



HAL
open science

A diversity-enriched variant of discrete PSO applied to the design of Water Distribution Networks

Idel Montalvo, Joaquín Izquierdo, Rafael Pérez, Pedro L. Iglesias

► **To cite this version:**

Idel Montalvo, Joaquín Izquierdo, Rafael Pérez, Pedro L. Iglesias. A diversity-enriched variant of discrete PSO applied to the design of Water Distribution Networks. *Engineering Optimization*, 2008, 40 (07), pp.655-668. 10.1080/03052150802010607. hal-00545357

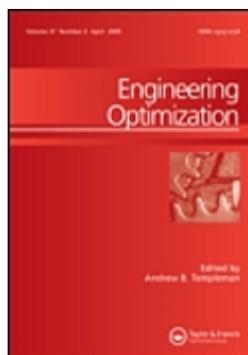
HAL Id: hal-00545357

<https://hal.science/hal-00545357>

Submitted on 10 Dec 2010

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



A diversity-enriched variant of discrete PSO applied to the design of Water Distribution Networks

Journal:	<i>Engineering Optimization</i>
Manuscript ID:	GENO-2007-0005.R3
Manuscript Type:	Original Article
Date Submitted by the Author:	17-Jan-2008
Complete List of Authors:	Montalvo, Idel; Universidad Politécnica de Valencia, Centro Multidisciplinar de Modelación de Fluidos Izquierdo, Joaquín; Universidad Politécnica de Valencia, Centro Multidisciplinar de Modelación de Fluidos Pérez, Rafael; Universidad Politécnica de Valencia, Centro Multidisciplinar de Modelación de Fluidos Iglesias, Pedro; Universidad Politécnica de Valencia, Centro Multidisciplinar de Modelación de Fluidos
Keywords:	particle swarm optimization, water distribution networks, optimal design, evolutionary algorithm



A diversity-enriched variant of discrete PSO applied to the design of Water Distribution Networks

I. Montalvo, J. Izquierdo¹, R. Pérez, P. L. Iglesias
Centro Multidisciplinar de Modelación de Fluidos
Universidad Politécnica de Valencia
Camino de Vera, s/n, 46022, Valencia, Spain

Abstract

In this [article](#) the design of Water Distribution Networks (WDN) is addressed by using a variant of the so-called PSO (Particle Swarm Optimization) algorithm. This variant, which makes use of a discrete version of PSO already considered by the authors, overcomes one of the PSO's main drawbacks, namely its difficulty to maintain acceptable levels of population diversity and to balance local and global searches. The performance of the variant herein proposed is investigated by applying the model to solve two already traditional benchmark problems in the literature, the Hanoi new water distribution network and the New York Tunnel water supply system. The obtained results show considerable improvements regarding both convergence characteristics and the quality of the final solutions, and near optimal results are shown to be consistently achieved at reduced computational cost.

Keywords: Particle Swarm Optimization, Water Distribution Networks, Optimal Design, Evolutionary Algorithm

1. Introduction

Optimal design of new WDN (Water Distribution Networks) can be defined by the best possible combination of reducing costs for its components, such that all water demands are met, given design constraints, including the occurrence of particular system failures. Nevertheless, even though the design of new systems is important in itself, in practice, situations in which the interest focuses in expansion, rehabilitation and/or just optimum operation design of existing systems are much more frequent. Due to the sundry factors influencing the design, in practice, this optimization can be highly complex.

For one thing, the objective function which will enter the optimization problem can take numerous forms depending on the nature of the problem (system expansion, rehabilitation, new design, operation, etc). Obviously, there exists no unique set of such main factors, even for various approaches to one and the same specific problem. This implies that the most effective techniques of such optimization have to adapt themselves easily to whatever objective function. Traditionally, decision variables have been in first place the diameters of the pipelines, more specifically, the diameters of new pipes and/or the diameters of additional, duplicated pipelines, which must be selected from a discrete set of commercially available pipe diameters. The inclusion of reservoirs and pumps into the optimization process requires that both the design and the operation of the network in extended period simulation should also be considered.

For the other, typically, the design constraints are given by minimal pressure head requirements at each demand node and the physical laws which govern the flow dynamics. Considering multiple demand conditions, the possibility of staging of construction over the lifetime of the project, reliability and redundancy of the network, adequate water quantity and

¹ Corresponding author: Joaquín Izquierdo.
Tel: +34 963879890 – Fax: +34 963877981 – e-mail address: jizquier@gmmf.upv.es

Deleted: paper

1
2 good water quality, optimum design capacity and hydraulic requirements add additional
3 constraints, resulting in a highly complex optimization problem.

