

# GENETIC ALGORITHMS FOR THE OPTIMIZATION OF PIPELINE SYSTEMS FOR LIQUID DISTRIBUTION (2)

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**T**his is the second of two articles presenting a Genetic Algorithm (GA) to obtain an optimal design, from an economical and operational point of view, of a pipeline system for the distribution of liquids, based on criteria such as complying with the laws of preservation of mass and energy, volume of flow requirements in the points of consumption where pressure is known, restriction in pressure value in those points of the system where it is unknown as well as in the velocity which must be under the erosion limit.

In this article the traditional techniques for designing a GA in this type of problems are combined with some ideas that have not been applied to this field previously. The proposed GA allows for the sizing of liquid distribution systems that include pipelines, nodes for consumption and provision, tanks, pumping equipment, nozzles, control valves and accessories.

The first article of this series (Galeano, 2003), presents the different formulations found in literature for the design of networks through optimization techniques and formulates mathematically, the optimization problem. In this article, the characteristics of the GA are specified and it is applied to solve the Alperovits and Shamir (1977) network and for a fireproof network, which allowed testing some of the characteristics of the model that are not found in the literature, such as the possibility of including pumping equipment, aspersion nozzles and accessories.

In addition, the contribution of the components and sensitivity are analyzed in order to investigate some characteristics and parameters of the implemented GA.

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**Keywords:** optimization, genetic algorithms, fluid distribution networks, pipe networks.

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**E**ste es el segundo de dos artículos en los que se presenta un Algoritmo Genético (AG) para obtener un diseño óptimo desde el punto de vista económico y de operación, de un sistema de tuberías para el transporte de líquidos, con base en criterios tales como el cumplimiento de las leyes de la conservación de la masa y la energía, exigencias de caudal en los puntos de consumo en donde se conoce la presión, restricciones en el valor de la presión en los puntos del sistema en donde se desconoce y en la velocidad, que debe ser inferior a la límite de erosión.

En él se combinan las técnicas tradicionales para el diseño de AG en este tipo de problemas, con algunas ideas que no se habían aplicado con anterioridad en este campo. El AG propuesto permite el dimensionamiento de sistemas de distribución de líquidos que incluyen tuberías, nodos de consumo y suministro, tanques, equipos de bombeo, boquillas, válvulas de control y accesorios.

En el primer artículo de esta serie (Galeano, 2003), se presentan las diferentes formulaciones que se encuentran en la literatura para el diseño de redes mediante técnicas de optimización y se hace la formulación matemática del problema de optimización. En éste artículo se especifican las características del AG diseñado y se aplica para la solución de la red de Alperovits y Shamir (1977) y de una red contra incendio, lo que permitió probar algunas de las características del modelo que no se encuentran en los reportados en la literatura, como son la posibilidad de incluir equipos de bombeo, boquillas de aspersion y accesorios. Adicionalmente, se realizan los análisis de la contribución de los componentes y de sensibilidad, con el fin de investigar algunas características y parámetros del AG implementado.

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**Palabras claves:** optimización, algoritmos genéticos, redes de distribución de fluidos, redes de tuberías.

## INTRODUCTION

The computer programs for the study of liquid distribution systems are very popular tools for the design, analysis and optimization of said systems. These programs operate on models that allow, among other things, the following:

- Simulation of different diameters and configurations of the system in order to determine the combination that may deliver the fluid with the pressure and flow necessary in the consumer points.
- Simulation of flow and pressure with different pumping equipment in operation, in order to make a good choice.
- Simulate the conditions to operate the system for different levels in the storage tanks, in order to determine the maximum and minimum permissible levels.
- Simulate the fluctuations in the tank levels for one period, as a response to the consumption variations in order to assess the different pumping strategies and thereby determine the most favorable conditions of operation.
- To recommend the diameter of the tubing to be used, taking into account minimization of costs under some given restrictions.

There may be two classification models: those that allow simulation of the distribution system and those that make use of the optimization theories.

The first ones predict the pressure, flow and may even calculate the levels of a tank in terms of timing. Users of these model aim to determine the most favorable dimensions for the tubing, through a trial and error process, whereby the engineer tests the different component of the network, makes the simulation and compares the values calculated with those required. In order to make the final decision, a cost estimate is made on each viable alternative, from a technical point of view.

The models based on optimization theories allow to obtain solutions that correspond to the minimum of a non-linear, highly structured and restricted optimization

problem. Due to the complexity of the problem, several techniques have been used to simplify the search for a solution. The methods used are based on numbering techniques, mathematical programming (linear and non-linear) and stochastic methods (genetic algorithms).

The algorithm shown below allows determination of the diameter of the tubing and pumps to be used, taking into account minimization of costs, under given restrictions. It solves the problem of optimization stated in the first part of this article (Galeano, 2003), operating based on a mathematical model of stable status and a cost equation that allow us to evaluate the system considering aspects that the models reported in literature have discarded.

