STUDY OF SENSITIVITY OF THE PARAMETERS OF A GENETIC ALGORITHM FOR DESIGN OF WATER DISTRIBUTION NETWORKS

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Abstract: The Genetic Algorithms (GAs) are a technique of optimization used for water distribution networks design. This work has been made with a modified pseudo genetic algorithm (PGA), whose main variation with a classical GA is a change in the codification of the chromosomes, which is made of numerical form instead of the binary codification. This variation entails a series of special characteristics in the codification and in the definition of the operations of mutation and crossover. Initially, the work displays the results of the PGA on a water network studied in the literature. The results show the kindness of the method. Also is made a statistical analysis of the obtained solutions. This analysis allows verifying the values of mutation and crossing probability more suitable for the proposed method. Finally, in the study of the analyzed water supply networks the concept of reliability in introduced. This concept is essential to understand the validity of the obtained results. The second part, starting with values optimized for the probability of crossing and mutation, the influence of the population size is analyzed in the final solutions on the network of Hanoi, widely studied in the bibliography. The aim is to find the most suitable configuration of the problem, so that good solutions are obtained in the less time.

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INTRODUCTION

The design of water distribution networks is extremely complex. It is well-known that when the diameters of the conductions are chosen as decision variables, the restrictions are implied functions of these variables of decision, so the space's region of solutions is a no convex type and the objective function becomes multimodal. Traditionally, water distribution network design, upgrade, or rehabilitation has been based on engineering judgment.

However, in the last three decades a significant amount of research has focused on the optimal design of water distribution networks. Initially, researchers have used linear programming to optimize a design of a pipe network (Alperovits & Shamir, 1977). Later studies applied nonlinear programming to the network design problems. Some examples are Su *et al.* (1987) that used non linear programming to optimize looped pipe networks or Lansey & Mays (1989), whose model was able to simulate pumps, tanks and multiple loading cases.

The application of heuristic techniques of optimization allows the search beyond these local minimums, which generally ample the field search and with it the capacity to obtain better solutions. The evolutionary algorithms are methods of search of solutions that are based in the natural beginning of the evolution. Inside the evolutionary algorithms, we can find Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony, Harmony Search, and so on.

Some investigators have compared these techniques to each other (Zecchin *et al.*, 2007), but it is difficult to say that one of them is clearly better than the others.

Genetics algorithms (GAs) are a searching method based on Darwin´s evolution theory (Holland, 1992). It works identically to the evolution of a population that is put under similar random actions to which they act in the biological evolution (mutations and genetic recombination). The individuals best adapted survive and the less ones are discarded, based in some established criteria.

Most of these methods, for a given network layout and demand, consider the minimization cost of a pipe network as the objective. In the field of hydraulic engineering, previous works like those of Goldberg (1987), Savic & Walters (1997), Iglesias *et al.* (2006), Fujiwara & Khang (1990) or Cunha & Sousa (1999), reflects the importance that these algorithms are implementing in the optimal design of water distribution networks.

Branched water distribution networks will have severe consequences in terms of reliability under failure conditions. To improve the performance of a water distribution network under failure conditions, Goulter & Bouchart (1990) have solved a reliability constrained least cost optimization problem.

Loops in a network increase its reliability, so that the system will have sufficient capacity to deliver during mechanical or hydraulic failures. Mora *et al.* (2006) uses GA for compare design of water distribution systems with and without reliability in the network.

However, explicit consideration of reliability in an optimization model is difficult, and there are no universally accepted definitions for reliability.

In the same way, GAs have been used for water network rehabilitation (Halhal *et al.*, 1997) and for the calibration of water distribution models (Balla & Lingireddy, 2000), where the manual adjustment of uncertain parameters as the pipe roughness coefficients and the water demand at nodes is highly inefficient and often unsuccessful.

This work shows the development of a method for the optimal design of water distribution networks based on the GA use. The aim is to minimize the necessary costs of investment for the implantation of a certain system, starting from the topological layout and the demands and requirements of pressure in the nodes. The proposed method develops a code based on the use of numerical chromosomes instead of binary chromosomes. It is also introduced the optimization of the different parameters which influence in the minimum achievement, like the probabilities of mutation and crossover, and the population size which the algorithm will work with.

METHODOLOGY

The GAs are systematic methods for the resolution of searching and optimization problems that apply the same methods of the biological evolution, as the selection based on the population, reproduction and mutation.

Traditionally, the GAs have been methods adapted for problems formulated in binary variables but not advisable for other searching methods. However, in the present work a formulation of the problem is introduced based on a numerical codification, non binary, of the solution.

The random character of the method does not guarantee a complete exploration of the space of solutions, nor supposes guarantee to reach a minimum of the objective function. However, the method offers a set of good solutions that try to improve. The work's elements of a GAs are defined perfectly in Iglesias *et al.* (2002) and in Matías (2003). Hereby is proposed a brief description emphasizing the adaptations made for the pseudo-genetic algorithm (PGA).