4 All in all, a general strategy to solve such optimization problems of WDN can be defined in
5 terms of a balanced combination of least cost for the layout and sizing using new components, the
6 reuse or substitution of existing components, and a working system configuration which fulfils all
7 water demands and the design constraints, guaranteeing of course a certain degree of reliability for
8 the system (Goulter and Bouchart, 1986, 1990).

9 For the last decade, many researchers in the field have shifted direction, leaving aside
10 traditional optimization techniques based on linear and nonlinear programming and embarking on
11 the implementation of Evolutionary Algorithms: Genetic Algorithms (Savic and Walters, 1995;
12 Wu and Simpson, 2001; Matias, 2003; Wu and Walski, 2005); Ant Colony Optimization (Maier et
13 al., 2003; Zecchin et al., 2005); Simulated Annealing (Cunha and Sousa, 1999); Shuffled Complex
14 Evolution (Liong and Atiquzzaman, 2004); and Harmony Search (Geem, 2006), amongst others.

15 As a result of the iterative nature of the generation of solutions using aforementioned
16 algorithms, these can be intuitively interpreted as algorithms which continually search through the
17 solution space. This process takes full advantage of all solutions found up to the moment and helps
18 to guide the search. Evolutionary Algorithms are characterized by two fundamental ingredients
19 (Colomi et al., 1996): exploration, which is the capability of an algorithm to pursue a broad search
20 within the solution space, and exploitation, which is the capability of an algorithm to search more
21 specifically in a local subset of the solution space close to where previously good solutions have
22 been found.

23 One of the evolutionary algorithms, which has shown its potential and good perspectives
24 for the solution of various optimization problems (Dong et al., 2005; Jin et al., 2007, Liao et al.,
25 2007), is Particle Swarm Optimization (PSO). The PSO algorithm was developed by (Kennedy and
26 Eberhart, 1995) and inspired by the social behaviour of a group of migrating birds trying to reach
27 an unknown destination. A discrete version of this algorithm has been used recently by the authors
28 (Montalvo et al., 2007) to address WDN design and another mixed continuous-discrete one to
29 tackle the design of wastewater systems (Izquierdo et al., 2007). In the current article, the discrete
30 version for WDN is extended with a new feature that provides the algorithm with increased
31 population diversity, thus improving both convergence characteristics and the quality of the final
32 solutions.

Deleted: paper

33 The rest of this article is organized as follows. First a description of the WDN optimal
34 design problem will be given. Next a discrete version of PSO endowed with the new feature will
35 be presented. Then, the results of its application to two standard benchmarking problems in the
36 field, including a comparison with the results obtained by other authors, will be presented. The
37 advantages of using the new feature will be stressed. Finally, a number of conclusions and
38 recommendations will be raised.

Deleted: paper

39 2. Optimal design of WDN setting

40 The problem of designing economically and optimally a WDN amounts to determining the
41 values of all involved variables in such a way that the investment and maintenance costs of the
42 system are minimal, subject to a number of constraints (Izquierdo et al., 2004).

43 Apart from the basic variables of the problem, which are the diameters of the new pipes,
44 one may require additional variables that depend on the design characteristics of the system:
45 storage volumes, pump head, the type of rehabilitation to be carried out for various parts of the
46 network, etc. The estimation of individual costs will always depend on these variables. The correct
47 approach to assess the costs for each element becomes important when defining the objective
48 function, which has to be fully adapted to the problem under consideration: design, enlargement,
49 rehabilitation, operation design, etc. On the other hand, it is important that the objective function
50
51
52
53
54
55
56
57
58
59
60

reflects to the utmost reliability the total cost of the system during its entire lifetime. Various authors have used in their optimization an objective function which only considers the costs of the pipelines (Maier et al., 2003; Zecchin et al., 2005), and others have taken into account some other costs involved (Matias, 2003; Dandy and Engelhardt, 2006). One very interesting approach to the objective function is presented in (Martínez, 2007).