In order to prove the genetic algorithm, a prototype software was designed which is applicable to the optimal design of liquid distribution system for the oil and gas industry, such as oil pipelines, gas pipelines, distribution networks of industrial services in the refineries, and in general, any chemical transformation plant, fire-proof networks and home natural gas networks, among others. The use of a tool such as the one shown, allows reduction of man hours, the hydraulic design of said systems, and the exploration of a larger number of configuration alternatives, tube diameter combinations and pumping equipment assessing the cost per year for each one of them. The foregoing allows the designer to have a wider search space and, therefore, increases the probability of finding the optimal design.

## GENETIC ALGORITHM

A GA is a search procedure based on natural selection and on the genetic population mechanisms, as well as the biological processes of survival and adaptation (Goldberg, 1989). The GA object of this article was specifically designed to optimize the hydraulic systems, where the operators are applied to two parents selected from the population elements, through a certain scheme, which in turn generates a new individual that replaces an existing one, through a replacement strategy. The GA operates on a simulation model of pressured flow lines developed by Narváez (1999), which allows for sizing hydraulic systems made up of pipelines, consumer and supply nodes, tanks, centrifugal and positive displacement

pumps, nozzles, control valves, processing equipment and accessories, and on the operational costs stated by Narváez and Galeano (2002), which takes into consideration, among other aspects, the costs of installation, maintenance and operation, including the pumping equipment. Following is a description of the main GA components.

**Representation**

Each individual in the populations is a parametric representation of a fluid transportation system that uses whole numbers. Each individual is codified with two chains of whole numbers, where the first part represents the diameters of each of the pipes in the network, and the second one is equivalent to the pumping equipment. The chains pick up the values of the set of whole numbers symbolizing the feasible diameters and pumping equipment. Figure 1 shows the hydraulic system representation scheme.

The adjustment of each individual is based on the hydraulic system's evaluation costs and on a penalty function. The cost is assessed once the network simulation takes place, applying the cost equation presented

in the first part of this article (Galeano, 2003). The penalty function is linked to violation of the restrictions imposed on the hydraulic system and it is defined by the following equation:

$$Adjustment = \frac{1}{(Cost\_of\_the\_network + Penalty)} \quad (1)$$

**Penalty function**

The penalty function is related to violations to the restrictions of the hydraulic system numbered in the mathematical formulation of the problem (Galeano, 2003). The simulation algorithm ensures compliance with the matter and energy conservation laws for each individual generated and the diameters of the pipes are chosen from a set of possible values in the codification system of each individual.

The restrictions 1 of velocity, flow and pressure, are not necessarily satisfied and they make a distinction between feasible and non-feasible solutions. Instead of ignoring non-feasible solutions and concentrating only on feasible solutions, the individuals that don't adjust completely to the restrictions of the system must be

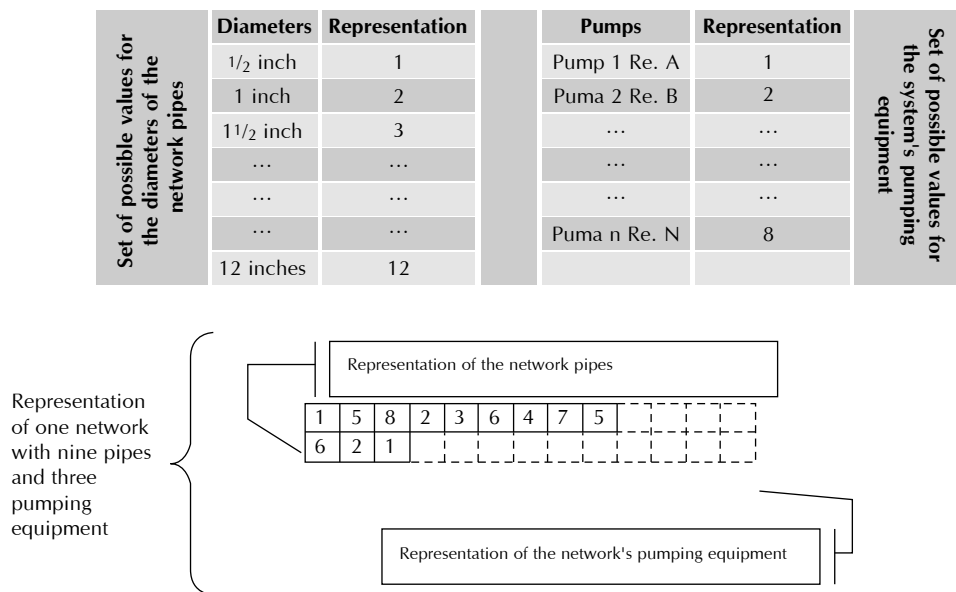


Figure 1. Representation scheme of the hydraulic system

<sup>1</sup> The equations that mathematically describe these restrictions, as well as energy and material balance, are shown in the first part of this article (Galeano, 2003).

considered as part of the population at a certain cost, because they are helpful in guiding the search.

