**	149,670	**7b**	148,980
Set 8 - 0.4064	**8a**	270,410	**8b**	270,410

*Total network cost obtained for optimal solution reported

Tables 4 and 5 provide the optimal diameters attained from each set of pipe size ranges that were investigated, for each segment in the network, corresponding to all optimal Cases (1a)-(8a).

Table 4. Optimized diameter values of Cases (1a)-(4a) obtained for each segment in the network

Branch	Setz 1	Set 2	Set 3	Set 4	Branch	Set 1	Set 2	Set 3	Set 4
	γ / m					γ / m			
	0.0254	0.0381	0.0508	0.0762		0.0254	0.0381	0.0508	0.0762
	Pipe diameter size, m					Pipe diameter size, m			
1	0.0254	0.0381	0.0508	0.4572	**41**	0.4572	0.0381	0.0508	0.0762
2	0.0254	0.4572	0.4572	0.0762	**42**	0.0508	0.0381	0.0508	0.0762
3	0.0254	0.1905	0.4572	0.0762	**43**	0.3048	0.4572	0.4572	0.0762
4	0.127	0.4572	0.0508	0.0762	**44**	0.4572	0.0381	0.0508	0.0762
5	0.4572	0.0381	0.0508	0.4572	**45**	0.1524	0.4572	0.0508	0.1524
6	0.4572	0.0381	0.4064	0.0762	**46**	0.0254	0.4572	0.0508	0.0762
7	0.0254	0.1905	0.0508	0.0762	**47**	0.4064	0.0381	0.4572	0.4572
8	0.4318	0.4572	0.4572	0.0762	**48**	0.4572	0.0381	0.0508	0.0762
9	0.0254	0.3429	0.0508	0.4572	**49**	0.4572	0.1905	0.0508	0.0762
10	0.1524	0.0381	0.0508	0.0762	**50**	0.4572	0.0381	0.0508	0.0762
11	0.1524	0.4572	0.4572	0.0762	**51**	0.0254	0.4572	0.0508	0.4572
12	0.0254	0.0381	0.0508	0.4572	**52**	0.0254	0.4572	0.4572	0.3048
13	0.0254	0.0381	0.4572	0.4572	**53**	0.0254	0.0381	0.4572	0.0762
14	0.0254	0.0381	0.0508	0.1524	**54**	0.4572	0.4572	0.4572	0.4572
15	0.0254	0.0381	0.4572	0.0762	**55**	0.4572	0.1524	0.0508	0.0762
16	0.4572	0.4572	0.4572	0.0762	**56**	0.0254	0.4572	0.1016	0.1524
17	0.4572	0.0381	0.0508	0.381	**57**	0.4572	0.4572	0.0508	0.0762
18	0.0254	0.0381	0.4572	0.4572	**58**	0.0254	0.0381	0.0508	0.4572

Branch	Setz 1	Set 2	Set 3	Set 4	Branch	Set 1	Set 2	Set 3	Set 4
	γ / m					γ / m			
	0.0254	0.0381	0.0508	0.0762		0.0254	0.0381	0.0508	0.0762
	Pipe diameter size, m					Pipe diameter size, m			
19	0.0254	0.4572	0.0508	0.4572	**59**	0.4572	0.4191	0.0508	0.0762
20	0.0254	0.4572	0.0508	0.0762	**60**	0.0254	0.4572	0.0508	0.381
21	0.4572	0.0381	0.0508	0.4572	**61**	0.0254	0.1143	0.1016	0.0762
22	0.4572	0.4572	0.0508	0.0762	**62**	0.4572	0.0381	0.4572	0.0762
23	0.0254	0.3429	0.4572	0.4572	**63**	0.4572	0.0381	0.4572	0.0762
24	0.4572	0.0381	0.4572	0.0762	**64**	0.4572	0.0381	0.4572	0.0762
25	0.4318	0.0381	0.4572	0.0762	**65**	0.4572	0.0381	0.0508	0.4572
26	0.0254	0.0381	0.0508	0.0762	**66**	0.127	0.2286	0.3048	0.0762
27	0.4572	0.4572	0.0508	0.2286	**67**	0.4572	0.0381	0.0508	0.4572
28	0.4572	0.0381	0.0508	0.4572	**68**	0.0254	0.0381	0.0508	0.0762
29	0.4572	0.2286	0.4572	0.0762	**69**	0.4572	0.0381	0.2032	0.0762
30	0.0254	0.0381	0.4572	0.0762	**70**	0.4572	0.0381	0.0508	0.0762
31	0.0254	0.4572	0.4572	0.0762	**71**	0.0254	0.4572	0.4572	0.0762
32	0.1016	0.0381	0.0508	0.0762	**72**	0.0254	0.0381	0.4572	0.0762
33	0.4572	0.0381	0.0508	0.0762	**73**	0.0254	0.0381	0.0508	0.4572
34	0.2286	0.0381	0.0508	0.4572	**74**	0.0254	0.4572	0.0508	0.0762
35	0.0254	0.0381	0.4572	0.0762	**75**	0.0254	0.0381	0.0508	0.4572
36	0.0254	0.0381	0.254	0.0762	**76**	0.2286	0.2286	0.0508	0.0762
37	0.4572	0.4572	0.0508	0.0762	**77**	0.4572	0.4572	0.0508	0.0762
38	0.0254	0.0381	0.0508	0.1524	**78**	0.0254	0.0381	0.4572	0.0762
39	0.0254	0.4572	0.0508	0.0762	**79**	0.1778	0.1143	0.1016	0.0762
40	0.0254	0.4572	0.4572	0.0762					

Table 5. Optimized diameter values of Cases (5a)-(8a) obtained for each segment in the network

Branch	Setz 5	Set 6	Set 7	Set 8	Branch	Set 5	Set 6	Set 7	Set 8
	γ / m					γ / m			
	0.1016	0.1524	0.2032	0.4064		0.1016	0.1524	0.2032	0.4064
	Pipe diameter size, m					Pipe diameter size, m			
1	0.1016	0.1524	0.4063	0.4064	**41**	0.1016	0.1524	0.2032	0.4064
2	0.1016	0.1524	0.2032	0.4064	**42**	0.1016	0.1524	0.2032	0.4064
3	0.4064	0.1524	0.4063	0.4064	**43**	0.1016	0.1524	0.2032	0.4064
4	0.3048	0.1524	0.2032	0.4064	**44**	0.1016	0.4572	0.2032	0.4064
5	0.2032	0.1524	0.2032	0.4064	**45**	0.1016	0.1524	0.2032	0.4064
6	0.1016	0.1524	0.4063	0.4064	**46**	0.1016	0.1524	0.2032	0.4064
7	0.1016	0.1524	0.2032	0.4064	**47**	0.1016	0.1524	0.4064	0.4064
8	0.1016	0.1524	0.2032	0.4064	**48**	0.1016	0.4571	0.2032	0.4064
9	0.1016	0.1524	0.2032	0.4064	**49**	0.1016	0.1524	0.4063	0.4064
10	0.1016	0.1524	0.4064	0.4064	**50**	0.1016	0.1524	0.4063	0.4064
11	0.1016	0.1524	0.2032	0.4064	**51**	0.1016	0.1524	0.2032	0.4064
12	0.1016	0.4571	0.2032	0.4064	**52**	0.1016	0.1524	0.2032	0.4064
13	0.1016	0.1524	0.2032	0.4064	**53**	0.1016	0.1524	0.2032	0.4064
14	0.1016	0.1524	0.2032	0.4064	**54**	0.1016	0.1524	0.2032	0.4064
15	0.1016	0.1524	0.2032	0.4064	**55**	0.1016	0.4571	0.2032	0.4064
16	0.1016	0.1524	0.4064	0.4064	**56**	0.1016	0.4571	0.2032	0.4064
17	0.1016	0.1524	0.2032	0.4064	**57**	0.4064	0.1524	0.2032	0.4064

Branch	Setz 5	Set 6	Set 7	Set 8	Branch	Set 5	Set 6	Set 7	Set 8
	γ / m					γ / m			
	0.1016	0.1524	0.2032	0.4064		0.1016	0.1524	0.2032	0.4064
	Pipe diameter size, m					Pipe diameter size, m			
18	0.1016	0.1524	0.2032	0.4064	**58**	0.1016	0.1524	0.2032	0.4064
19	0.1016	0.1524	0.2032	0.4064	**59**	0.1016	0.4572	0.2032	0.4064
20	0.4064	0.1524	0.4063	0.4064	**60**	0.1016	0.1524	0.2032	0.4064
21	0.1016	0.4572	0.4064	0.4064	**61**	0.1016	0.1524	0.2032	0.4064
22	0.2032	0.1524	0.2032	0.4064	**62**	0.1016	0.1524	0.2032	0.4064
23	0.1016	0.4572	0.2032	0.4064	**63**	0.2032	0.4571	0.4063	0.4064
24	0.1016	0.1524	0.2032	0.4064	**64**	0.1016	0.1524	0.2032	0.4064
25	0.1016	0.1524	0.2032	0.4064	**65**	0.1016	0.1524	0.4063	0.4064
26	0.1016	0.3048	0.2032	0.4064	**66**	0.1016	0.4572	0.2032	0.4064
27	0.1016	0.4571	0.4064	0.4064	**67**	0.2032	0.1524	0.4064	0.4064
28	0.1016	0.1524	0.2032	0.4064	**68**	0.1016	0.1524	0.2032	0.4064
29	0.1016	0.1524	0.2032	0.4064	**69**	0.1016	0.1524	0.2032	0.4064
30	0.1016	0.4571	0.4064	0.4064	**70**	0.1016	0.1524	0.2032	0.4064
31	0.1016	0.1524	0.2032	0.4064	**71**	0.1016	0.4572	0.4064	0.4064
32	0.1016	0.4571	0.2032	0.4064	**72**	0.1016	0.4572	0.2032	0.4064
33	0.1016	0.1524	0.2032	0.4064	**73**	0.4064	0.1524	0.4064	0.4064
34	0.2032	0.1524	0.2032	0.4064	**74**	0.1016	0.1524	0.2032	0.4064
35	0.4064	0.3048	0.2032	0.4064	**75**	0.1016	0.1524	0.4064	0.4064
36	0.1016	0.1524	0.2032	0.4064	**76**	0.1016	0.3048	0.4064	0.4064
37	0.1016	0.1524	0.2032	0.4064	**77**	0.1016	0.1524	0.2032	0.4064
38	0.2032	0.1524	0.2032	0.4064	**78**	0.1016	0.1524	0.2032	0.4064
39	0.1016	0.4572	0.2032	0.4064	**79**	0.1016	0.1524	0.2032	0.4064
40	0.1016	0.1524	0.2032	0.4064					

From the results presented in Table 5, it has been observed that the Sets 4 and 5 yielded the best performing solutions in terms of the total network cost attained, while Set 8 resulted in the least performing solutions. Moreover, it has been found that only diameter Sets 1, 2 and 7 yielded improved results after the utilization of mutation/crossover function that generated new individuals at every generation which satisfy all the linear constraints/bounds of the problem, unlike the rest of the cases that have been investigated. It was also observed that the optimal solution which has been reported for Cases 8(a) and 8(b) were identical, since only one diameter size was explored within this set. In case a smaller diameter value is utilized in this set, no feasible designs are attainable. As it can be seen from the results provided in Table 5, Cases 8 (“a” and “b”) yielded the most expensive solutions. As it has been expected, having only a single size option was found to be the most expensive when compared to all other cases. Nevertheless, what is quite interesting to note from the trends observed was the fact that a more inclusive size range does not necessarily yield the most optimal solutions, even though it was expected that having more pipe sizes within the set would probably enhance the quality of the solutions attained in terms of the costs of the optimal network designs reported. Hence, the best selection of sizes to incorporate into these problems was found to be somewhere between the most inclusive size rage, and the least inclusive.

In order to provide an idea of how the solutions compare in terms of the changes that have been explored for cases “a” compared to cases “b”, Figures 5 and 6 provide an illustration of the pressure relief design sensitivity of the optimal solution which have been reported for each Case “b” scenario compared to the respective Case “a” solution.

All segments presented in red were unchanged (amongst the two optimal solutions reported for each), while all the segments presented in black underwent a diameter change in the new optimal solution. As it can be noted from the illustrations, there were 20 segments associated with Case 1 that remained unchanged between their respective “a” and “b”. As for the remaining cases, 32 segments associated with Case 3 remained unchanged, 31 segments associated with Case 4 remained unchanged, 47 segments associated with Cases 4 and 5 remained unchanged, and 53 segments associated with Case 6 remained unchanged. Unlike all other cases, and since only 1 diameter value was involved in Set 8, all diameters that have been reported for Case 8 "a" and 8 "b" remain unchanged. Hence, it can be noted that the solutions involving the highest number of segments associated with a diameter change between the respective cases "a" and "b" was attributed to the most inclusive set of diameters (Set 1), while the solutions that did not report any diameter change between the respective cases "a" and "b" was attributed to the least inclusive set of diameters (Set 8). Hence, it was found that incorporating more size options do not necessarily yield better solutions. To date, in literature does not exist any work that has provided any insight in such effects on the design of pressure relief systems, especially in terms of cost-effectiveness and applicability.

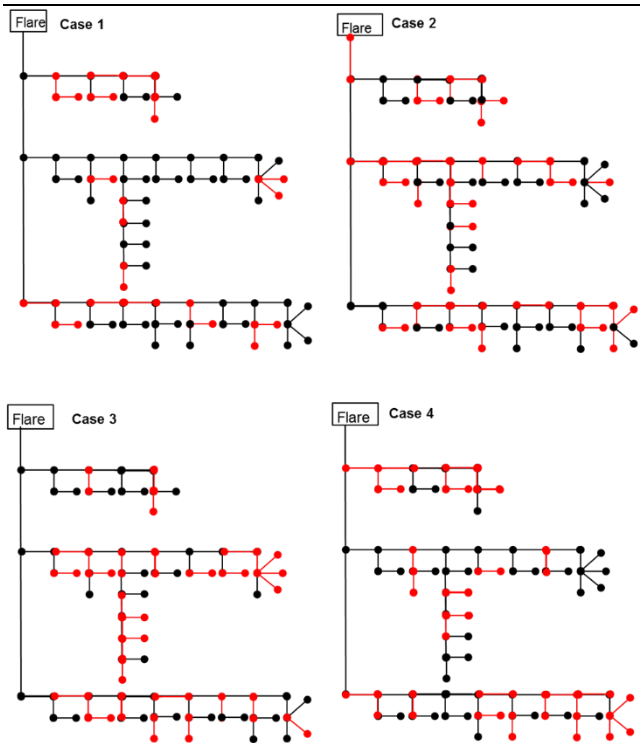

Figure 5. Pipe diameter sensitivity demonstrated for Sets 1-4 for each Case "b" solution compared to Case "a". Segments highlighted in red remain unchanged, while all black segments indicated a diameter change across the 2 solutions

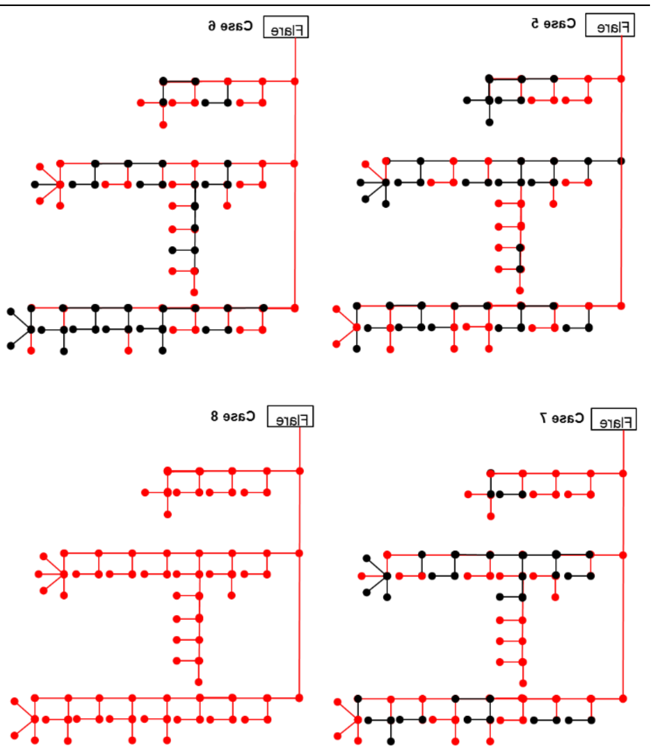

Figure 6. Pipe diameter sensitivity demonstrated for Sets 5-8 for each Case "b" solution compared to Case "a". Segments highlighted in red remain unchanged, while all black segments indicated a diameter change across the 2 solutions

6. CONCLUSIONS

A pressure relief network design problem has been attempted in this work by applying a practical search-based optimization *via* genetic algorithms. The main objective was to provide an alternative search technique that is capable of providing higher accuracy levels in the solutions reported. The problem involves minimizing a cost objective that evaluates the network design performance according to the sizing of the pipes. The most inclusive pipe size range that was investigated involved a total of 18 different diameters, while the least inclusive pipe size range involved a single pipe size only. Even though it was predicted that having a more inclusive pipe size variety to select from would probably enhance the quality of the solutions attained, it was found that the pipe size range which provided the most cost-effective solutions involved a total of 4 different pipe sizes only. It was evident that the evolutionary algorithm applied in this work was able to report high-quality solutions to this optimization problem, using different sets of pipe segments in each case. Obviously, the sensitivity of pipe sizes in the pipe relief network was highly dependent on the diameter sets. Furthermore, employing machine learning techniques from which new solutions can be sampled or generated, as a result of a more guided-crossover scheme, can be utilized in line with the above problem. Alternatively, a multiobjective optimization approach may be considered, in which the effect of several conflicting design variables that generate multi-dimensional outputs may be explored with the help of Pareto optimal outcomes.

NOMENCLATURE

C^{PRN} / $	Cost of pressure relief network
d / m	Diameters of segments in pressure relief network
f	Friction factor
g_c / kg m N^{-1} s^{-2}	Gravitational constant
K_i	Backpressure constraint constant for individual pressure relief network segments
b_i / Pa^2	Upper bound pressure drop constraint for individual nodes in pressure relief network
P_A / *Pa*	Upstream pressure
P_B / Pa	Downstream pressure
l_{eq} / m	Equivalent length
l_s / m	Straight length
R / kJ mol^{-1} K^{-1})	Ideal gas constant
T / K	Absolute temperature
W / kg/s^{-1}	Mass flowrate in pressure relief pipe segments
M / kg kmol^{-1}	Molecular weight
C^{IWIN} / $ year^{-1}	Cost of interplant water integration network
μ / N s m^{-2}	Viscosity = 2.5 10^{-5}
α / $ m^{-1}	Cost coefficient=7.1243
β / $ m^{-2}	Cost coefficient=341.05 $/m^2
γ / m	Custom step size for pipe diameter range
P_c	Crossover probability
P_m	Mutation probability

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SAŽETAK

Analiza osetljivosti prečnika cevi pri projektovanju sistema baklje upotrebom genetskog algoritma

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(Naučni rad)

Ovaj rad koristi stohastički pristup optimizaciji koristeći genetske algoritme, za sprovođenje rigoroznih procena osetljivosti veličine cevi u dizajnu sistema baklje. Sistem koji je razmatran u ovom radu prethodno je objavljen u literaturi. Problem je ograničen i uključuje minimizovanje cene koštanja, tako da procenjuje sveukupne performanse sistema u kom bi trebalo izabrati najbolju kombinaciju veličine cevi za svaki segment. Opšti cilj ovog rada bio je iznalaženje ekonomičnih rešenja za cevovod za sistem baklje istraživanjem različitih opsega prečnika cevi koji su dostupni za svaki segment i poređenjem uticaja na celokupnu konfiguraciju sistema, kada postoji veliki broj mogućnosti izbora za veličinu cevi.

Ključne reči: projektovanje; model; optimizacija.