The gene is the basic unit of information that adopts a binary value (0/1). In the method each one of the decision variables can have a rank of possible different solutions, which is represented with an alphanumerical variable. With this codification is possible to identify each gene with a variable decision, which did not
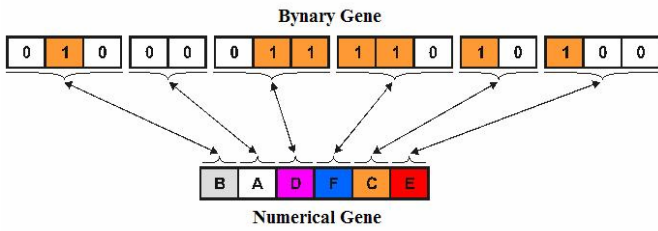
Fig. 1 Definition of chromosome and gene in a genetic algorithm (GA) and of the proposed pseudo-genetic algorithm (PGA).

happen in the classic GA. In the design of water distribution networks, each gene is represented with a number or a letter that identifies the diameter of each one of the lines (**Fig. 1**). The detail on the codification and the variables can follow in Iglesias *et al.* (2002).

A chromosome represents a solution to the problem. This solution is constituted by a serial of genes that defines a unique solution of the optimization process. When designing a water distribution network without considering pumps and valves, the genes are the representation of the diameter that adopts each tube in each one of the solutions.

In order to solve the optimization problem it is necessary to have a discrete set of possible solutions (chromosomes). This set of chromosomes is what also forms the population of the GA and the PGA. In the PGA a generic chain X is constituted by an equal number of genes to the number of decision variables (NVD), so that generic chain i of a P population is defined as a vector of numerical values.

$$X^i = \left\{ X_1^i, X_2^i, \ldots, X_{N_{VD}}^i \right\} \quad (1)$$

The characteristic that measures "kindness" or capacity of a certain chromosome's survival regarding the others is known like aptitude. The aptitude of a certain generic chromosome is identified through the value that adopts the objective function for the codified solution. In the case of the PGA proposed for design and extension of supplying networks this objective function is defined as

$$F(X^i) = \sum_{j=1}^{N_{VD}} C_j \left(X_j^i \right) \cdot L_j + \lambda \cdot \sum_{s=1}^{N_S} \sum_{k=1}^{N_R} \delta_{k.s} \cdot \left(H_{min,k} - H_{k,s} \right) \quad (2)$$

where C_j is the associated unit cost to the decision variable's value contained in link j of chromosome i; and L_j is the length of conduction of pipe j. Moreover, they are N_R imposed restrictions that must achieve the possible solutions of the problem. These restrictions have been including through a penalty in the total cost of the solution that later affects the aptitude of the chromosome.

The restrictions that must be fulfilled are the derived ones to satisfy the restrictions with minimum pressure height ($H_{min,k}$) in each node k. These restrictions must be verified in all the analyzed scenes

N_S, that usually are the on-speed operation of the system and its operation under the scene of failure of some of the conductions. The function penalty represents the difference between the head height of the node k in scene s ($H_{k,s}$) and the required minimum height ($H_{min,k}$). In order to compute this penalty two variables are defined. One of them ($\delta_{k,s}$) is a binary variable that adopts value 1 if $H_{k,s} < H_{min,k}$, and it adopts null value in opposite case. The parameter λ represents a weight function that establishes the penalty's value for not verifying the restrictions of minimum pressure in the nodes. Pressure is considered as a hard constraint, and λ is big enough (10^7) for reject all solutions that violates the constraint.

In this paper the only network components that are considered are the pipes, but it is possible incorporate elements as pumps, tanks, valves and reservoirs without invalidating the algorithms.

The method of the proposed PGA tries the evolution of a random population through a parallelism similar to the laws of the natural selection, as it happens with the classic GA (Matías, 2003; Iglesias *et al.*, 2002). This is obtained through three basic processes: reproduction, crossover and mutation.

The reproduction is the process through we select between the chromosomes of the P population, those that will survive the following generation. Between all the existing methods of reproduction (Matías, 2003) it is been selected the constant reproduction method.

This method orders the individuals of a population in increasing order according to its cost: from the cheapest individual to the most expensive. Later, a probability is assigned to each chromosome of the population to become one of the following generation. This probability will be included between a maximum probability p_{max}, associated with the individual of smaller cost, and a minimum probability, associated to the solution of greater cost. Both probabilities are defined as

$$p_{max} = \frac{\beta}{N_C} \quad p_{min} = \frac{2 - \beta}{N_C} \quad (3)$$

when β is a constant whose value must be comprised between 1.5 and 2 (Wang, 1991) and N_C is the number of chromosomes.