In order to achieve this, the adjustment function includes a penalty term, which quantifies the system's violations to the speed, flow and/or pressure restrictions, in such a way that its adjustment is reduced with relation to the other individuals of the population. The defined penalty equations are as follows:

1. Velocity Restriction:

$$f.pen_{speed} = pv \times \{ \max [ \max (V_j - V_{LE}, 0) ] \} \quad (2)$$

$$\forall j \in R$$

Where  $pv$  is the velocity penalty coefficient, the term in brackets corresponds to maximum violation of the velocity restriction and  $R$  is the set of network connectors.

2. Flow Restriction:

$$f.pen_{speed} = pc \times \{ \max [ \max (G(Q_j), 0) ] \}$$

$$\forall j \in N_{EC}$$

$$\text{For } G(Q_j) = \begin{cases} Q_j - (Q_{j\_min} + \Delta Q_j) \\ Q_{j\_min} - Q_j \\ 0 \end{cases} \quad (3)$$

if  $Q_j > Q_{j\_min} + \Delta Q_j$   
 if  $Q_j < Q_{j\_min}$   
 if  $Q_{j\_min} < Q_j < Q_{j\_min} + \Delta Q_j$

Where,  $pc$  is the flow penalty coefficient, the term in brackets corresponds to the maximum violation of the flow restriction and  $N_{EC}$  is the set of known energy nodes in the network.

3. Pressure Restriction:

$$f.pen_{pressure} = pp \times \{ \max [ \max (K(P_j), 0) ] \}$$

$$\forall j \in N_{ED}$$

$$\text{For } K(P_j) = \begin{cases} P_j - P_{j\_max} & \text{if } \forall P_j > P_{j\_max} \\ P_{j\_min} - P_j & \text{if } \forall P_j < P_{j\_min} \\ 0 & \text{if } P_{j\_min} < P_j < P_{j\_max} \end{cases} \quad (4)$$

Where  $pp$  is the pressure penalty coefficient, the term in brackets corresponds to the maximum violation of pressure restriction and  $N_{ED}$  is the set of known energy nodes in the network.

An important feature of the proposed GA is its ability to adjust the magnitude of each of the penalty coefficients depending on the situation, taking into account that it is better to use a modest penalty in the initial states in order to ensure the adequate sampling in the search space and then, gradually increase the penalty to force optimization convergence to a feasible solution. (Mohamed, 1998; Savic, 1994).

The coefficient is the function of the generation number that allows a gradual increase of the penalty term.

$$p = \text{initial } p \times \left( \frac{\#\_population}{\#\_generations} \right)^n \quad (5)$$

Where  $\text{initial } p$  and  $n$  are constant, so that the penalty coefficient is an increasing monotonous function that guarantees that after final execution of the GA, the penalty coefficient has a value that prevents the best non-feasible solution to be superior to any of the population's feasible solutions.

**Initializing strategy**

In order to initialize the evolution process of the GA, an initial population of solution vector must be generated. The method used is that of random initializing, where the initial population contains random vectors uniformly distributed in the search space, which are formed through designation of numbers randomly selected within a set of possible values for each of the two chains that constitute the individual (Galeano, 2000).

**Selection strategy**

The selection strategy decides on how to choose individuals to convert them into parents of the following generation. The prototype allows the selection of any of the following strategies: by roulette, tournament with roulette, by chance, by expected value, by deterministic sampling, stochastic without reposition, stochastic with reposition and binary tournament.

## Genetic operators

The genetic operators are used to generate new individuals in the population, by applying to the selected parents any of the selection schemes. These operators may be grouped in two: binary crossover operators which take two parents and produce new individuals based on their chains and individual operators (mutation) which take one individual and produced a perturbed version of it.

### Crossover operators

The basic operation of a GA is the crossover that combines the merits of several individual to produce a better one. The possible crossover operations for the GA that were implemented in the prototype software are: simple one-point, simple two-points, interspersed, uniform, whole arithmetical, simple arithmetical, based on position, by partial adjustment and by orderly partial adjustment.

### Mutation operators

This operation introduces new genetic information to the population, with the purpose of exploring new regions and maintaining the diversity. The mutation operators who fit the prototype are: simple uniform, simple non-uniform, by interchange and by proximity.

### Replacement strategy

The GA allows the overlap between populations in a way similar to De Jong's proposal as stated by Goldberg (1989), who proposes the overlap in an amount estimated by the user. In each generation the GA creates a temporary population of individuals which add themselves to the previous population, soon to eliminate the worse individuals so that the population will be equal size to the original one (Wall, 1996).