In this work, due to the nature of the two case studies we have chosen, use is made of an objective function which only takes into account pipeline costs. Nevertheless, a generalization to broader classes of objective functions is straightforward. The examples we address have traditionally been used in the literature and provide a standardized and simplified environment to carry out a wide range of tests and analyses. Hence, in order to facilitate the comparison with results obtained by other authors, we employ the following objective function to estimate the costs:

$$F(D) = \sum_{i=1}^N C(D_i) \cdot L_i, \quad (1)$$

where N is the number of pipes in the network, $D = (D_i)$ is the vector of pipes' diameters, which is N -dimensional, $C(D_i)$ is the unit cost of commercially available pipe of diameter D_i , and L_i the length of the i -th pipe. It has to be noted that C is a non-linear function of diameter.

Obviously, some combinations of pipe diameters can violate the system constraints resulting in infeasible solutions. The evaluation of illegal solutions in optimization problems with constraints is crucial, especially for non-linear programming problems, as the one herein considered. Therefore, the handling of system constraints, particularly the energy equations, which are nonlinear, and the assessment of infeasible solutions are of research interest. Currently, several methods have been developed to deal with system constraints. These methods mainly consider preserving feasibility of solutions, penalty strategies and searching for feasible solutions, and they have several drawbacks. Among them, the penalty function methods are particularly promising, as evidenced by recent developments (Fung et al.; 2002, amongst others), and this is the approach used here. Even though there are more sophisticated methods for constraint handling (Farmani and Wright, 2003; Afshar, 2007), use is made of a simple approach that works in the same way for all heuristics under investigation.

Also, in order to restrict ourselves to the same rules used in the literature to deal with the benchmark problems, only three kinds of constraints are considered here: continuity and energy equations, which are enforced by the use of EPANET2 (Rossman, 2000), and lack of satisfaction of minimum pressures at demand nodes, which are added as penalty costs to the cost (1) of the network. As a consequence, the total cost of the network is defined as

$$F = \sum_{i=1}^N C(D_i) \cdot L_i + \sum_{j=1}^K p_j \cdot v_j^2, \quad (2)$$

where K is the number of constraints, v_j is the j -th constraint violation and p_j represents the penalty parameter corresponding to constraint j with a large value to ensure that infeasible solutions will have a cost greater than any feasible solution.

One therefore deals with determining the values which minimize the total cost of the pipelines while complying with the minimal pressure requirements of the network.

The problems faced in the optimal design of WDNs are huge. Furthermore, this simple variant for the design of a water supply system belongs to a class of problems known as NP-hard problems, which are intractable and it is not practical to perform a full enumeration using any rigorous algorithm, due to the huge amount of computational time required. For instance, one of

the networks considered in this [article](#) with 34 pipes and 6 potential pipe diameters has 6^{34} possible pipe diameter combinations, which constitute the search space of the problem. This (really) modest network would require a considerable amount of time for an exhaustive search algorithm to navigate the entire search space of almost $2.87 \cdot 10^{26}$ potential solutions.

Deleted: paper

3. Description of PSO and the proposed variant

Particle Swarm Optimization is an evolutionary computation technique that was first developed by (Kennedy and Eberhart, 1995). Their first original idea was to simulate the social behaviour of a flock of birds in their endeavour to reach, when flying through the field (search space), their unknown destination (fitness function), e.g. the location of food resources. In PSO, each bird of the flock is a potential solution and is referred to as a particle. Initially a number of particles are randomly generated. Then, particles evolve in terms of their individual and social behaviour and mutually coordinate their movement towards their destination (Shi and Eberhart, 1998).

The i -th particle represents a solution of the hydraulic problem and is characterized by its location in an N -dimensional space, where N corresponds to the number of variables of the problem. Any set of values of the N variables, determining a particle's locations, represents a candidate solution for the optimization problem.

During the process each particle i is associated with three vectors:

- its current location

$$X_i = (x_{i1}, x_{i2}, \dots, x_{iN})^t$$

(3)

Deleted: 1

- the better location it has reached so far,

$$P_i = (p_{i1}, p_{i2}, \dots, p_{iN})^t$$

(4)

Deleted: 2

- and its velocity, which enables it to evolve to a new location,

$$V_i = (v_{i1}, v_{i2}, \dots, v_{iN})^t$$

(5)

Deleted: 3

Also, in each cycle (iteration) the particle that best fits the objective function is obtained; its location, P_g , plays an important role in the calculation of the movement evolution of every other bird.