The crossover process (**Fig. 2**) consists in matching in a random way the chromosomes of the intermediate population and making a change of the different genes from a certain *crossover gene*, determined in a random way. It does not matter if two descendants of same parents are matched, since it guarantees the perpetuation of an individual with good score. However, it is not advisable to repeat this situation too much, since the population could get dominated by the descendants of some gene, which could cause the falling of the calculation in a local minimum.
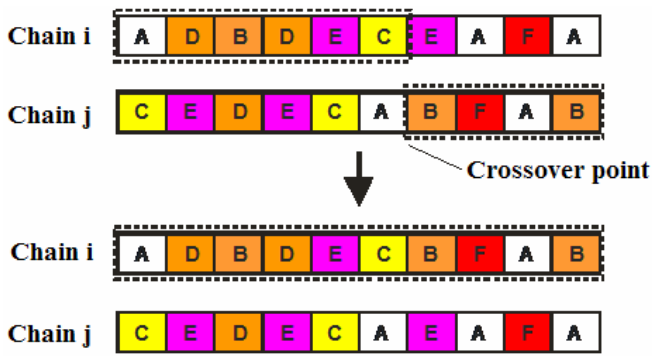
Fig. 2 Process of crossover.

Fig. 3 Process of mutation of a PGA.

One of the fundamental characteristics of the PGA is the effect generated when crossing different chromosomes. If the codification is binary, the crossover process cut the chain in a random point. This can originate the fraction of the binary code that identifies one of the possible variables of decision. In case of implementing the PGA the selection of a crossing link does not generate this effect. This is the reason using the PGA generates minor change possibility in the final solutions that the classic GA.

The mutation process is applied to the obtained population after the crossing and reproduction process. Once established the mutation frequency, for example, one by thousands, is examined each gene of each chromosome when an individual is created from its parents. If a random generated number is under that probability, the gene will change. If no, it will be left as it is.

Once chosen the mutation gene this bit is determined randomly whether it must be increased or decreased in one unit. **Fig. 3** shows the mutation process, where gene B could evolve to A or C. This is the way to determine the value of the link in the following generation. Both the crossing process and the chromosome's codification cause the generation of new alternatives in PGA being inferior to the one of a classic GA. For this reason the probability of mutation in the PGA is slightly superior.

The mutation is a parameter which is not convenient to abuse; it is a generating mechanism of diversity, but also it reduces the genetic algorithm to a random search. It is always more advisable to use other mechanisms of diversity generation, like increasing the size of the population, or guarantee the randomness of the initial population.

This way, the size of the population will have to be enough in order to guarantee the diversity of solutions, and, in addition, it must grow with the number of chromosome's bits. The main problem that is generated when using high populations is that convergence time of the algorithm is bigger. Therefore it is necessary to reach a commitment solution depending on the approach of the problem.

The following sections analyze the capacity of the proposed PGA to obtain equal or better solutions to the existing ones in the references. It has been analyzed
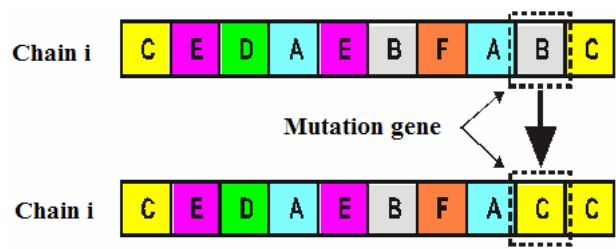
different water distribution networks, determining the minimum cost of design them. The initials studies of the proposed model had been realized about Alperovits & Shamir network (1977), achieving the same minimum results obtained in bibliography (Iglesias *et al.*, 2006). However, the reduced size of this network did not allowed to deepen in the kindness of the method.

Thus, working on the network of Hanoi, the influence of the different parameters has been analyzed on the final solution, dividing the work in two phases: First stage where the best combination of the crossover and mutation probabilities are analyzed, and one second phase, where from the first optimization the population size's influence in obtaining the minimum value of design is analyzed.

In each calculation it is necessary to determine pressure in nodes and flow in lines. These calculations are made by means of the model EPANET, developed by the Water Supply and Water Resources Division of the U.S. Environmental Protection Agency's National Risk Management Research Laboratory, whose foundations can be followed in Iglesias (2004). The massive treatment of simulations to obtain the parameters of the PGA has been made with a specific application, as it is described in Iglesias (2006).

APPLICATION EXAMPLE

The analysis of the proposed model has been made on the network of Hanoi (**Fig. 4**), as propose by Fujiwara & Khang (1990). As it is a water network of important size and with a real layout, there is a wide range of solutions obtained with different models of design in the bibliography, which has allowed us to compare the results of the different models of design.

The network consists of one reservoir (node 1), 31 demand nodes and 34 pipes. The minimum pressure head required at each node is 30 m.

One of the characteristics that contribute to define the optimal solution of the network is the range of diameters used. For the study we used the original range of the bibliography (**Table 1**).

The work displayed by Iglesias *et al.* (2006) shows the results obtained by the different researchers, as well as the obtained by the proposed method. This work deals with fixed populations of 100 individuals, being the aim the optimization of crossover and mutation
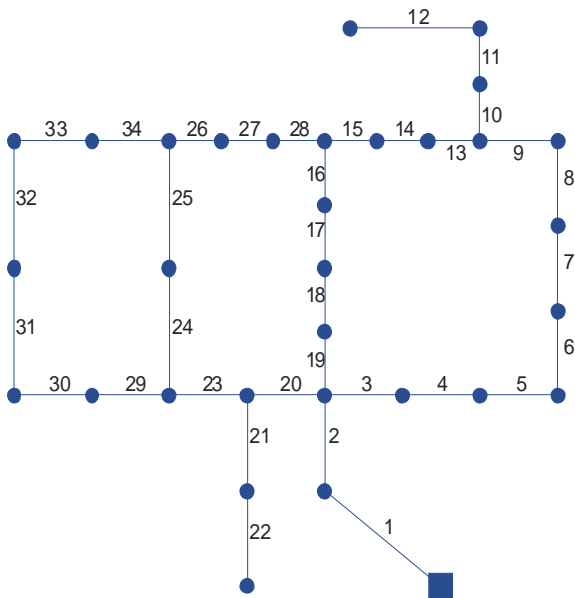
Fig. 4 Network of Hanoi.

Fig. 5 Diagram of frequencies and accumulated probability of the obtained solutions.

parameters. **Table 2** shows the solution's variation obtained by some researchers, as well as its corresponding total cost.

It is worth mentioning that in the column Sol 2 of **Table 2** we consider the burst of the pipes that close loop network. For this reason prevails as condition that the pressure restrictions must even verify when a breakdown takes place in any of the pipes and this increases the cost of the network.

If we rely on the obtained minimum value, we observe that the PGA improves those of all his competitors but the one of Cunha & Sousa, in terms of the used heuristic method does not fulfil the pressure specifications.

In the solution where the reliability concept is introduced, the cost of the network grows, logical circumstance, since the diameters to guarantee the provision in case of breakage must be greater. In the real case that one appears next has considered this fact, reason why all the given data already consider the reliability concept.

ANALYSIS OF THE RESULTS

One of the main characteristics of a GA is that it works in a random way. The characteristics of the method do

Table 1. Range of diameters used for the design of the water distribution network

No. Diameter	Original range	
	Diameter (mm)	Cost (mu/m)
A	304.8	45.73
B	406.4	70.40
C	508.0	98.39
D	609.6	129.33
E	762.0	180.75
F	1016.0	278.28
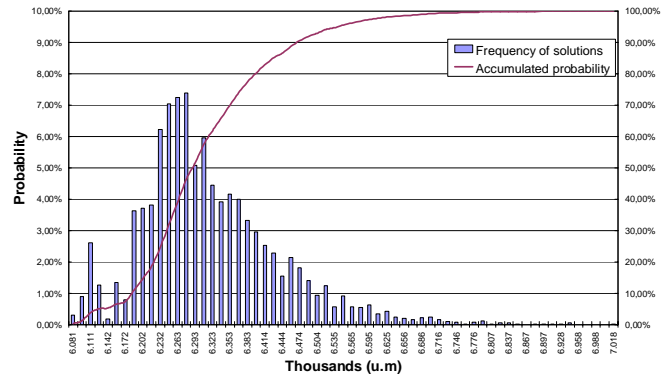
not guarantee with certainty the obtaining of the optimal value of the system. In addition, the obtained result can suffer sometimes certain variations. In order to analyze this randomness it is necessary to make statistical analyses that will study the influence that have the different parameters from the PGA proposed in the solution of the analyzed network, with the purpose of optimizing them to increase the probability of obtaining the minimum.

In a first study, the mutation and crossover probabilities were modified, maintaining the size of the chain constant. Later, from the best values obtained for both parameters another study was made, with the objective to study the influence of the population in the search of the best solution. For it they have been made more than 50 000 simulations altogether. For the calculation of these simulations we use a computer system in parallel with 23 computers AMD Duron to 1400 MHz and 128 MB of ram.

Influence of crossover and mutation probability

Initially a histogram is made (**Fig. 5**). This graph incorporates the accumulated probability of the obtained solutions. The graph allows to detect the more frequent solutions, as well as to determine the probability of obtaining a given solution better to one given. It is important to consider that the histogram represents the totality of obtained costs, varying crossover and mutation probabilities, with a fixed population of 100 individuals.

In order to determine the influence of mutation and crossover probability in the obtaining of the minimum cost value, we adopted the solution corresponding to 6081 thousands of monetary units. This minimum was considered the optimal value of design, as it was the minimum obtained. Fixed this value it has been analyzed for each value's combination of mutation and crossover, the probability that method PGA obtains the optimal value. The representation of this rate of success obtaining the minimum is shown in **Fig. 6**. In it we remark that there are combinations of values of the

Table 2. Comparison of diameters (mm) obtained as solution for the network of Hanoi

Line	Bibliography Solutions				Obtained Solutions	
	Matías[1]	Savic1[2]	Savic2[3]	Cunha[4]	Sol 1[5]	Sol 2[6]
1	1016	1016	1016	1016	1016	1270
2	1016	1016	1016	1016	1016	1270
3	1016	1016	1016	1016	1016	1016
4	1016	1016	1016	1016	1016	1016
5	1016	1016	1016	1016	1016	1016
6	1016	1016	1016	1016	1016	762
7	1016	1016	1016	1016	1016	762
8	1016	1016	1016	1016	1016	762
9	1016	762	1016	1016	1016	762
10	762	762	762	762	762	609.6
11	609.6	762	609.6	609.6	609.6	609.6
12	609.6	609.6	609.6	609.6	609.6	508
13	508	406.4	508	508	508	1016
14	406.4	406.4	406.4	406.4	406.4	762
15	304.8	304.8	304.8	304.8	304.8	1016
16	304.8	406.4	304.8	304.8	304.8	1016
17	406.4	508	406.4	406.4	406.4	1016
18	609.6	609.6	508	508	609.6	1016
19	609.6	609.6	508	508	508	1016
20	1016	1016	1016	1016	1016	1016
21	508	508	508	508	508	609.6
22	304.8	304.8	304.8	304.8	304.8	406.4
23	1016	1016	1016	1016	1016	1016
24	762	762	762	762	762	762
25	762	762	762	762	762	1016
26	508	508	508	508	508	1016
27	304.8	304.8	304.8	304.8	304.8	1016
28	304.8	304.8	304.8	304.8	304.8	1016
29	406.4	406.4	406.4	406.4	406.4	508
30	304.8	406.4	406.4	304.8	304.8	508
31	304.8	304.8	304.8	304.8	304.8	508
32	406.4	304.8	304.8	406.4	406.4	304.8
33	406.4	406.4	406.4	406.4	406.4	406.4
34	609.6	508	508	609.6	609.6	406.4
Cost (thousands um)	6.093	6.187	6.073	6.056	6.081	8.068

[1] Obtained solutions by Matías (2003).
[2] Obtained solutions by Savic & Walters (1997).
[3] Obtained solutions by Savic & Walters (1997), no pressure restrictions accomplished.
[4] Obtained solutions with a heuristic method (Cunha & Sousa, 1999). This solution does not verify the pressure restrictions.
[5] Best solution obtained with the proposed method.
[6] Obtained solution considering the burst of the pipes that close loop network.
Highlighted in grey the diameters that are different from the proposed solution of Savic & Walters, which verifies the restrictions of pressure in the nodes.

mutation probability and crossover that never generate a optimal.

The maximum rate of success is obtained approximately for a probability of mutation of 3–4% and a crossover probability around 90%. Definitely, it entails to cross practically all the chains and approximately to make one mutation of a little more of a gene of each chain.

The concept of "good solution" is introduced now. One of the characteristics of the GA in general and the PGA proposed is the capacity to obtain not only one single optimal value, but to obtain a set of "good solutions" on the design problem.
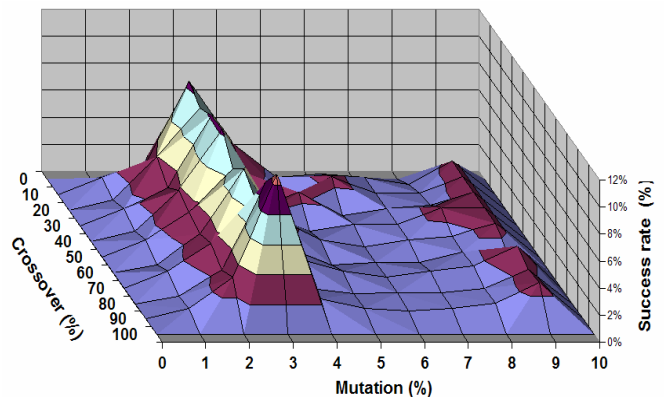

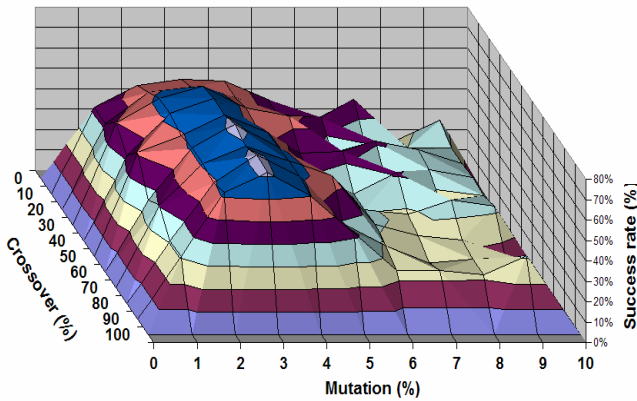**Fig. 6** Probability of obtain the minimum about mutation and crossover probability.

Fig. 7 Probability of obtain a "good solution".

Fig. 9 Probability of obtaining a solution based on the overcost respect to the solution of minimum cost.

In this work "good solution" is defined with whose cost is over the minimum cost until in a 3%.

Thus, **Fig. 7** indicates the probability of obtaining a "good solution" for each combination of mutation and crossover probabilities. This chart shows greater values of the success rate than **Fig. 7**. This shows the capacity of the method not only to obtain minimum values, but also to obtain with relative frequency values very near the optimal one defined.

The statistical analysis of the simulations allows verifying the robustness of the method. Thus, around the values of mutation probability best adapted, the effect of the crossing probability becomes smaller. This is shown, not only in the process of obtaining the minimum cost solution, but in the obtaining of solutions near the optimal one.

Figure 8 shows the little influence that has the crossover probability in the obtaining of minimum values or "good solutions". This figure indicates for values of mutation around 3% the probability of obtaining a solution based in different crossover values and the overcost that the solution has respect to the minimum value, defined like optimal.

Also this analysis has allowed limiting the process more. **Figure 9** shows the global probability of the proposed method, assuming a suitable selection of the optimization parameters based on the maximum overcost permissible respect to the minimum value. A null overcost supposes to select the probability of obtaining the solution of minimum cost.
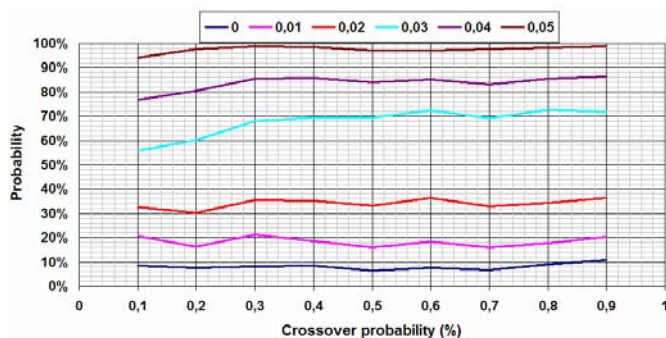
Optimization of the initial population

In the previous statistically analysis the collected data show that certain combinations of crossing and mutation generate greater rates of success to obtain the optimal one. Concretely it is observed that for a probability of mutation of 3% (something more of a link by chromosome) we have a 10–12% of possibilities obtaining the minimum. On the other hand, we deduce from the analysis that the crossing probability does not influence in the probability of obtaining the minimum value of design when the population is of 100 units.

The present analysis considers as optimal parameters of design the crossover and mutation probability proposed in the previous section, aiming the study in the optimization of the individuals initial population. They have been made more than 25 000 simulations with populations that go from the 25 to the 225 individuals, fixing the mutation to a 3% and varying the possibility of crossing between the 10 and 90%.

Initially a histogram is made (**Fig. 10**). It is important to consider that the histogram represents the totality of obtained costs, including all the possible combinations of population individuals, crossover and mutation.

We have adopted again as optimal value the solution that corresponds to a cost of 6081 thousands of monetary units. Fixed this value we analyze for each combination of the population values and probability of crossing, the probability that the PGA obtains the

Fig. 8 Influence of crossover probability in the obtaining solutions with different overcost, about the minimum cost solution.
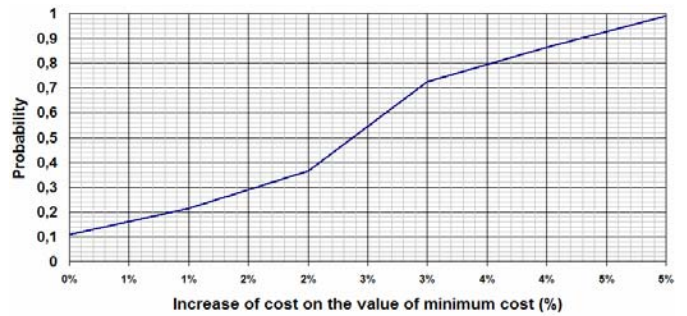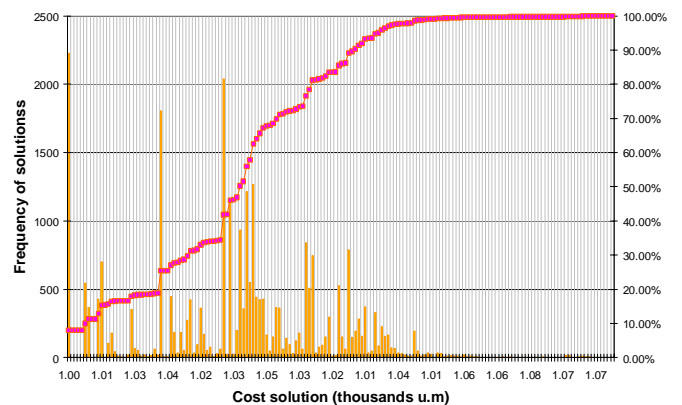

Fig. 10 Diagram of frequencies and accumulated probability of the obtained solutions.

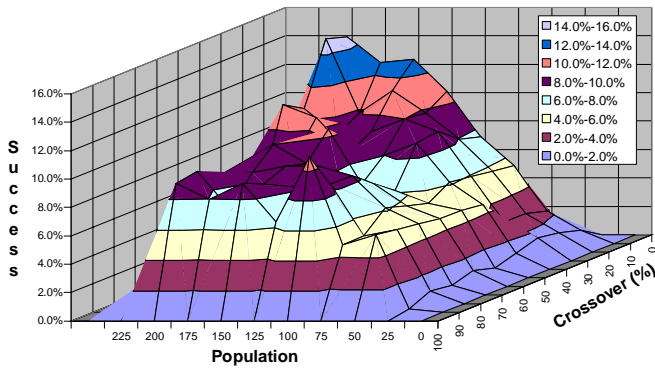**Fig. 11** Probability of obtain the minimum respect to the size of the initial population and the crossover probability.

Fig. 13 Probability of obtaining a "good solution" by number of simulations ($\times 10^7$).

optimal solution. **Figure 11** displays the representation of this rate of success in the obtaining of the minimum. This graph shows that as the initial population increases the probability of obtaining the minimum value also grows, although this increase becomes stable at a certain point. At first sight the best combination of values is in populations of 200 with a probability of crossing of 10%, but it will be necessary to evaluate if it compensates this slight improvement with the diminution of the calculation speed caused working with greater populations.

The previous graph displays an important difference to we see the previous section, where it was highlighted the fact that the probability of crossing for a population of 100 did not influence in the results. When extending the rank of populations that make the calculation we can affirm that the crossing probability acquires importance when the population is greater. In the same way, it is possible to emphasize that for smaller populations of 50 the algorithm is less effective for finding minimums, as no practically occurs.

Now we analyze the probability of obtaining the minimum by number of simulations (**Fig. 12**), study that make clearer the convenience using greater initial populations, since they slow down the calculation. The graph is not very enlightening regarding the best combinations, taking place tips in diverse zones of the representation. Thus, in **Fig. 13** is shown the probability of obtaining a "good solution" by number of solutions.
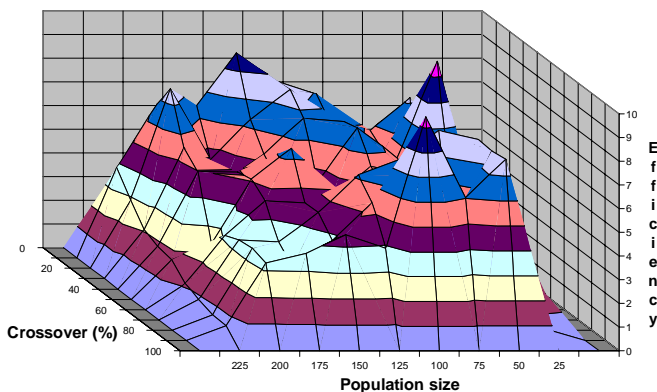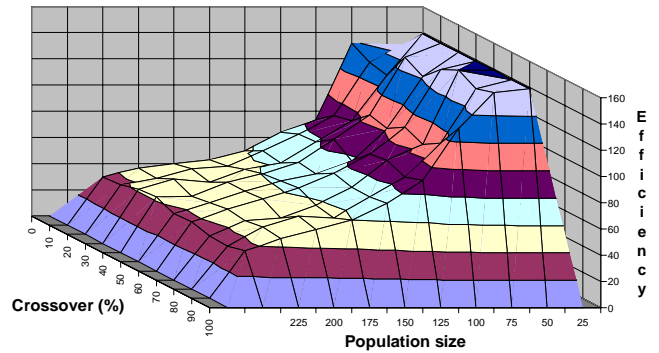
As it is observed in the graph, if we extended the rank of valid solutions in a 3%, the lower populations work that the high population far better, since the probability of obtaining a good solution with a smaller number of iterations is much greater. The inferior limit of population would be established for this case in 50 individuals, since even considering only the good solutions improvement is not observed in inferior populations. However, it has demonstrated that the smaller is the population the less is the probability of finding minimums for the system.

Conclusions

The main objective of this work consists of making the design of a water distribution network, using for it a method based on PGA. The economic design in the Water Distribution Networks is of great interest, as it allows us to choose a solution between the different alternatives that verify the imposed hydraulic conditions.

Thus, of the statistical analysis of the results in the proposed model it is possible to emphasize the following conclusions:

- The statistical analysis allows to as much establish the rate of success in the obtaining of minimum cost solutions. In the same way, we can establish the rate of success in the obtaining of good solutions that defer an inferior amount to 3%.

- When the population of individuals is fixed, the PGA displays a great robustness to the values of the crossing probability. On the other hand the mutation probability is a much more sensible parameter. For the analyzed example it must be approximately between 3–4%, which supposes to make the mutation of one gene by chain.

- In agreement the initials is increased of individuals increases the number of obtained minimums. Despite it arrives a moment while in that light improvement can not compensate the greater time of calculation than it causes introducing greater populations, reason why it

Fig. 12 Probability of obtaining the minimum by number of simulations ($\times 10^7$).

becomes necessary to reach a commitment solution.

- If it is not required to find the minimum of the system, but only a set of good solutions is recommendable to use populations of few individuals, since they work fast. However, it exist a minimum population in each case, and once exceeded this one the results get worse.
- The exposed results for the variation of the population are valid in this model, reason why the verification is necessary from the hypotheses raised here with different models, since excessively small populations can not give good results in networks greater than the here propose one.
- Finally, it seems that the convergence towards final solutions, and therefore the time of necessary calculation is inferior to the methods based on classic GA.

Really, the proposed model seems valid for the water distribution networks. The adjustment of its parameters has been verified with the statistical analysis. The obtained results can be extrapolated to other problems of design. However, the made study must extend to the case of design considering the reliability criterion. This fact can modify the obtained solutions remarkably and probably the necessary parameters. Another statistical study similar to the made can illuminate some of the shades that at the present time exist.

REFERENCES

Alperovits, E. & Shamir, U. (1977) Design of optimal water distribution systems. *Water Resour. Res.* **12**(6), 885–900.

Balla, M.C & Lingireddy, S. (2000); Distributed genetic algorithm model on network of personal computers. *J. Comput. in Civil Eng.* **14**(3), 199–205.

Cunha, M.C. & Sousa, J. (1999) Water distribution networks design optimization: simulated annealing approach. *J. Water Resour. Plng. Management* **125**(4), 215–221.

Fujiwara, O.Y. & Khang, D.B. (1990) A two-phase decomposition method for optimal design of looped water distribution networks. *Water Resour. Res* **26**(4), 539–549.

Golberg, D.E. (1987) Genetic algorithms in pipeline optimization. *J. Comput. in Civil Eng.*, **1**(2), 148–141.

Goulter, I.C. & Bouchart, F. (1990) Reliability-constrained pipe network model. *J. Hydraul. Div. ASCE* **116**(2), 211–229.

Halhal, D., Walters, G.A., Ouazar, D. & Savic, D.A. (1997) Water network rehabilitation with structured messy genetic algorithm. *J. Water Resour. Plng. Management* **123**(3), 137–146.

Holland, J. (1992). Algoritmos Genéticos. Investigación y Ciencia. Septiembre 1992, 38–45.

Iglesias, P.L., Lopez, P.A., Martinez, F.J. & Perez, R. (2002). Dimensionado económico de impulsiones mediante algoritmos genéticos. Proc. Seminario Hispano Brasileño sobre Planificación, Proyecto y Operación de Redes de Abastecimiento de Agua, 2002.

Iglesias, P.L., Mora, D., Fuertes, V. & Martinez, F.J. (2006). Análisis estadístico de soluciones de diseño de Redes de Abastecimiento de Agua mediante Algoritmos Genéticos. Proc. Congreso Latinoamericano de Hidráulica. Ciudad Guayana. Venezuela.

Mora, D., Iglesias, P.L., Fuertes, V & Martinez, F.J (2006). Metodología para diseño y ampliación de redes de abastecimiento mediante Algoritmos Genéticos. XII Congreso Internacional de Ingeniería de Proyectos. Valencia. Spain.

Lansey, K.E. & Mays, L.W. (1989) Optimization model for water distribution system design. *J. Hydr. Engrg. ASCE* **115**(10), 1401–1418.

Matías, A (2003). Diseño de redes de distribución de agua contemplando la fiabilidad mediante algoritmos genéticos. Tesis Doctoral (Ingeniería Hidráulica y Medio Ambiente). Universidad Politécnica de Valencia.

Rey, P.L.I., López, P.A., López, G. & Martinez, F.J. (2004) Epanet 2.0vE. Manual de usuario. Ed. Grupo Multidisciplinar de Modelación de Fluidos, Valencia. (Traducción comentada del texto original de Rossmann, L. Epanet 2.0 Users Manual).

Su, Y.C., Mays, L.W., Duan, N. & Lansey, K.E. (1987) Reliability-based optimization model for water distribution Systems. *J. Hydr. Engrg. ASCE* **114**(12), 1539–1556.

Savic, D.A. & Walters, G.A. (1997) genetic algorithms for least-cost design of water distribution systems. *J. Water Resour. Plng. Management* **125**(2), 67–77.

Wang, Q.J. (1991) The genetic algorithm and its application to calibrating conceptual rainfall-runoff models. *Water Resour. Res* **27**(9), 2467–2471.

Zecchin, A.C., Maier, H.R., Simpson, A.R., Leonard, M. & Nixon, J.B. (2007) Ant colony optimization applied to water distribution system design: comparative study of five algorithms. *J. Water Resour. Plng. Management* **133**(1), 87–92.