### Scaling strategies

At the beginning of the evolution it is common to have a small number of extraordinary individuals in the middle of a population of bad individuals, and if the rule of normal selection is used, first they will take the population in few generations, causing the premature convergence of the algorithm. In addition, in the later stages of the evolution, sufficient diversity must be ensured, to obtain optimums closer to a global optimal. The scaling aims at preventing these situations, through

the normalization of the adjustment values. The prototype has strategies of linear and exponential scaling.

## IMPLEMENTATION OF THE GENETIC ALGORITHM

The GA previously proposed was implemented as part of a software prototype for the sizing and optimization of piping networks for the transportation of liquids that was programmed as Dynamic Bond Library (DBL) in Borlan Delphi Language, which was called UN-Nethyc. The development process of this prototype was guided through the application of the methodological process of unified software development, and guided by an iterative and incremental methodology (Jacobson, 1999) based on a tool for software analysis, design and modeling, which allows to document the process in all the stages of development (Galeano, 2000).

## GENETIC ALGORITHM TEST

In order to evaluate the implemented algorithm, a comparison was made of the solutions of a classic optimization problem reported in literature, the Alperovits and Shamir network, with those obtained ones using UN-Nethyc. The results were obtained by different investigators in this area, who obtained solutions by applying different solution methods such as, linear programming, non-linear programming, algorithms and simulated tempering. Additionally it was proved with a fire protective network with automatic sprayers and pumping system.

### Alperovits and Shamir network

In this problem, presented by Alperovits and Shamir (1977), and solved, among others, by Goulter *et al.*; Kessler *et al.* (1989); Eiger *et al.* (1994); Savic and Walters (1997); Montesinos and García-Guzmán (1996) and Cunha and Sousa (1999); the work fluid is water at 20°C. All the network piping is 1000 m long and a material roughness of 1,5e-4 m, and the minimum pressure requirement in nodes 2 to 7 is 30 m on the reference level. The topology and the network data studied are shown in Figure 2 and Table 1. For the optimization, a group of 14 available diameters is selected and Table 1 shows the cost by unit of length

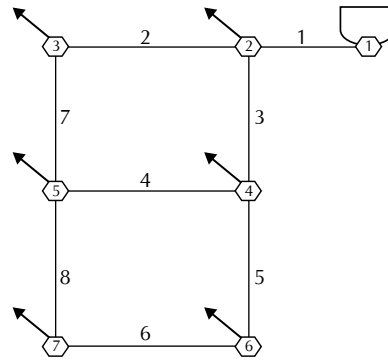


Figure 2. Topology of the Alperovits and Shamir network

Table 1. Data of the nodes and diameters available for the Alperovits and Shamir problem

Node	Demand (m <sup>3</sup> /h)	Height (m)	Diameter (inches)	Cost (units)	Diameter (inches)	Cost (units)
1	(Tank)	210	1	2	12	50
2	100	150	2	5	14	60
3	100	160	3	8	16	90
4	120	155	4	11	18	130
5	270	150	6	16	20	170
6	330	165	8	23	22	300
7	200	160	10	32	24	550

for each one of them. The foregoing requirements were introduced on the UN-Nethyc prototype, specifying as available diameters for the optimization those shown in Table 1.

In order to compare the results obtained with those reported in literature, the cost function was limited to determining the cost of the tubing without including any other factor.

Table 2 lists the less costly solutions reported since 1977, the values of diameters and the lengths shown just as they are found in literature. This shows the solutions obtained by different optimization methods, such as:

- Linear Programming: Alperovits and Shamir (1977); Goulter *et al.*, Kessler and Shamir (1989); Eiger *et al.* (1994), whose solution is made up of tubing segmented in various sections.

- Genetic Algorithms: Savic and Walters (1997), Montesinos and García-Guzmán (1996), show the best solutions reported for a GA with a configuration similar to the one used in this work. The results obtained by Montesinos were converted to the units presented in order to make them comparable.

- Simulated Tempering: Cunha and Sousa (1999).

- UN-Nethyc, the last two columns show the results obtained by the proposed GA using a configuration similar to the one used by the aforementioned authors.

It is important to take into account that UN-Nethyc uses a method of hydraulic simulation different from the one used by the other systems reported in literature, therefore the hydraulic results obtained defer somewhat

Table 2. Solutions for the Alperovits and Shamir problem

Tubing	Alperovits and Shamir		Goulter <i>et al.</i>		Kessler and Shamir		Eiger <i>et al.</i>	
	L	D	L	D	L	D	L	D
1	256,00	20	383,00	20	1,000,00	18	1,000,00	18
	744,00	18	617,00	18				
2	996,38	8	1,000,00	10	66,00	12	238,02	12
	3,62	6			934,00	10	761,98	10
3	1,000,00	18	1,000,00	16	1,000,00	16	1,000,00	16
4	319,38	8	687,00	6	713,00	3	1,000,00	1
	680,62	6	313,00	4	287,00	2		
5	1,000,00	16	1,000,00	16	836,00	16	628,86	16
					164,00	14	317,14	14
6	784,94	12	98,00	12	109,00	12	989,05	10
	215,06	10	902,00	10	891,00	10	10,95	8
7	1,000,00	6	492,00	10	819,00	10	921,86	10
			508,00	8	181,00	8	78,14	8
8	990,93	6	20,00	2	920,00	3	1,000,00	1
	9,07	4	980,00	1	80,00	2		
<b>Cost (units)</b>	497,525		435,015		417,500		402,352	

Tubing	Savic and Walters		Montesinos	Cunha	UN-NETHYC	
	D	D	D	D	D (S1)	D (S2)
1	18	20	20	18	18	18
2	10	10	10	10	14	10
3	16	16	16	16	14	16
4	4	1	4	4	3	12
5	16	14	16	16	14	14
6	10	10	10	10	1	2
7	10	10	8	10	14	6
8	1	1	3	1	10	10
<b>Cost (units)</b>	419,000	420,000	456,000	419,000	412,000	415,000

Note: L = Length (m), D = Diameter (inches)



from those reported, although the orders of magnitude are always preserved.

Figure 3 shows a typical graph of the cost of the network in the optimization evolution process. The GA uses the mechanism of selection by roulette, applies the simple one-point crossover with simple uniform mutation, without replacement strategy, with crossover probabilities equal to 1,0 and mutation probabilities equal to 0,3333. The tests were performed for populations with 50 individuals allowing 500 generations. With this configuration 10 runs were carried out, of which the best two are shown in Table 2. Each run took approximately 50 seconds of calculation time in a 450 Mhz Pentium III unit.

Emphasis must be made in that, having a system with eight pipes and a set of fourteen possible diameters, the solution space contains a total of  $14^8 = 1,48 \times 10^9$  different designs, of which samples of 250 000 individuals were evaluated (50 chromosomes x 500 generations) which represents 0,0169% of the solution space.

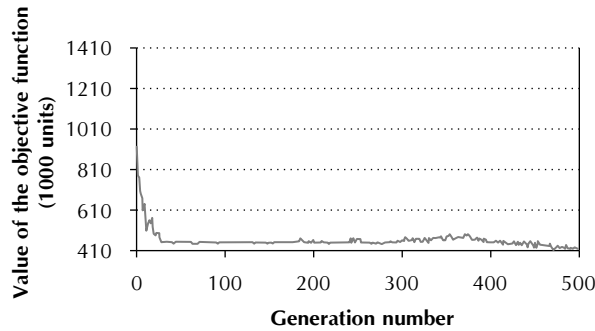


Figure 3. Evolution of the GA for the Alperovits and Shamir problem

In order to evaluate the quality of the solutions obtained and to compare it with those reported in literature, Table 3 shows the pressures associated with each node for the lower cost reported networks.

As it can be observed, the results obtained with UN-Nethyc, are comparable to those reported in literature, and even obtained better solutions than those reached by other GAs used. The values achieved by Eiger *et al.* (1994), are smaller than those achieved in this work, which is explained by the fact that said solution divides the 2, 5, 6 and 7 pipes in sections of different diameter, which in some cases can be inconvenient from the technical or economic point of view, particularly with pipes of diameter greater than 6 inches.

**Fireproof network**

With the purpose of evaluating the GA in a complex system where, in addition to pipe sections, accessories, pumping equipment and aspersion nozzles are included, consider the optimization of a fireproof network of a building, that is currently installed and operating, and which was designed by a civil engineer with over 20 years experience in design and installation of hydraulic and gas networks in buildings, using a simulation tool to evaluate pressure and flow for a set of diameters that he defined based on his experience.

The network consists of 41 sections of tubing, with 41 nodes of interest, of which 16 belong to the aspersion nozzles. For this problem the tubing material used is caliber 40 carbon steel. Of the diameters

Table 3. Node pressures for the Alperovits and Shamir problems

Node	Alperovits and Shamir	Goulter <i>et al.</i>	Kessler and Shamir	Eiger <i>et al.</i>	Savic and Walters	Cunha	UN-Nethyc (S1)	UN-Nethyc (S2)
2	53,96	54,30	53,26	53,26	53,26	55,97	53,55	53,55
3	32,32	33,19	30,08	30,30	30,45	30,77	38,62	39,07
4	44,97	44,19	43,64	43,87	43,48	46,60	43,52	42,64
5	32,31	32,32	30,10	30,62	33,77	32,29	45,43	43,91
6	31,19	31,19	30,08	29,85	30,49	30,86	31,19	30,17
7	31,57	31,57	30,09	29,85	30,62	30,99	31,38	30,34

commercially available for the specified material and schedule, the set of possible diameters used is in the range between  $\frac{1}{2}$  and 4 inches. On the other hand, the pumping equipment available is selected depending on the volume of flow to be handled, which according to the area to be protected, will be in the 15 to 25 l/s range. A set of 23 pumping equipment of those available in the UN-Nethyc data table, were used for the tests. It is expected that each of the nozzles in operation will have a minimum flow volume of 0,9 l/s in each sprinkler, with a minimum water column pressure of 50 m in the cabinet of the analyzed section. Solutions per each algorithm run were analyzed. The cost obtained with the developed prototype is \$7 631 820,47 per year. The annual cost of the installed network, calculated with the UN-Nethyc simulation module, introducing the diameters of tubing and the pumping equipment, is in the order of \$17 000 000 per year.

## COMPONENT CONTRIBUTION ANALYSIS

This section shows the performance of some of the components of the GA implemented in a UN-Nethyc. It shows how some have a notorious influence in the optimization behavior, making it very important to carry out a thorough study in order to be able to conclude precisely the effect it has on this type of problems.

### Usefulness of the replacement scheme

In order to be able to show the effect of the replacement strategy on optimization, all the other components and its default values were kept constant, so that only

the replacement strategy used was modified. This is how runs were performed allowing the replacement of a very small part of the population among generations (two individual) maintaining the rest of the individuals in the population. On the other hand, the replacement of approximately half of the population among generations was allowed.

Figure 4 shows the effect of the replacement strategy in the Alperovits and Shamir problem, where one can clearly observe how the behavior of the GA degrades when using this component, although replacement in half the population allows a faster convergence.

### Effect of the selection scheme per expected valued

In order to explore the effect of the selection scheme for the optimization mechanism, the selection per expected value was used, which is characterized by reducing the influence of the stochastic errors of the processes based on the roulette selections used in the standard GA. Figure 5 shows the test results obtained with the Alperovits and Shamir network, where the negative effect of the studied selection scheme can be clearly observed, showing a clear degradation in optimization evolution.

For the fireproof network problem, this selection mechanism did not find the region of feasible solutions preventing its comparison with the selection scheme by default. The fact that feasible solutions were not reached during the tests performed does not imply that the algorithm does not work, but rather that other set of parameters must be proven or more repetitions on the same test should be performed.

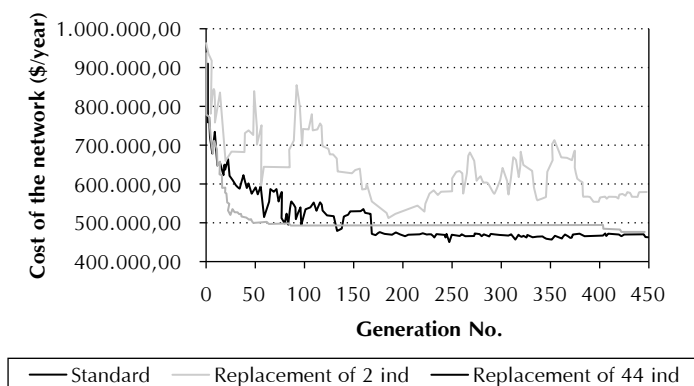


Figure 4. Replacement strategy effect (Alperovits and Shamir problem).

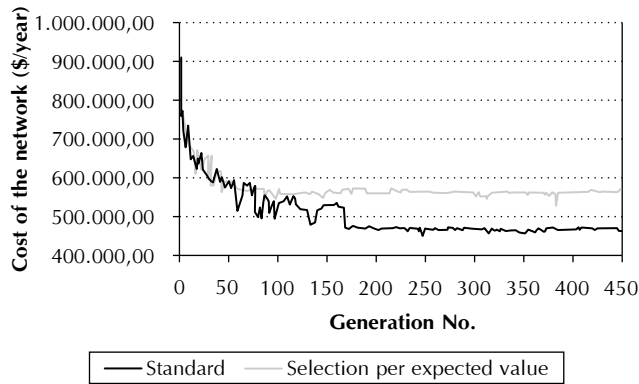


Figure 5. Effect of the selection strategy (Alperovits and Shamir problem)

### Use of the dynamic penalty function

In order to show the effect of the proposed penalty function, tests were done to see how the GA behaved in the three problems without applying this component, that is to say, a fixed value for the penalty constant was used tests avoiding that would depend on the number of evolutions made by the GA. The results obtained for Alperovits and Shamir network (Figure 6) show how the evolution behavior is favored when using the dynamic penalty function in this problem.

For the fireproof network problem, the use of the penalty function allowed the finding of favorable results. However, by not using the dynamic penalty function, the region of feasibly solutions was not reached and, therefore, it is impossible to verify its effect.

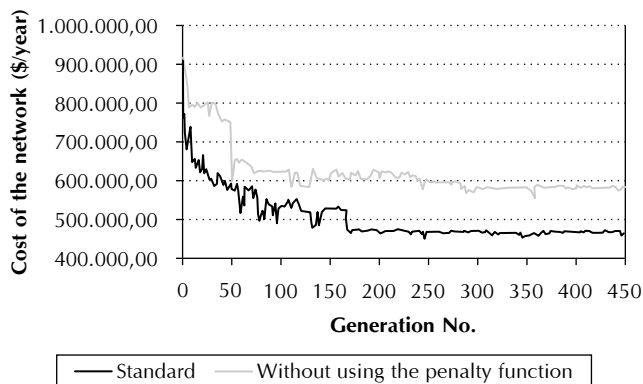


Figure 6. Effect of the use of the dynamic penalty function (Alperovits and Shamir problem)

### Usefulness of the non-uniform simple mutation scheme

In order to show the effect of the application of this factor to the optimization of the analyzed problems, the evolutionary processes of the standard GA (maintaining the parameters and components by default) were compared with another GA using the aforementioned mutation scheme which tries to influence the individuals of the population in a controlled manner that is greater at the beginning of the evolution, so that later on its effect is reduced to a continuous value mutation whether by excess or defect.

For Alperovits and Shamir network problem (Figure 7) it is evident that there is a remarkable increase in optimization because it increases the convergence speed while at the same time achieving a local optimum of lesser value.

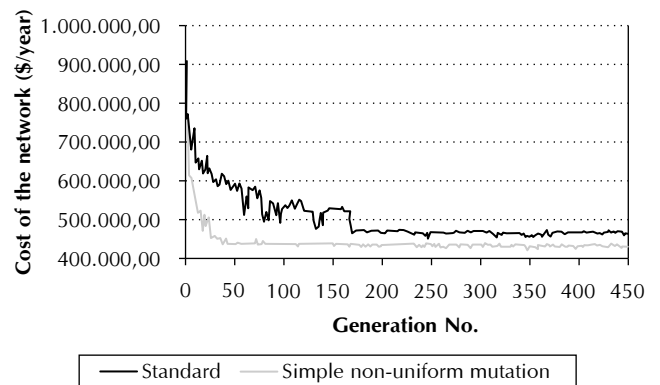


Figure 7. Effect of the mutation scheme (Alperovits and Shamir problem)

In the case of the fireproof network problem, this scheme allowed finding a region of feasible solutions with higher speed. However, the general behavior of the optimization is not favored when reaching a local optimum of higher value than the one found with the standard GA.

## SENSITIVITY ANALYSIS

The purpose of this section is to investigate the effect of the variation of some of the parameters of the GA implemented in UN-Nethyc. This type of study is important to assess the limitations of the UN-Nethyc in the optimization of hydraulic systems, while at the same time analyzing its degree of stability.

### Size of the population

The average optimization behavior was compared with the two problems analyzed, using three different types of population:

- Using the default value<sup>2</sup> (10 times the size of the solution space).
- Using a large population (20 times the size of the solution space).
- Using a small population (5 times the size of the solution space).

The results for the Alperovits and Shamir problem (Figure 8) show that the GA with a large population behaves better for this problem. On the other hand, none of the tests performed reached the region of feasible solutions for the fireproof network problem and therefore the effect of this factor can not be verified.

### Variation in the probability of mutation

In order to show the effect of various in this parameter, tests were carried out with three different values, keeping the rest of the GA options constant:

- Probability of normal mutation ( $P_m = 0,01$ ).
- Probability of low mutation ( $P_m = 0$ ).
- Probability of high mutation ( $P_m = 0,5$ ).

The results for the Alperovits and Shamir problem are shown in Figure 9, where it can be clearly seen that the behavior of the GA degrades when using a probability of mutation that is too high or too low. The same results were obtained for a problem in the fireproof network problem, proving the importance of this component and its value in the evolution of the GA. From the results obtained, it is clear that a high probability of mutation converts optimization in a random search. On the other hand, the absence of mutation prevents the exploration of the solution space, allowing the GA to be trapped in a local optimum.

### Effect of the value of penalty constants.

These tests compared the average behavior of the UN-Nethyc in the problems studied, with three different values of the initial contacts of the penalty functions:

- With a normal value equal to one time the default value for each penalty function used in each problem<sup>3</sup>.
- With a large penalty value equal to 10 000 times the default value for each penalty function used.
- With a small penalty value equal to 0,0001 times the default value for each penalty function used.

The results obtained for the Alperovits and Shamir problem (Figure 10) show as the optimization result is

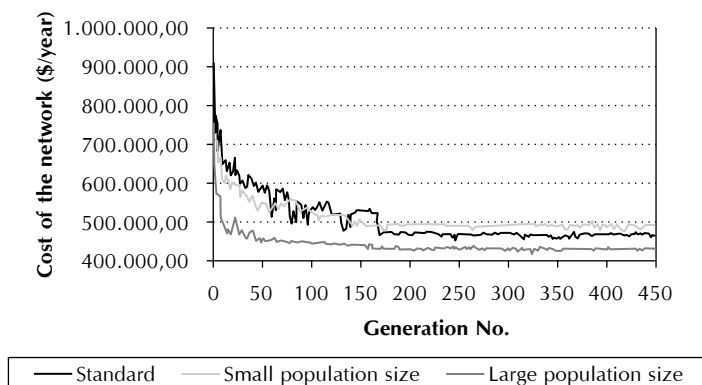


Figure 8. Effect of the size of the population(Alperovits and Shamir problem)

<sup>2</sup> For the Alperovits and Shamir problem, the size of the default population is 90 individuals and for the fireproof network problem the default value is 630 individuals.

<sup>3</sup> For the Alperovits and Shamir problem, the default value of  $1 \times 10^8$  is used for the pressure penalty function constant. For the fireproof network problem the constant penalty value used for pressure is  $1 \times 10^8$  and for volume of flow is  $1 \times 10^{12}$ .

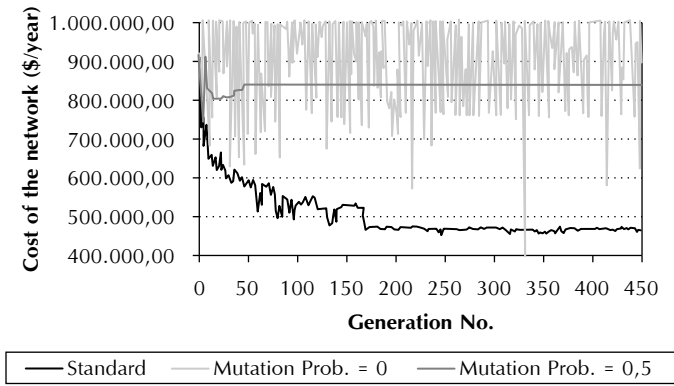


Figure 9. Effect of variation in the probability of mutation (Alperovits and Shamir problem)

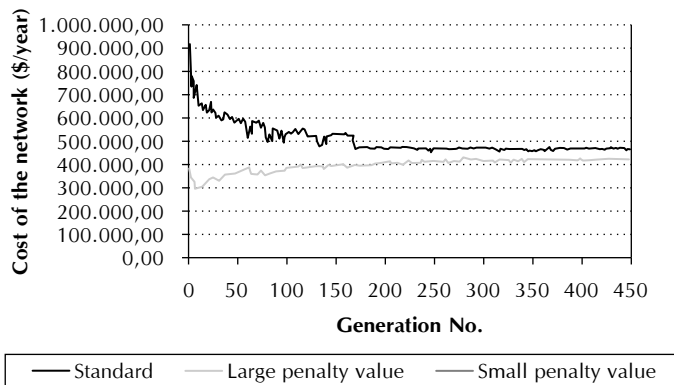


Figure 10. Effect of the value of the penalty constants (Alperovits and Shamir problem)<sup>4</sup>

affected when a region of feasible solutions is not found in any of the problems analyzed using the penalty function values proposed. This fact shows how important it is to use this factor because it guides the GA search process, preventing the finding of at least one feasible solution in the search space. This same phenomenon was observed in the fireproof network tests.

## CONCLUSIONS

- A flexible GA was designed and implemented, that includes great variety of operators and allows finding an optimal one for liquid transportation piping systems such as aqueducts, pipe lines, industrial service distribution networks in refineries and other chemical transformation plants, fireproof networks, and that can be extended to networks and gas transportation lines. The algorithm operates on a hydraulic model that allows the optimization of complex systems which include pumps, nozzles, control valves, processing equipment and accessories, and based on a cost equation that includes the costs of pump installation, maintenance and operation and with fluids in a liquid phase different from water, including petroleum and its derivatives.
- Once the results obtained in a classic problem and the fireproof network problems were analyzed, the main characteristics and kindness of the proposed GA were verified. The results obtained in the network Alperovits and Shamir, network are very close

<sup>4</sup> The figure doesn't show the evolution curve for the test with big penalty value for the Alperovits and Shamir problem, because its values are outside the range shown.

to those reported in literature, applying the different optimization methods, a fact that shows that the GA are an excellent tool to be applied in this domain. The problem of the fireproof network allowed an evaluation of the performance of the GA in complex systems, and a 45% decrease of the cost raised by an expert.

- The analyses of the contribution and sensitivity components motivate the accomplishment of future exploration work of the characteristics of the proposed GA, because of the variation of components and the parameters used considerably affect the results obtained in the optimization process, making it necessary to perform a thorough study. In addition, it is necessary to explore the applicability of UN-Nethyc in the optimization of hydraulic systems different from those analyzed in this work, with the purpose of expanding its field of use.
- In addition, the calculation times used are smaller than those reported even for different optimization methods, which ratifies the advantages of UN-Nethyc when obtaining excellent results in acceptable calculation times, making this technique an excellent tool capable of locating solutions at very low cost.

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