In a coordinated way each bird evolves by changing its location

$$newX_i = currentX_i + newV_i,$$

(6)

Deleted: 4

with updated new velocity

$$newV_i = fix(\omega \cdot currentV_i + c_1 \cdot rand(\cdot) \cdot (P_i - currentX_i) + c_2 \cdot rand(\cdot) \cdot (P_g - currentX_i)),$$

(7)

Deleted: 5

so that it accelerates towards both its best position, P_i , and the best position obtained so far by any bird in the flock (best global position), P_g .

This enables each bird to explore in the search space from its new location. The process is repeated until the best bird reaches certain desired location. It is worth noting here that, according to the description, the process involves not only intelligent behaviour but also social interaction. This way, birds learn both from their own experience (local search) and from the group experience (global search).

The new elements in equation (7) are as follows.

Deleted: 5

- $fix(\cdot)$ is a function that takes the integer part of its argument, so that the new velocity vector will be an integer vector and, as a consequence, the new updated positions will share this characteristic since the initial population, in its turn, must also have been generated by using only integer numbers.
- c_1 and c_2 are the acceleration constants and represent the weighting of the stochastic acceleration terms that pull each particle simultaneously towards its best position and the best global position. These constants are also sometimes referred to as learning rates or factors.
- $rand()$ is a function generating uniform pseudo-random numbers between 0 and 1. Note that both $rand()$ numbers in (7) are independently generated.
- ω is an inertia term, proposed by (Shi and Eberhart, 1998), that controls the impact of the velocities history into the new velocity, provides improved performance in a number of applications and can be suitably adapted during the calculation process. This operator allows a balance between local and global search and typically decreases with time, so that initially global search is favoured, but this trend is shifted towards local search as the solution process evolves, and results in less iteration on average to find an optimal solution.

Deleted: 5

A more complete description of this discrete version of PSO applied to WDN design can be found in (Montalvo et al., 2007).

Particles' velocities on each dimension are confined to minimum and maximum velocities, which are user defined parameters.

$$V_{\min} \leq V_i \leq V_{\max}$$

(8)

Deleted: 6

If the sum of accelerations causes the velocity on a specific dimension to fall out of the accepted range, then this velocity is sensibly limited to either V_{\min} or V_{\max} . These are very important parameters. They determine the resolution with which regions between the present position and the target (best so far) positions are searched. If V_{\max} is too high, particles might fly through good solutions. If V_{\max} is too small, on the other hand, particles may not explore sufficiently beyond locally good regions. In fact, in this case, they could easily be trapped in local optima and unable to move far enough to reach a better position in the problem space.

PSO shares with other evolutionary techniques that it does not guarantee the global optimum. But, on the other hand, PSO does not need specific operators (such as crossover and mutation in the case of Genetic Algorithms, or pheromone updating in Ant Colony Optimization, amongst others), since particles update themselves with internal velocity. They also have memory and receive information only from the best particle in history, which is a simpler mechanism of information transmission than those used in Genetic Algorithms, for example. Particles try to converge to the best solution quickly, but PSO's main drawback is that it is difficult to keep good levels of population diversity and to balance local and global search, so that suboptimal solutions are prematurely obtained (Dong et al., 2005). Some evolutionary techniques maintain population diversity by using certain more or less sophisticated operators or parameters, as the mutation parameter in the case of Genetic Algorithms. Several other mechanisms forcing diversity can be found in the literature. For instance, the artificial immune systems especially designed to maintain diversity in optimization modal problems (Forrest et al., 1990; Smith et al., 1993) and afterwards extended to solve optimization problems with constraints (Hajela and Lee, 1996; Yoo and Hajela, 1999). In general, the random character typical of evolutionary algorithm's features adds, without doubt, some degree of diversity to their genotypes, phenotypes or individuals integrating the manipulated populations. Nevertheless, in discrete PSO those random components are unable to add, in general, sufficient amount of diversity. In effect, after conducting a specific study on the discrete PSO performance, the authors have detected frequent superpositions of birds in the search space, especially onto the leader. This, in fact, causes the effective population size to be lower and,

as a consequence, the algorithm effectiveness impaired. This led us to try to devise some kind of affordable action to effectively limit bird's superposition. To check all the birds for possible superpositions was deemed unaffordable (and unnecessary). After a number of trials a decision was made to check only superposition with the best bird in the flock and to re-generate completely at random a new bird if superposition occurred. This random re-generation of the many birds that tend to occupy the leader's position has shown to avoid premature convergence since it prevents clone populations from dominating the search. The inclusion of this procedure into the discrete PSO produces greatly increased diversity and, according to the results shown in the next paragraph, improved convergence characteristics and quality of the final solutions.

The modified algorithm can be given by the next pseudo code.

- Generate a random population of M particles (hydraulic solutions)
- Select the best particle
- Repeat the next block until fulfilment of termination condition
 - Determine the value of the inertia parameter ω
 - Begin cycle from 1 to number of particles
 - Start
 - Calculate fitness function for particle i
 - If particle i has better fitness value than the fitness value of the best particle in history then set particle i as the new best particle in history
 - If particle i is not currently the best particle but coincides with the best particle then re-generate particle i randomly
 - Calculate new velocity for particle i according to (7)
 - Update position of particle i according to (6)
 - End
 - Show the solution given by the best particle

Deleted: 5

Deleted: 4

The termination condition may be stated either in terms of a maximum number of iterations or in the event that certain value of the fitness function has been achieved (Shi et al., 2007). In this work, the algorithm will stop if after a number of a priori defined iterations the best found solution has not changed.

The performance of the approach herein introduced to avoid particles' superposition with the best particle can be observed from the results obtained for the two benchmark problems studied in the next paragraph.

4. Testing benchmark problems

The first case is the Hanoi pipe network (Figure 1), which has been considered several times in the literature (Savic and Walters, 1995; Cunha and Sousa, 1999; Matias, 2003; Zecchin, 2003; Zecchin et al., 2005; Iglesias et al., 2006). The complete setting can be found in (Wu and Simpson, 2001). The second case is the New York Tunnel water supply network (Figure 2), which similarly to the Hanoi water distribution problem, has been studied extensively by various researchers (Savic and Walters, 1995; Maier et al., 2003; Matias, 2003). Also, a complete detailed description can be seen in (Dandy et al., 1996). Both cases are very well-known benchmark problems in the literature.

The parameters used by this algorithm have been selected after preliminary tuning experiments following a number of suggestions (Shi and Eberhart, 1998; Jin et al., 2007; Liao et al., 2007; Shi et al., 2007):

- $c1 = 3, \quad c2 = 2;$
- $\omega = 0.5 + \frac{1}{2(\ln(k)+1)},$ where k is the iteration number;
- $V_{\max} = 50\%$ of variable range, which is problem dependent (for example, for one of the problems addressed in the next paragraph the number of commercially available pipes is 6, for the other is 15 plus the ‘do nothing’ option);
- $V_{\min} = -V_{\max};$
- Number of particles (population size) = 100.

The termination condition stopped the process if after 800 iterations no improvement in the solution had been obtained. Both designs were optimized 100 times initially. The obtained results and comparisons with other methods are presented now. It is worth observing that only solutions assessed as being feasible by EPANET2, which is the benchmark hydraulic analysis tool used in this research, are considered.

4.1 Hanoi water supply system

This network consists of a single fixed head source at elevation of 100m, 34 pipes and 31 demand nodes organized in three loops and two ramified branches. One has to find the diameters (from a set of six commercially available diameters) for the 34 pipes such that the total cost of the network is minimal and the pressure at each node of consumption is at least 30m.

Figure 3 shows the best costs obtained by the 100 runs performed when using the proposed algorithm. These results can be compared, Figure 4, with the ones obtained in (Montalvo et al., 2007) by standard discrete PSO, that is to say, without performing the re-generation-on-superposition option herein described. It can be observed that the inclusion of the re-generation option clearly outperforms standard PSO. Besides observing the difference between the scales in the two figures, it is worth to state that while the average for the 100 runs in Figure 4 was 6.487 million dollars, the one for Figure 3 is 6.297 million dollars, which can be viewed as a substantial improvement.

Furthermore, the best solution found after the inclusion of the re-generation option is shown in Table 1, together with other best solutions found in the literature.

4.2 New York Tunnel supply system

The system has a fixed head reservoir, 21 tunnels and 19 nodes. The objective of the New York Tunnel (NYT) problem was to determine the most economically effective design for addition to the existing system of tunnels that constituted the primary water distribution system of the city of New York. Because of age and increased demands, the existing gravity flow tunnels were found to be inadequate to meet the pressure requirements for the projected consumption level. In fact, minimum pressures at nodes 16 to 20 were not guaranteed. The construction of additional gravity flow tunnels parallel to the existing ones was considered. All 21 tunnels are considered for

1
2 duplication. There are 15 available discrete diameters and one extra possible decision which is the
3 “do nothing” option.

4 Figure 5 shows the best costs obtained by the 100 runs performed when using the proposed
5 algorithm. These results can be compared with the ones obtained in (Montalvo et al., 2007) by
6 standard discrete PSO, that is to say, without performing the re-generation-on-superposition option
7 herein described, given in Figure 6. It can also be observed that the inclusion of the re-generation
8 option clearly outperforms standard PSO. Also, observe the different scales in both figures, and
9 that the average for the 100 runs in Figure 6 was 48.039 million dollars, while the one for Figure 5
10 is 39.761 million dollars, which can be viewed as a substantial improvement, since it is a mere
11 2.9% higher than the best to date known and published solution.

12 Furthermore, the best solution found after the inclusion of the re-generation option is
13 shown in Table 2, together with other best solutions found in the literature.

14 15 16 **4.3 Probability of first-run ‘good’ solution**

17 Many ‘best’ solutions found in the literature regarding these two problems have been
18 obtained after never-ending computer dedication and, as a consequence, with huge computational
19 effort. This is an important drawback for the application of evolutionary algorithms to the solution
20 of ‘real-world’ problems where cost and time constraints prohibit repeated runs of the algorithm
21 and evaluations of the network. In order to study the performance of the proposed algorithm the
22 following experiment was carried out. First a set of 1000 runs were performed for both benchmark
23 cases. Then, using the obtained results, the probability for a single run of obtaining a solution
24 differing by less than a certain per cent from the best known solution was obtained. These
25 probabilities have been plotted in Figure 7. In order to confirm this study a second set of 2000
26 independent runs was performed again for both problems. Also, Figure 7 shows the obtained
27 curves. It can be easily seen from the outset that the curves for 1000 and for 2000 runs are almost
28 identical for both problems. As a consequence, it could be thought that those probability values
29 seem to be independent of the used sample of runs. One can, then, say, for example, that by
30 running only once the re-generation PSO algorithm described in this [article](#), the probability of
31 obtaining the best known solution is almost 30% for the NYT system and 5% for the Hanoi
32 system. But, from a practical point of view, where ‘early’ almost optimal solutions are much better
33 than ‘too late’ best solutions, this chart gives very important information. For example, one single
34 run of our algorithm guarantees a solution not more expensive than 5.5% of the best known
35 solution with a probability of 86%, for both studied problems. And there is almost complete
36 guarantee of obtaining a solution with cost under 1.1 times the best known solution cost by only
37 one single run of the algorithm.

Deleted: paper

38 It is also worth to observe that the average cost of the 1000 solutions was 6.299 million
39 dollars, only 3.59% higher than the best known solution, for the Hanoi system. The average cost of
40 the 2000 solutions, for this same system, was 6.295 million dollars, 3.51% over the best solution.
41 In the case of the NYT system these figures are 39.738 for the 1000-run set or 2.8% over the best
42 known solution and 39.688 for the 2000-run set or 2.7% above the cost of the best solution. These
43 figures do not need further explanation regarding the quality of the algorithm described in this
44 [article](#).

Deleted: paper

45 On the other hand, the average number of generations to obtain the best solutions for the
46 Hanoi systems is 700, 105 being the minimum number of generations to obtain the best solution.
47 Regarding the NYT problem these figures are 230 generations for the best solutions and 16 the
48 minimum number of generations to obtain the best solution. These figures make it clear that the
49 algorithm is really inexpensive. For example, the solution for the NYT system obtained in (Lippai
50
51
52
53
54
55
56
57
58
59
60

1
2 et al., 1999) of 45.73 million dollars was found after 80,000 evaluation trials. (Savic and Walters,
3 1997) reported two sets of solutions based on different hydraulic coefficients. The number of
4 generations allowed for their Genetic Algorithm was 10,000. (Farmani et al., 2005) used also
5 Genetic Algorithms, where the population size was 20 and the maximum number of generations
6 was set to 2,000. This improvement in the efficiency is mainly due to the self-adaptive fitness
7 formulation for evolutionary constraint optimization they propose. As an indication, one execution
8 of the variant proposed here with the Hanoi problem last on average 1 minute 5 seconds in a PC
9 with a processor Intel Core 2 Duo T5500, 1.66 GHz. Thus, running the algorithm 20 times for the
10 Hanoi problem, which virtually guarantees the optimum according to Figure 7, takes around 20
11 minutes. Times are shorter for the lower dimensional NYT problem.

12 By observing the curves in Figure 7 it can be clearly inferred that they are strongly problem
13 dependent. As a consequence, these results cannot be directly extrapolated to other problems. But,
14 again, it is seen that the algorithm presented in this [article](#) was able to find the optimum or near-
15 optimum solution with considerably low computational effort.

Deleted: paper

17 5. Conclusions

18 Several modifications have been devised to adapt PSO to discrete problems. In (Montalvo
19 et al., 2007) the excellent behaviour of one of these modifications when applied to the design of
20 WDN has been shown, specifically by studying two benchmark problems, e. g. the Hanoi and the
21 NYT systems. The results obtained in (Montalvo et al., 2007) are in the same order of other
22 published results obtained using different methodologies.

23 This [article](#) introduces a re-generation-on-superposition formulation for PSO of water
24 systems, which improves further the performance of standard discrete PSO. The performance of
25 the algorithm introduced in this [article](#) has been illustrated by application to the same two
26 benchmark networks and the results have been compared with those obtained using other
27 evolutionary algorithms. Comparison of the results shows that this formulation is able to find
28 optimum or near-optimum solutions much more efficiently and with considerably less
29 computational effort. The improved performance of the algorithm described here is due to the
30 richer population diversity it introduces. The main advantages of the method are that it does not
31 require sophisticated operators or parameters, thus being simpler than other evolutionary
32 techniques; it does not need initial feasible particles, nor the re-generated particles need to be
33 feasible; and it is robust in handling of diverse fitness functions and different constraints, as well.
34 Furthermore, having a low number of generations is a major advantage in real water distribution
35 systems, where cost and time constraints prohibit repeated runs of the algorithm and hydraulic
36 evaluation. From the studied benchmark problems it can be inferred that obtaining 'good' solutions
37 with the proposed algorithm is really inexpensive. It can be concluded that the algorithm
38 developed has better performance in solving highly constrained water distribution problems.

Deleted: paper

Deleted: paper

39 The results provided by the proposed method are really good for the networks we have
40 herein studied. Nevertheless, other theoretical and real problems should also be considered in order
41 to consolidate the proposed re-generation-on-superposition PSO algorithm. For one thing,
42 checking superpositions not only with the leader but with other good birds from the swarm or with
43 the leaders of several subwarms will certainly improve the proposed algorithm. For the other, even
44 though the number of parameters used by PSO is really very reduced, their influence in the
45 algorithm's performance should be studied. Also, more sophisticated treatment of the constraints
46 should be tried. These aspects should be included in the future work to be developed regarding the
47 application of PSO in general and to the design of WDN in particular.

Acknowledgements

This work has been performed under the support of the projects Investigación Interdisciplinar nº 5706 (UPV) and DPI2004-04430 of the Dirección General de Investigación del Ministerio de Educación y Ciencia (Spain), including the support for I+D+i projects from the Consellería de Empresa, Universidad y Ciencia of the Generalitat Valenciana, and FEDER funds.

6. References

- Afshar, M.H., 2007. Partially constrained ant colony optimization algorithm for the solution of constrained optimization problems: Application to storm water network design. *Advances in Water Resources*, 30(4), 954-965.
- Colomi, A., Dorigo, M., Maffioli, F., Maniezzo, V., Righini, G. and Trubian, M., 1996. Heuristics from nature for hard combinatorial optimization problems. *International Transactions in Operational Research*, 3 (1), 1-21.
- Cunha, M.C. and Sousa, J., 1999. Water distribution network design optimization: simulated annealing approach. *Journal of Water Resources Planning and Management*, 125 (4), 214-221.
- Dandy, G.C. and Engelhardt, M.O., 2006. Multi-objective trade-offs between cost and reliability in the replacement of water mains. *Journal of Water Resources Planning and Management*, 132 (2), 79-88.
- Dandy, G.C., Simpson, A.R. and Murphy, L.J., 1996. An improved genetic algorithm for pipe network optimization. *Water Resources Research*, 32 (2), 449-458.
- Dong, Y., Tang, B.X.J. and Wang, D., 2005. An application of swarm optimization to nonlinear programming. *Computers & Mathematics with Applications*, 49 (11-12), 1655-1668.
- Farmani, R. and Wright, J.A., 2003. Self-adaptive fitness formulation for constrained optimization. *IEEE Trans. Evol. Comput.*, 7(5), 445-455.
- Farmani, R., Wright, J.A., Savic, D.A. and Walters, G.A., 2005. Self-Adaptive Fitness Formulation for Evolutionary Constrained Optimization of Water Systems. *Journal of Computing in Civil Engineering*, 19(2), 212-216.
- Forrest, S. and Perelson, A. S., 1990. Genetic algorithms and the immune system. In: H.P. Schwefel and R. Männer, eds. *Proceedings of the First International Conference on Parallel Problem Solving from Nature (PPSN-I)*, Dortmund, Germany, 320-325.
- Fung, R.Y.K., Tang, J.F. and Wang, D., 2002. Extension of a hybrid genetic algorithm for nonlinear programming problems with equality and inequality constraints. *Computers and Operations Research*, 29, 261-274.
- Geem, Z.W., 2006. Optimal cost design of water distribution networks using harmony search. *Engineering Optimization*, 38 (3), 259-280.
- Goulter, I.C. and Bouchart, F., 1986. Quantitative approaches to reliability assessment in pipe networks. *Journal of Transportation Engineering*, 112 (3), 287-301.
- Goulter, I.C. and Bouchart, F., 1990. Reliability-constrained pipe network model. *Journal of Hydraulic Engineering*, 116 (2), 211-229.
- Hajela, P. and Lee, J., 1996. Constrained genetic search via schema adaptation. An immune network solution. *Struct. Optim.*, 12(1), 11-5.
- Iglesias, P.L., Mora, D., Fuertes, V.S. and Martínez, F.J., 2006. Análisis estadístico de soluciones de diseño de Redes de Abastecimiento de Agua mediante Algoritmos Genéticos. In: XXII Congreso

- 1
2 Latinoamericano de Hidráulica, Ciudad Guayana, Venezuela.
- 3 Izquierdo, J., Montalvo, I., Pérez, R. and Fuertes, V.S., 2007. Design optimization of wastewater
4 collection networks by PSO, *Computers & Mathematics with Applications*, accepted for
5 publication.
- 6 Izquierdo, J., Pérez, R. and Iglesias, P.L., 2004. Mathematical models and methods in the water
7 industry. *Mathematical and Computer Modelling*, 39 (11-12), 1353–1374.
- 8 Jin, Y.X., Cheng, H.Z. et al., 2007. New discrete method for particle swarm optimization and its
9 application in transmission network expansion planning. *Electric Power Systems Research*, 77 (3-
10 4), 227-233.
- 11 Kennedy, J. and Eberhart, R.C., 1995. Particle swarm optimization. *In: Proceedings of the IEEE*
12 *International Conference on Neural Networks*, Piscataway, NJ, 1942-1948.
- 13 Liao, C.J., Chao-Tang, T. et al., 2007. A discrete version of particle swarm optimization for flowshop
14 scheduling problems. *Computers and Operations Research*, 34 (10), 3099-3111.
- 15 Liong, S.Y. and Atiquzzaman, M., 2004. Optimal design of water distribution network using shuffled
16 complex evolution. *Journal of The Institution of Engineers, Singapore*, 44 (1), 93–107.
- 17 Lippai, I., Heaney, J.P. and Laguna M., 1999. Robust water system design with commercial
18 intelligent search optimizers. *J. Comput. Civ. Eng.*, 13 (3), 135–143.
- 19 Maier, H.R., Simpson, A.R., Zecchin, A.C., Foong, W.K., Phang, K.Y., Seah, H.Y. and Tan, C.L.,
20 2003. Ant colony optimization for design of water distribution systems. *Journal of Water*
21 *Resources Planning and Management*, 129 (3), 200–209.
- 22 Martínez, J.B., 2007. Quantifying the economy of water supply looped networks. *Journal of*
23 *Hydraulic Engineering*, 133 (1), 88–97.
- 24 Matías, A.S., 2003. *Diseño de redes de distribución de agua contemplando la fiabilidad, mediante*
25 *algoritmos genéticos*. Thesis (PhD). Universidad Politécnica de Valencia, Valencia, Spain.
- 26 Montalvo, I., Izquierdo, J., Pérez, R. and Tung, M.M., 2007. Particle Swarm Optimization applied to
27 the design of water supply systems. *Computers & Mathematics with Applications*, accepted for
28 publication.
- 29 Rossman, L.A., 2000. EPANET, users manual, U.S. Environmental Protection Agency, Cincinnati.
- 30 Savić, D.A. and Walters, G.A., 1995. