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# Metaheuristic algorithm for parametric optimization of liquid nitrogen pumping in hydrocarbon and allied fluids piping systems

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## HIGHLIGHTS

- Liquid nitrogen pumping is used for leak testing in hydrocarbon and allied fluid piping systems.
- Process parameters were optimized using population-based metaheuristic techniques.
- Multi-objective genetic algorithms were applied to achieve optimal solutions.
- Optimal pumping performance and control parameters were identified.
- The achieved process enhanced efficiency with minimal energy consumption and operational

**Keywords:**
Liquid nitrogen pumping; hydrocarbon and allied fluids; piping systems leak test; metaheuristic optimization; MOGAs.

## ABSTRACT

This study applied a population-based metaheuristic algorithm to optimize liquid nitrogen pumping in hydrocarbon and allied fluids piping systems to ensure optimal process efficiency, minimize energy consumption, and minimize operational costs without extensive computational tasks while considering uncertainties and variability. Liquid nitrogen pumping in hydrocarbon and allied fluids piping systems involves a heat and mass transfer process where by liquid nitrogen flows from the storage tank to the pump unit and is converted to the gaseous state in an integrated heat exchanger. The continuous high pressure from the triplex reciprocating pump pushes the gaseous nitrogen to the hydrocarbon and allied fluids piping systems. Hence, the pumping is for purging, inerting, or pneumatic testing of the piping systems. Thus, the pumping process was parameterized and parametrically characterized to define the performance and control parameters quantitatively. Surrogate optimization models were formulated using an efficient response surface method. Since the models are multiparametric, multi-objective genetic algorithms were utilized to provide global optimal solution sets for the models. The results show that 3.79% decrease in pressurized volume of the piping systems, 1.48% decrease in test pressure of the piping systems, 3.42% increase in maximum discharge pressure of the liquid nitrogen pump and 1.08% increase in maximum flow rate of the liquid nitrogen pump across test packs increased total volume of liquid nitrogen pumped by 40.00%, decreased test duration by 0.70%, decreased pumping duration by 0.70% and increased total volume of liquid nitrogen used by 8.00% and vice versa.

## 1. Introduction

Finding the optimal settings for liquid nitrogen pumping in hydrocarbon and allied fluids piping systems is a practically complex challenge and impossible by the classical mathematical methods. This is because of the multi-parametric complexities that must be inherently considered. Ushakov [1] opined that the only possibility of solving such problems is the heuristic procedure, but the assurance of the correctness of the solution is not guaranteed. A heuristic function is a problem-dependent approximate measure of the quality of one candidate solution [2]. According to [3,4], though the heuristic procedure is iterative, sufficiently efficient in dealing with huge problems, and capable of providing a perfectly feasible solution, it does not guarantee optimality; therefore, a more advanced approach that explores and exploits all feasible search spaces and strategies to provide an efficiently near-optimal solution is sacrosanct. This approach is the metaheuristic algorithm. Thus, metaheuristic algorithms are higher-level heuristic algorithms and have a far better chance of providing the best solutions [5]. Also, according to [2], metaheuristics is a method for solving general classes of stochastic problems [6]. The metaheuristic approaches are often nature-inspired algorithms, which include genetic algorithms, simulated annealing, differential evolution, ant and bee algorithms, particle swarm optimization, harmony search, firefly algorithm, cuckoo search, and others, and they are iterative; genetic algorithms are a part of evolutionary algorithms (EA) [4,7,8].

Gosavi [9], noted that successfully implementing the classical optimization algorithms in the parametric scenarios proves difficult due to the inherent complexities and nonlinearity of the objective function and randomness of the data set. Also, classical optimization algorithms like linear programming and nonlinear programming are limited in their application to parametric optimization due to difficulties of differentiability, nonlinearity, and non-convexity [10]. Thus, the meta-heuristic approach has



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proved efficient in solving difficult problems over time [11–13]. Majid and Arshad [14], applied a metaheuristic approach reliably in solving acoustic source localization problems when other available approaches failed. Apitzsch et al. [15], noted that metaheuristics provide convincing results in solving complex multi-parametric problems. From the inception of the concept of metaheuristics till recent times, many metaheuristic optimization algorithms or techniques, such as genetic algorithms, etc., have been developed and implemented in different instances [10,16–21]. Ahmad et al. [22], pointed out that the genetic algorithm is one of the most popular meta-heuristic approaches for solving complex problems.

Furthermore, the concepts and applications of evolutionary algorithms are expounded in [23]. It effectively solves several large and complex optimization problems [24]. When the optimization problem involves several objectives at the same time, it is called a multi-objective evolutionary algorithm (MOEA) [25], and it consists of genetic algorithms [26]. Genetic algorithms constitute the most popular population-based metaheuristic algorithms with a wide range of application spectra, including quantitative modeling and optimization of systems/processes [22]. Gupta and Jawdekar [27], noted that they are probabilistic and population-based. They have also been applied successfully in solving complex multi-objective optimization problems, hence multi-objective genetic algorithms (MOGA) [24]. Fonseca and Fleming [28], used genetic algorithms successfully in multi-objective optimization, obtained a satisfactory solution to the problem under study, and showed that multi-objective genetic algorithms can uniformly sample regions of the trade-off surface. Jabri et al. [29], applied genetic algorithms in the multi-objective optimization of cutting parameters and obtained a Pareto front that helped decision-making. Therefore, metaheuristic optimization algorithms demystify the task of parametric optimization of liquid nitrogen pumping for leak tests of hydrocarbon fluids piping systems.

Arthur et al. [30], recommended the more recent and improved heuristic and metaheuristic optimization algorithms like artificial bee colony optimization algorithm, binary particle swarm optimization algorithm, Egyptian vulture optimization algorithm, spiral optimization algorithm, simulated annealing optimization algorithm, differential evolutionary algorithm, evolutionary programming, improved teaching learning based optimization algorithm, neural networks, etc. for global or near-global solution instead of the conventional optimization algorithms like dynamic programming, Lagrange's technique and lambda-iteration, etc. due to their low convergence rate, large computation time, poor local optima avoidance and algorithm complexity. A genetic algorithm was employed to optimize a multi-parametric energy system due to its ability to effectively deal with a large multi-dimensional design space, unfeasible design candidate, and improve convergence [31]. Sibalija [32], noted that a genetic algorithm is a metaheuristic evolutionary algorithm in an evolutionary computing-based approach to parametric optimization. The multi-objective differential evolution algorithm is another metaheuristic algorithm that has been applied successfully in the parametric optimization of an energy-related system in recent times [33]. Weaver-Rosen et al. [34], noted that parametric optimization is an alternative approach that can simultaneously solve a family of related optimization problems. The genetic algorithm is a suitable algorithm for nonlinear multi-parametric optimization. Also, the genetic algorithm is the most popular evolutionary algorithm, and evolutionary algorithm (evolutionary computation) is a branch of the algorithmic population-based soft computing techniques and the most powerful metaheuristic techniques used in multi-objective, non-continuous and non-differentiable stochastic global optimization [35]. Thus, the genetic algorithm has been rated the most effective among all the parametric optimization algorithms with the fastest processing time [36]. This work aims to ensure optimal process efficiency and minimize energy consumption and operational costs without extensive computational tasks while considering uncertainties and variability.

It showed the application of a population-based metaheuristic algorithm, MOGA, in the solutions of optimization problems involving liquid nitrogen pumping for nitrogen leak test of hydrocarbon and allied fluids piping systems considering multiple parameters simultaneously. MOGAs have been applied in solving different pump and pumping optimization problems including cryogenic fluids, however, there is no evidence of their application in liquid nitrogen pumping for leak test of hydrocarbon and allied fluids piping systems. Shao et al [37] used MOGAs to improve the hydraulic efficiency and cavitation performance of a partial emission liquid nitrogen pump. Sivasree and Nitin [38] applied MOGA to optimize the design of nitrogen jackets for liquid hydrogen pipelines thereby minimizing heat inleak and pressure drop. Tan et al [39] applied MOGA in optimization of a liquid oxygen vacuum subcooling system using an ejector and liquid ring pump considering mass flow rate of the working fluid, pressure of the working fluid, intermediate pressure and pump speed. Hence, none of these literatures is directly related to liquid nitrogen pumping in hydrocarbon and allied fluids piping systems. Therefore, this work is novel.

## 2. Materials and methods

### 2.1 Pumping systems and the setup

Equipment rig-up connects the pumping systems to the hydrocarbon and allied fluids piping systems in the order illustrated in Figure 1. The figure comprises liquid nitrogen tank and its piping, cryogenic hose, boost pump and its piping, triplex pump and its piping, heat exchanger, control panel, temporary manifold and hydrocarbon and allied fluids piping system. It involves using hand tools and utmost carefulness, leakage of the liquid or gas, and sudden disconnection of the line under pressure. After system preparation, valve alignment, isolation, and equipment rig up, the requisite checklist in the job procedure was completed and duly signed.

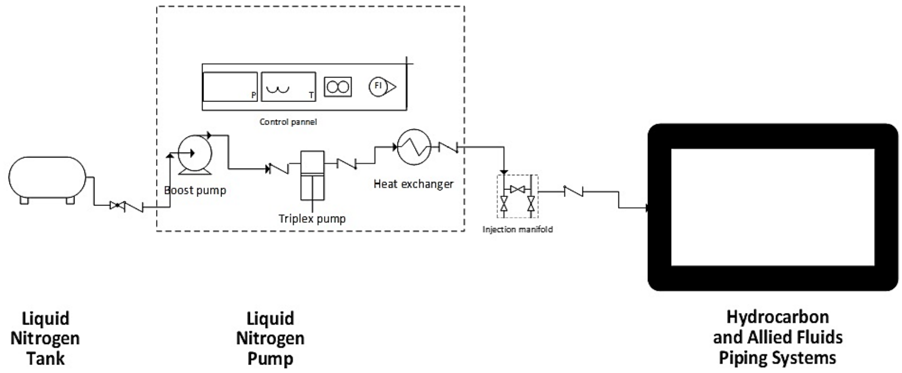


**Figure 1:** Schematic of the connection of equipment rig-up

This was followed by a public address notifying every personnel on site of when the operation would commence and the safe and unsafe zones. Unauthorized persons are, therefore, warned to stay away from the exclusion zones to avoid injury to personnel during the test. Thus, the pumping process was parameterized and parametrically characterized. The implied parameters were then quantified and analyzed to formulate adequate optimization models. Since the models are multiparametric (comprising multiple outputs as performance parameters and multiple inputs as control parameters), a multi-objective optimization method was used to define the optimal settings.

## 2.2 Multi-objective optimization method

Since the final optimization models are multi-objective, the optimal settings of the performance and control parameters were defined using MATLAB's multi-objective optimization algorithm toolbox. Multi-Objective Genetic Algorithms (MOGAs) were applied in this study to set the optimal techno-economic values for nitrogen pumping in hydrocarbon fluids piping systems. This is because the process involves considering multiple objectives dependent on many random variables, which must be sorted simultaneously.

Genetic algorithms are population-based evolutionary algorithms with less computation time and a strong ability for global search [22]. It is the most widely known metaheuristic algorithm and performs well within the considered number of iterations and in handling stochastic optimization problems [40– 42]. GAs have also been argued, among other metaheuristic methods, to have demonstrated an impressive ability to locate optima in large, complex, and noisy search spaces [43]. MOGA is a multi-objective genetic algorithm is a multi-objective evolutionary algorithm (MOEA) used to optimize multiple conflicting objective functions simultaneously [44]. Optimization of the functions seeks to find the minimum, target, or maximum values of the functions. Therefore, the multi-objective optimization here was set up as

F(R)= {f_1 (V_1 ),f_2 (D_t ),f_3 (D_p ),f_4 (V_2 )} (1)

where F(R) is a set of objective functions, is an objective function. The optimization process was performed with MATLAB software. Thus, the optimization model of the performance parameters in terms of the actual value of the control parameters is given in Equations (1- 4);

$$V_1 = 1.0333 - 0.01223P_t - 0.005027P_d + 0.000021P_tP_d + 0.003178P_tQ_N + 0.000031P_t^2 + 0.000013P_d^2 + 0.2196Q_N^2 - 0.000000006338V_pP_tP_d - 0.00000001136V_pP_t^2 \quad (2)$$

$$D_t = 2.4849 + 0.003702V_p - 0.007001P_t - 0.01094P_d - 0.000006021V_pP_t - 0.000011V_pP_d - 0.001384V_pQ_N - 0.002293P_tQ_N - 0.004213P_dQ_N - 0.000001034V_p^2 + 0.000038P_t^2 + 0.0000515P_d^2 + 0.7934Q_N^2 - 0.000000004319V_pP_tP_d + 0.000001549V_pP_tQ_N + 0.000002199V_pP_dQ_N + 0.000005491P_tP_dQ_N + 0.000000001959V_p^2P_t + 0.000000003951V_p^2P_d + 0.0000003610V_p^2Q_N \quad (3)$$

$$D_p = 1.5482 + 0.001956V_p - 0.003685P_t - 0.005760P_d - 0.000003164V_pP_t - 0.000006027V_pP_d - 0.000733V_pQ_N - 0.001205P_tQ_N - 0.002227P_dQ_N - 0.0000005460V_p^2 + 0.00002P_t^2 + 0.000027P_d^2 + 0.4182Q_N^2 - 0.000000002279V_pP_tP_d + 0.00000008125V_pP_tQ_N + 0.000001166V_pP_dQ_N + 0.000002897P_tP_dQ_N + 0.000000001025V_p^2P_t + 0.000000002089V_p^2P_d + 0.0000001908V_p^2Q_N \quad (4)$$

$$V_2 = 1.0110 - 0.01457P_t + 0.000023P_tP_d + 0.004543P_tQ_N + 0.000036P_t^2 + 0.000013P_d^2 + 0.2293Q_N^2 - 0.000000006056V_pP_tP_d - 0.000009686P_tP_dQ_N - 0.00000001539V_pP_t^2 \quad (5)$$

These equations are the surrogate models of the dataset from liquid nitrogen pumping in hydrocarbon and allied fluids piping system, showing the relationships between the performance and control parameters of the process. Hence, the performance parameters are total volume of liquid nitrogen pumped ($V_1$), test duration ($D_t$), pumping duration ($D_p$) and total volume of liquid nitrogen used ($V_2$); while the control parameters are the pressurized volume of the piping systems ($V_p$), test pressure of the piping system ($P_t$), discharge pressure of the liquid nitrogen pump ($P_d$) and flow rate of the liquid nitrogen pump ($Q_N$).

According to [45], the terminologies and operators of genetic algorithms considered in the multi-objective optimization include objective functions, decision variables, evaluation, fitness function, initialization, population, Pareto front, non-dominated sorting, selection, crossover, mutation, termination criteria, replacement, and termination. The objective functions are the performance parameters to be optimized. Decision variables are the control parameters to be adjusted to optimize the objective functions. Evaluation is the process of checking each individual's fitness using the objective functions. The fitness function is a function that evaluates how well each individual in the population meets the objectives; fitness here represents the objective to be evaluated. Initialization involves the generation of potential solutions for the initial population. Population is the set of potential solutions (individuals) currently involved in the search process, while individuals are solution sets generated. The Pareto front is the set of non-dominated solutions representing the balance between different objectives. Non-dominated sorting ranks the potential solutions based on their dominance over multiple objectives. Selection is the initial step in the breeding process as it involves choosing two parents to cross at a time from the population. It is a reproduction process and can take any method:

roulette wheel selection, random selection, rank selection, tournament selection, Boltzmann selection, and stochastic universal sampling, Sivanandam and Deepa [45].

Crossover in genetic algorithms involves recombining parent solutions to produce offspring with better characteristics. It can take any of the following techniques: single-point crossover, two-point crossover, multi-point crossover, uniform crossover, three-parent crossover, reduced surrogate crossover, shuffle crossover, precedence preservative crossover, ordered crossover, and partially matched crossover. The mutation introduces new genetic structures in the population by randomly modifying some of its building blocks, which helps escape from local minima's trap and maintains diversity in the population. Replacement is the process of replacing the old population with the new one. Termination criteria determine when the algorithm should stop, such as a maximum number of generations or a satisfactory fitness level. Then, termination involves checking and stopping the algorithm if the termination criteria are met.

## 2.3 Optimization software and algorithm

MATLAB optimization tool was used to run the optimization. It offers the double vector, bit string, and custom population types, with a default size of 50 for five or fewer variables, otherwise 200. However, a population size of 70 was specified to enable a feasible, not-too-large solution set for the nonlinear feasible population in the creation function tab. However, the creation function tab provides for constrained dependent, uniform, feasible population, nonlinear feasible population, and custom tabs. The choice of a nonlinear feasible population was predicated on the nonlinear nature of the fitness functions. Also, the double vector population type allows for constrained dependent, Gaussian, uniform, adaptive feasible, and custom mutation functions, and constrained dependent, scattered, single point, two-point, heuristic, arithmetic, and custom crossover functions. The bit string population type limits the creation function tab to uniform and custom only, ignores all the constraints, and sets the bound constraints to [0 1]. These limitations equally limit the search space, thereby making it non-robust. The custom population type requires that a custom creation function or initial population is provided. This would make the solution set more deterministic rather than probabilistic or stochastic. Therefore, the double vector population type with a nonlinear feasible population creation function was used in this optimization process. Also, the tournament selection function with a default tournament size of 2 and crossover fraction of 0.8, adaptive feasible mutation function, heuristic crossover function with a default ratio of 1.2, and specific generations of 800 (i.e., 200 times the number of variables) was used in the optimization toolset. These choices were predicated on the fact that the objective function and the associated variables values must be non-negative (non-negative lower bounds must be provided), and the search process must be stochastic and robust. Thus, the adopted optimization algorithms are presented in Figure 2.

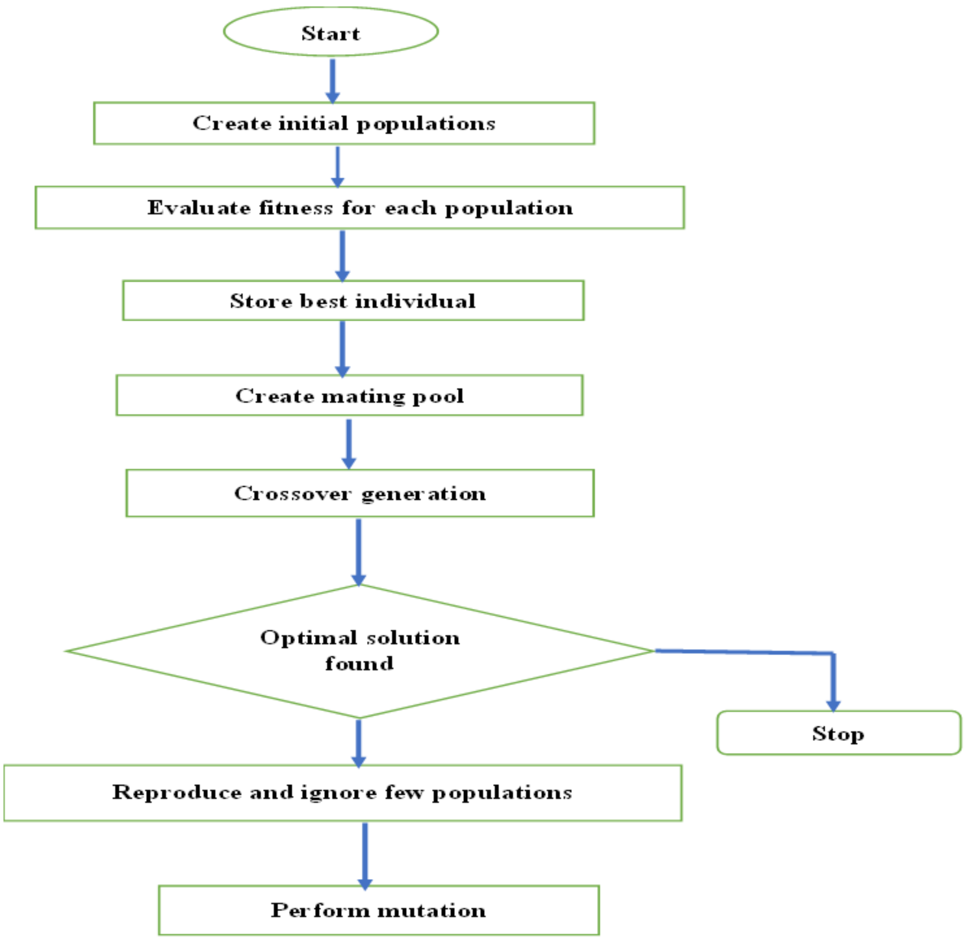


**Figure 2:** Flowchart of the optimization algorithms

## 3. Results and discussion

### 3.1 Multi-objective optimization using genetic algorithms

The solution set of the objective functions and the corresponding variables are shown in Table 1. This indicates the optimal values of the performance and control parameters simultaneously.

**Table 1:** Optimal solutions for performance parameters

| Index | $V_{o1}$ | $D_{ot}$ | $D_{op}$ | $V_{o2}$ | $V_{op}$ | $P_{ot}$ | $P_{od}$ | $Q_{oN}$ |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.02 | 1.89 | 1.25 | 0.27 | 208.96 | 121.77 | 80.10 | 0.38 |
| 2 | 0.21 | 1.53 | 1.04 | 0.80 | 10.94 | 77.84 | 148.60 | 0.47 |
| 3 | 0.11 | 1.58 | 1.07 | 0.56 | 94.78 | 99.00 | 122.05 | 0.42 |
| 4 | 0.22 | 1.53 | 1.04 | 0.79 | 17.63 | 76.59 | 143.68 | 0.47 |
| 5 | 0.22 | 1.53 | 1.04 | 0.81 | 13.52 | 77.36 | 146.69 | 0.47 |
| 6 | 0.04 | 1.71 | 1.15 | 0.39 | 157.89 | 113.00 | 100.22 | 0.37 |
| 7 | 0.11 | 1.63 | 1.10 | 0.50 | 118.46 | 100.22 | 110.02 | 0.42 |
| 8 | 0.13 | 1.60 | 1.08 | 0.55 | 103.23 | 97.87 | 116.26 | 0.44 |
| 9 | 0.02 | 1.89 | 1.25 | 0.27 | 208.63 | 121.59 | 80.12 | 0.37 |
| 10 | 0.11 | 1.62 | 1.10 | 0.51 | 112.64 | 99.03 | 112.13 | 0.41 |
| 11 | 0.17 | 1.54 | 1.05 | 0.69 | 51.74 | 87.13 | 134.74 | 0.44 |
| 12 | 0.09 | 1.65 | 1.12 | 0.47 | 131.00 | 104.41 | 107.02 | 0.42 |
| 13 | 0.14 | 1.57 | 1.07 | 0.60 | 79.27 | 89.83 | 121.98 | 0.42 |
| 14 | 0.06 | 1.69 | 1.13 | 0.42 | 146.37 | 109.75 | 103.54 | 0.38 |
| 15 | 0.19 | 1.54 | 1.04 | 0.72 | 42.16 | 83.71 | 136.81 | 0.46 |
| 16 | 0.05 | 1.78 | 1.19 | 0.36 | 187.86 | 122.03 | 92.13 | 0.43 |
| 17 | 0.08 | 1.67 | 1.12 | 0.45 | 136.76 | 104.66 | 104.06 | 0.40 |
| 18 | 0.02 | 1.89 | 1.25 | 0.27 | 208.63 | 121.59 | 80.12 | 0.37 |
| 19 | 0.20 | 1.89 | 1.25 | 0.76 | 29.58 | 81.10 | 141.30 | 0.46 |
| 20 | 0.05 | 1.74 | 1.17 | 0.37 | 166.81 | 113.26 | 95.49 | 0.39 |
| 21 | 0.03 | 1.84 | 1.22 | 0.30 | 194.69 | 117.70 | 84.18 | 0.38 |
| 22 | 0.05 | 1.71 | 1.15 | 0.39 | 155.78 | 111.56 | 100.02 | 0.38 |
| 23 | 0.04 | 1.79 | 1.19 | 0.33 | 182.33 | 116.23 | 89.67 | 0.38 |
| 24 | 0.06 | 1.69 | 1.13 | 0.42 | 146.37 | 109.75 | 103.53 | 0.38 |
| 25 | 0.13 | 1.60 | 1.08 | 0.55 | 103.24 | 97.88 | 116.27 | 0.44 |

### 3.2 Plot functions for multi-objective genetic algorithms

The plot functions associated with multi-objective optimization using genetic algorithms or simply multi-objective genetic algorithms (MOGA) include the distance function plot, genealogy function plot, selection function plot, stopping function plot, average Pareto distance function plot, rank histogram function plot, and average Pareto spread function plot. The distance function plot, plots the average distance between individuals in each generation. It is shown in Figure 3, and a histogram of average distance is plotted against individuals in each generation. Thus, the height of each bin is proportional to the distance of the individuals in a given generation. The plot indicates that 57 individuals out of 70 have the highest distance in a generation.

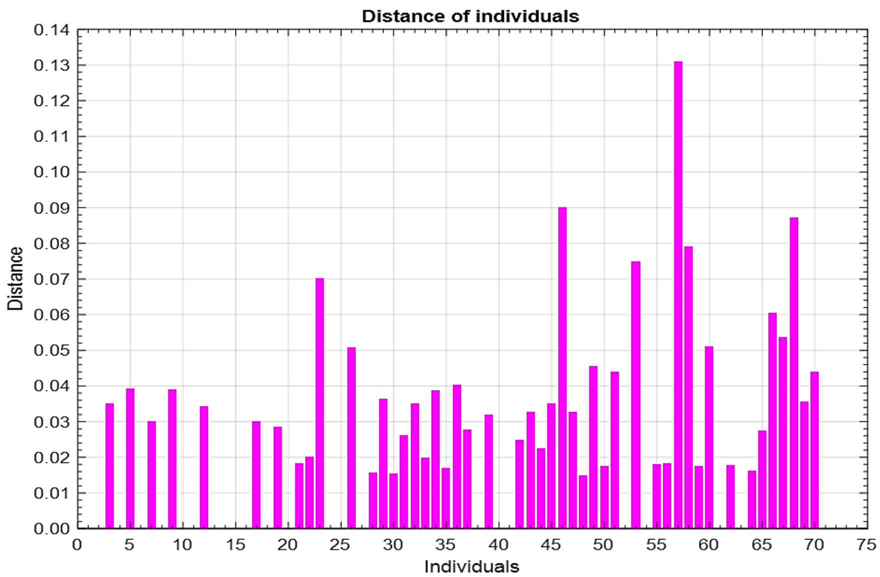


**Figure 3:** Distance function plot

The genealogy function plots individuals' genealogy such that the lines from generation to generation are color-coded red, blue, and black. The red lines indicate mutation children, the blue lines indicate crossover children, and the black lines indicate elite individuals. Thus, the population was set at type double vector, size of 70, and creation function of the nonlinear feasible population; mutation is adaptively feasible since the solution set is constrained and the crossover function is heuristic. The genealogy plot for 783 iterations is shown in Figure 4.

Figure 5 shows the selection function plot. A histogram of parents shows which parent contributes to each generation. The selection function considered is a tournament, and the tournament size is 2, the default.

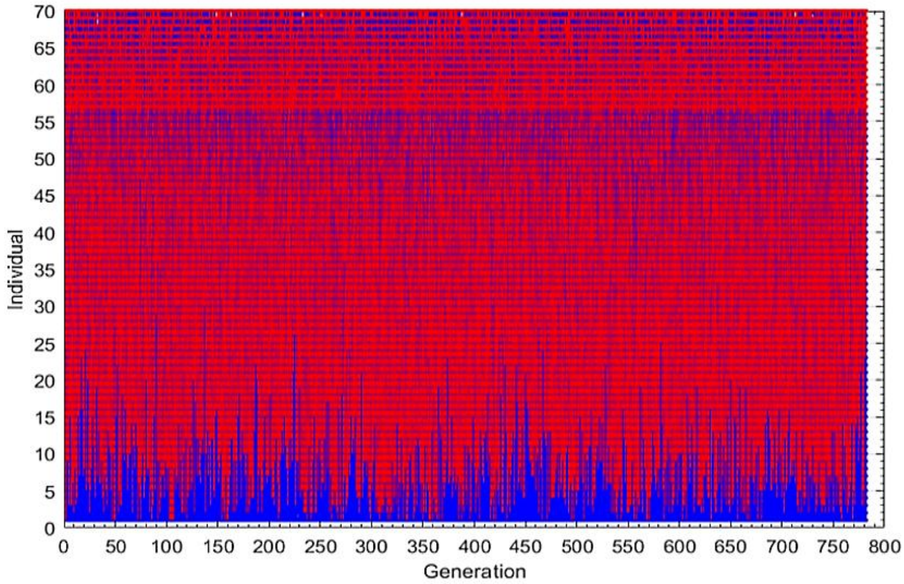


**Figure 4:** Genealogy function plot

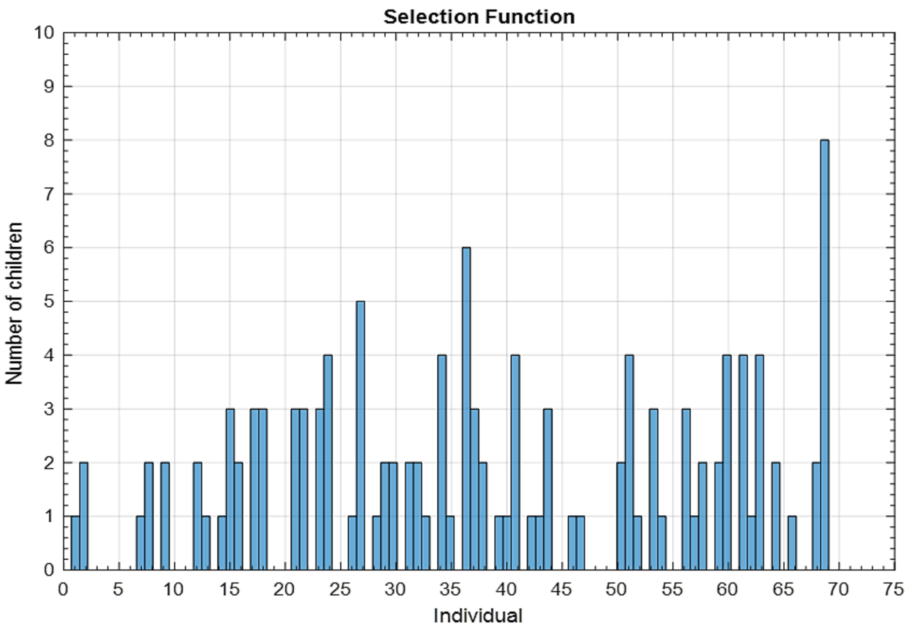


**Figure 5:** Selection function plot

The stopping criteria levels were plotted in the stopping function plot shown in Figure 6. After 783 iterations, the generation meets 98% of the criteria. The average Pareto distance plot Figure 7 plots the average distance between individuals against the generation of individuals. The points on the 2-D plot show the distribution of individuals in a given generation such that a generation encompasses several individuals. According to the plot, there are more than 600 generations. The rank histogram plot in Figure 8 plots the fraction of individuals in each Pareto tier. The number of individuals in each fraction is plotted against the ranks numbering 1 to 6, such that the rank 1 individual is rated the best, followed by the rank 2 individuals. The individuals are dominated in the order of their ranks successively from 1 to 6. Thus, rank 1 individuals dominate 2 individuals, rank 3 individuals are dominated by rank 1 and 2 individuals, rank 4 individuals are dominated by rank 1, rank 2 and rank 3 individuals, and so on. Also, the average Pareto spread plot is shown in Figure 9, which plots the change in distance measure of individuals concerning the previous generation. The average spread ranges from 0 to 1, and the plot shows the distribution in each generation of about 800. It also illustrates how many individuals exist in each generation. Thus, an average spread of 0.178948 is indicated.

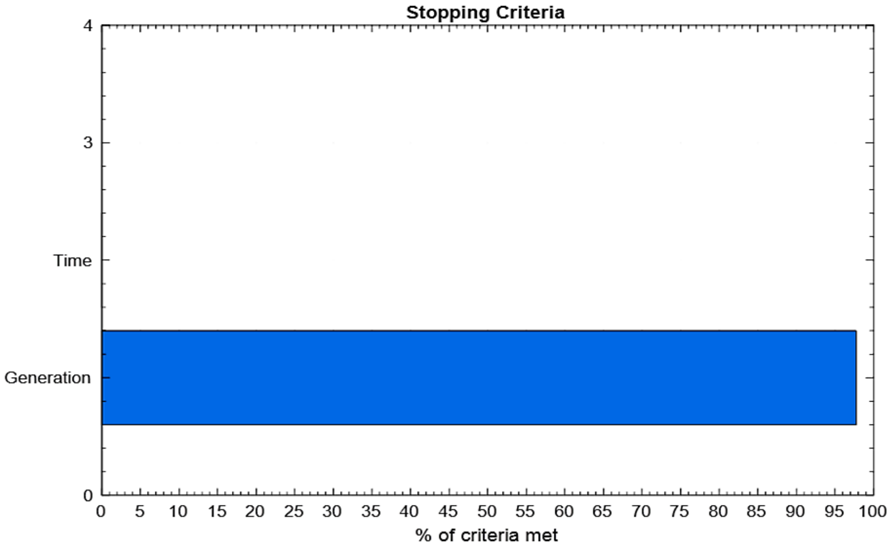


**Figure 6:** Stopping function plot

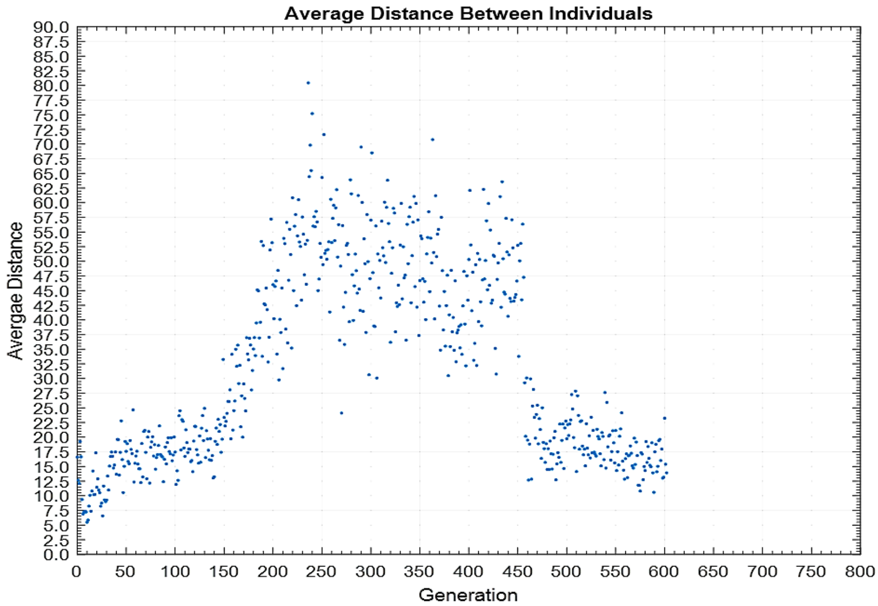


**Figure 7:** Average pareto distance function plot

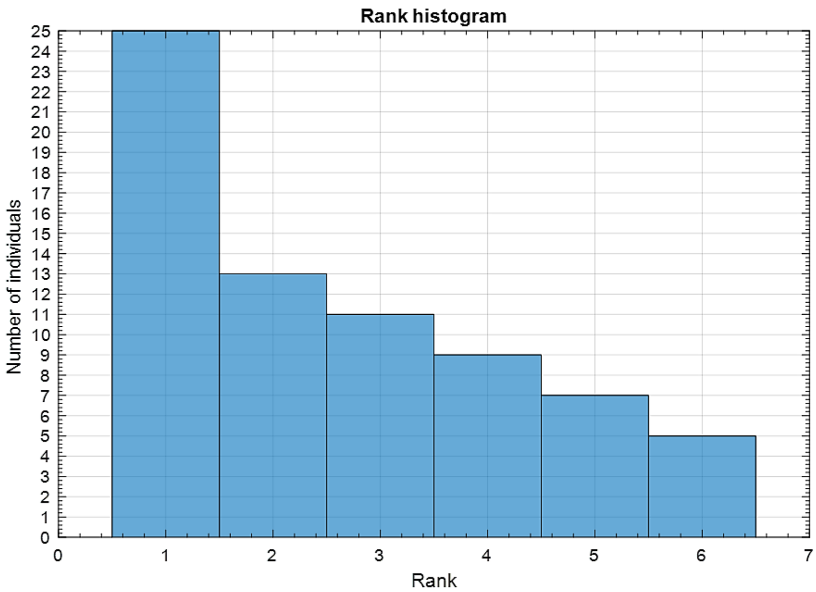


**Figure 8:** Rank histogram function plot

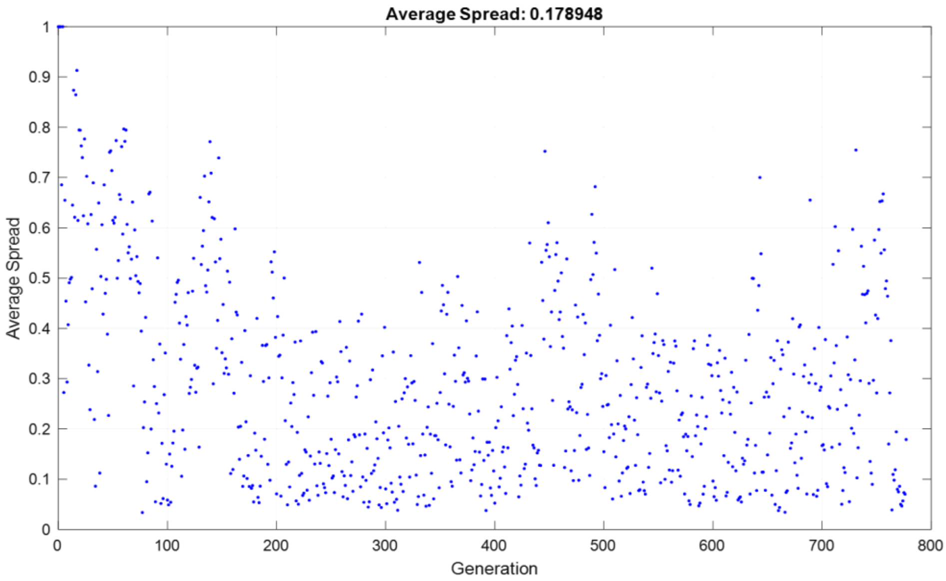


**Figure 9:** Average pareto spread function plot

## 3.3 Score diversity for multi-objective genetic algorithms

Results of the multi-objective optimization using genetic algorithms are presented for all the performance parameters in the score histogram shown in Figure 10. The histogram is a plot of score diversity showing the scores at each generation at the end of 800 serial iterations. The score diversity shows the distribution of the range of solutions for each objective function for the individual population. It measures the difference that lies within the solution sets. The result indicates that for 25 individuals (solution sets), the optimal solution ranges from approximately. $0.02\ m^3$ to $0.22\ m^3$, $1.53$ hr to $1.89$ hr, $1.04$ hr to $1.25$ hr, and $0.27\ m^3$ to $0.81\ m^3$ for the total volume of liquid nitrogen pumped, test duration, pumping duration, and the total volume of liquid nitrogen used, respectively.

The solution sets for each performance parameter displayed on the score histogram represent the Pareto front as the set of non-dominated solutions. Non-dominated solutions refer to optimal solutions (values) of the objective functions. Thus, the values of the objective functions displayed on the score histogram and the range of best minimum values of the respective performance parameters. This is so since the optimization is the minimization of the performance parameters. The bins' heights represent the scores' distribution to various individuals. The diversity in the scores presents better trade-offs in the solution sets. Also, diversity helps attain a globally optimal solution, thereby preventing iteration from terminating or converging at the local level. Thus, the solution is metaheuristic.

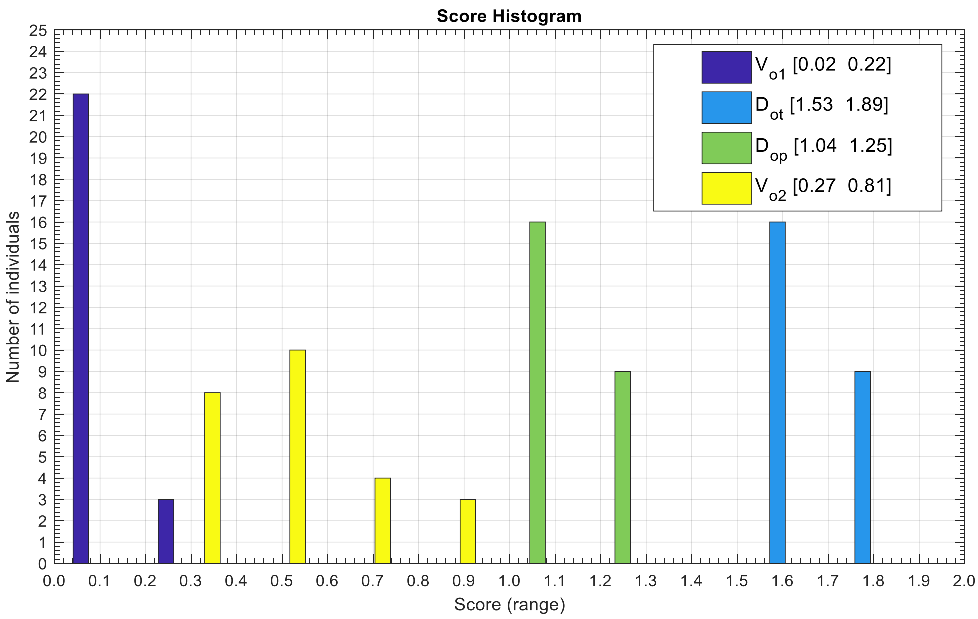


**Figure 10:** Score diversity for multi-objective optimization using genetic algorithms

### 3.4 Pareto frontiers of multi-objective genetic algorithms

Pareto frontiers are plot tools that graphically show the relationship between any two objective functions. In each plot, one objective function is assigned the first objective function, and the other is assigned the second. They plot the function values for all non-inferior solutions with scatters used to represent the solutions along the Pareto front such that each point represents different solutions. The Pareto fronts are shown in Figure (4-15) for different combinations of the performance parameters.

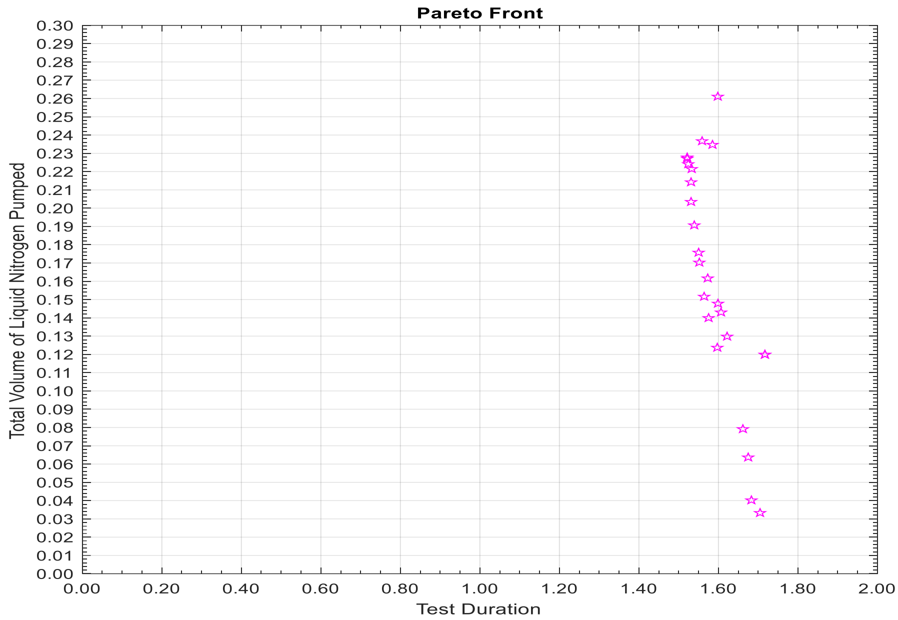


**Figure 11:** Pareto frontier of total volume of liquid nitrogen pumped against test duration

Figure 11, plots the Pareto front of the total volume of liquid nitrogen pumped against test duration. In the plot, the scatter approximates a parabola, indicating a sharp increase in the optimal total volume of liquid nitrogen pumped due to a slight decrease in the optimal test duration. This shape of the Pareto front represents the solution sets presented in Table (1) above. Thus, the optimal total volume of liquid nitrogen pumped is minimum when the optimal test duration is maximum. This relationship is accounted for by the possible losses due to pump charging.

Also, Figure 12 is the plot of Pareto in front of the total volume of liquid nitrogen pumped against the pumping duration. Like Figure 11, there is a sharp increase in the total volume of liquid nitrogen pumped for a slight decrease in the pumping duration. Noting that pumping duration is the time the pumping takes to pressurize a given hydrocarbon piping system to the specified test pressure, the above relationship is accounted for by the pump’s operational deficiencies, losses during pump charging, and other fugitive losses.

Figure 13, shows the plot of the Pareto front for the total volume of liquid nitrogen pumped against the total volume of liquid nitrogen used. It presents a linear relationship between the two parameters, such that the total volume of liquid nitrogen pumped increases proportionately to the total volume of liquid nitrogen used. However, the total volume of liquid nitrogen used advanced further than that of liquid nitrogen pumped due to fugitive losses before, during, and after the pumping operation.

Figure 14, shows the Pareto front of test duration against pumping duration. The scatter points are clustered as shown, and the plot shows a linear relationship between the test duration and pumping duration, such that the two parameters increase proportionally. However, the Pareto front drifts towards a higher test duration than the pumping duration. This means the test duration is slightly longer than the pumping duration since the former encompasses pressurization, holding, and depressurization time. Furthermore, Figure 15 is a Pareto plot of test duration against the total volume of liquid nitrogen used. This approximate curvature indicates the relationship between the test duration and the total volume of liquid nitrogen used. As the test duration increases, the total volume of liquid nitrogen used decreases, and the rate at which the test duration changes is reasonably low compared to the rate at which the total volume of liquid nitrogen changes. This discrepancy is due to losses due to pumping operations and other fugitive losses. Hence, the reduction in the test duration reduces pressurization time and, then, the losses.

Lastly, the Pareto plot of pumping duration against the total volume of liquid nitrogen is shown in Figure 16. Its curvature indicates decreasing pumping duration as the total volume of liquid nitrogen used increases, though their rates of change are not equal. This high volume is due to liquid losses during pump charging (priming), venting and vaporization of the tank to build pressure, manual and automatic venting of the tank to control surge and possible pressure hazards, and other fugitive losses.

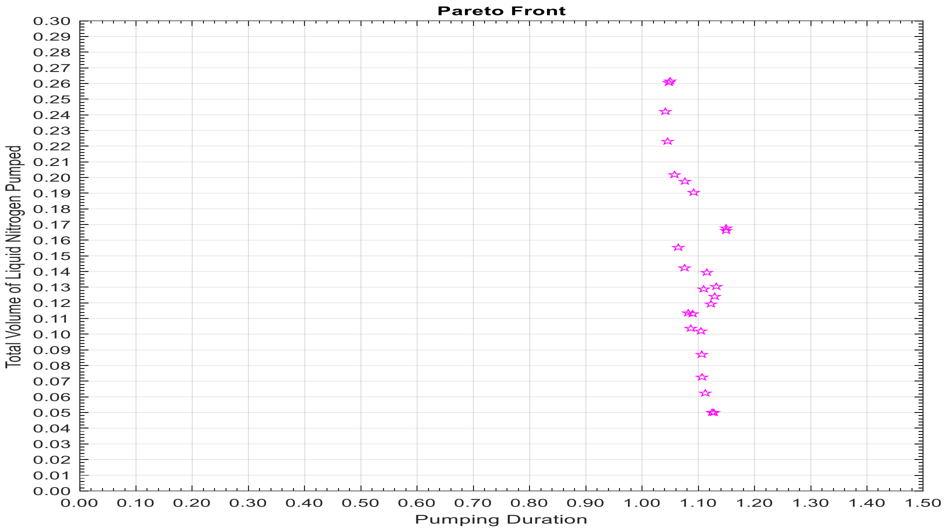


**Figure 12:** Pareto frontier of total volume of liquid nitrogen pumped against pumping duration

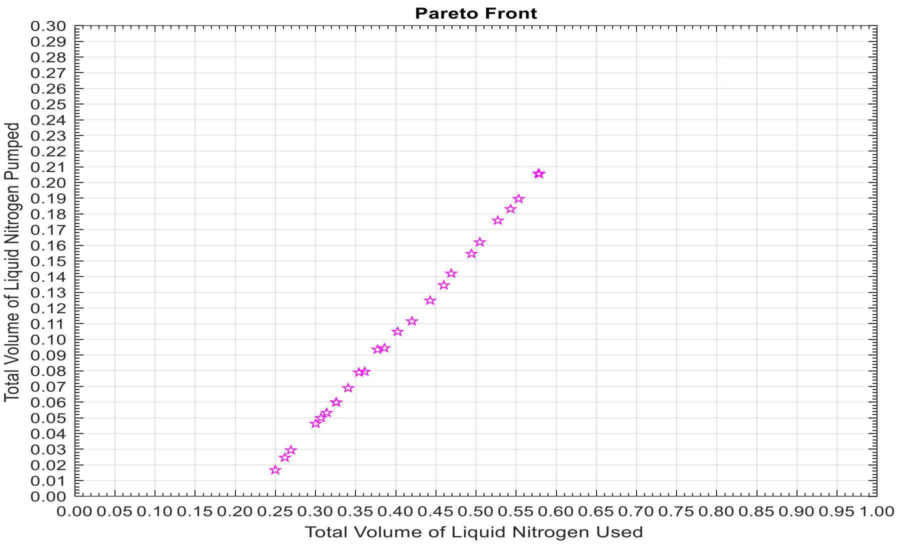


**Figure 13:** Pareto frontier of total volume of liquid nitrogen pumped against total volume of liquid nitrogen used

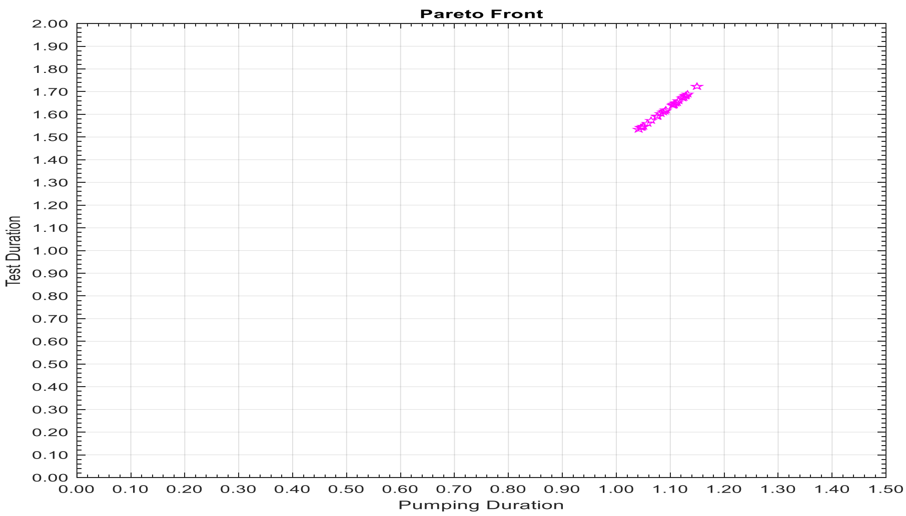


**Figure 14:** Pareto frontier of test duration against pumping duration

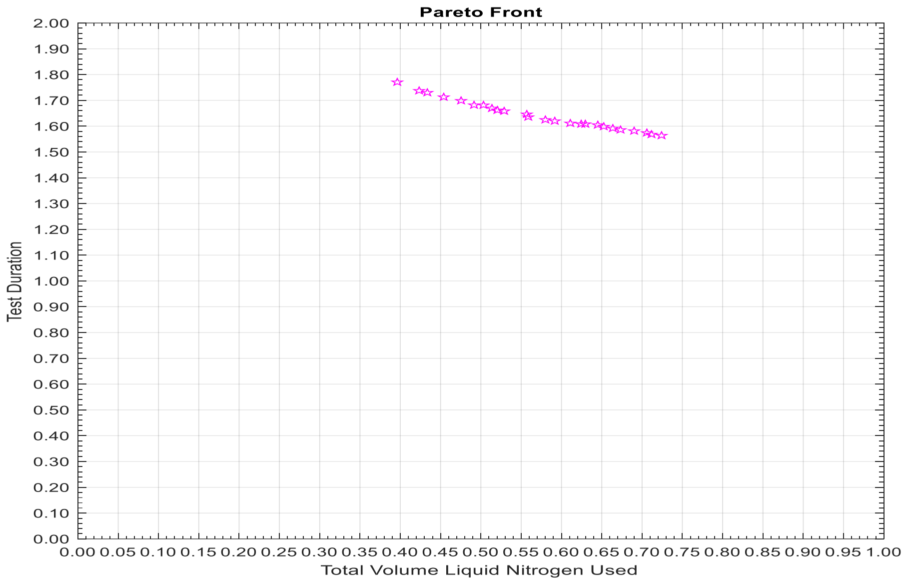


**Figure 15:** Pareto frontier of test duration against total volume of liquid nitrogen used

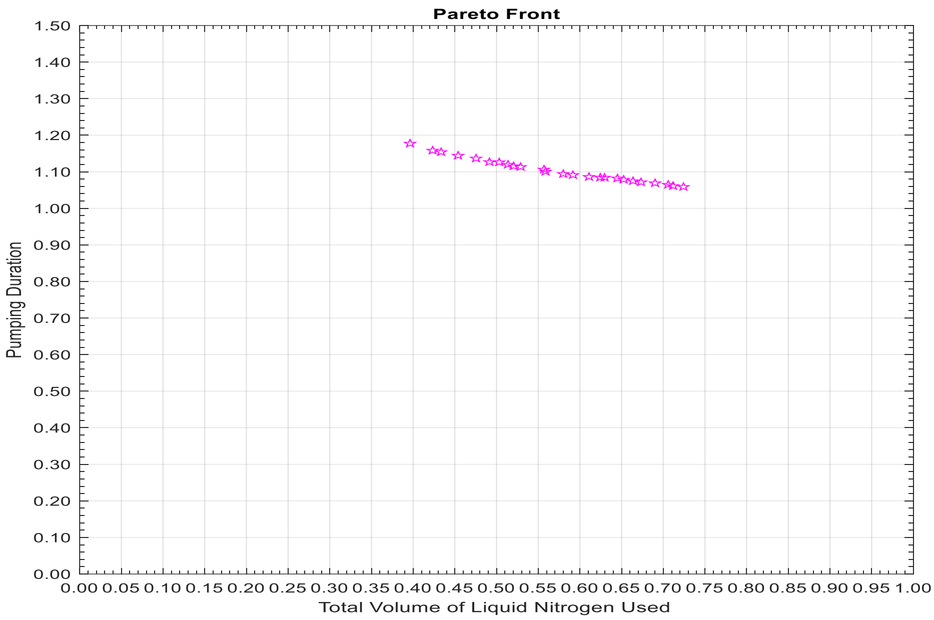


**Figure 16:** Pareto frontier of pumping duration against total volume of liquid nitrogen used

## 4. Conclusion

This study utilized a multi-objective genetic algorithm to optimize the liquid nitrogen pumping process during the pneumatic leak test of hydrocarbon and allied fluids piping systems. A multi-objective genetic algorithm is one of the population-based metaheuristic algorithms that employ evolutionary computation principles to generate solution sets for a set of complex multiparametric and nonlinear mathematical models simultaneously. Metaheuristic algorithms provide global or near-global solutions to optimization models. Therefore, liquid nitrogen pumping was parameterized and parametrically characterized. Then, the quantitative values of the parameters were taken from a typical field leak test operation. Thus, the optimal settings of the performance parameters respectively range from $0.02\ \mathrm{m}^3$ to $0.22\ \mathrm{m}^3$, $1.89$ hr to $1.53$ hr, $1.25$ hr to $1.04$ hr and $0.27\ \mathrm{m}^3$ to $0.81\ \mathrm{m}^3$; and those of the control parameters respectively range from $208.96\ \mathrm{m}^3$ to $10.94\ \mathrm{m}^3$, $121.77$ bar to $76.59$ bar, $80.10$bar to $148.60$ bar and $0.37\ m^3/hr$ to $0.47\ m^3/hr$ respectively. This implies that 3.79% decrease in pressurized volume of the piping systems, 1.48% decrease in test pressure of the piping systems, 3.42% increase in maximum discharge pressure of the liquid nitrogen pump and 1.08% increase in maximum flow rate of the liquid nitrogen pump across test packs increased total volume of liquid nitrogen pumped by 40.00%, decreased test duration by 0.70%, decreased pumping duration by 0.70% and increased total volume of liquid nitrogen used by 8.00% and vice versa. The process efficiency, energy efficiency, and operational cost were greatly enhanced.

This work will spur further research opportunities in other metaheuristic algorithms like particle swarm optimization (PSO) and other multi-objective optimization algorithms for liquid nitrogen pumping in hydrocarbon and allied fluids piping systems. Also, uncertainty quantification and sensitivity analysis of the optimization models are recommended for future study.

## Author contributions

Conceptualization, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**; data curation, **S. Isaac; C. Kadurumba; H. Ugwu;** and **F. Abam**.; formal analysis, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**.; investigation, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**.; methodology, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**.; project administration, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**, resources, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**.; software, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**.; validation, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**.; visualization, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**.; writing—original draft preparation, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**.; writing—review and editing, **S. Isaac; C. Kadurumba; H. Ugwu**; and **F. Abam**. All authors have read and agreed to the published version of the manuscript.

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## Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

## Conflicts of interest

The authors declare that there is no conflict of interest.

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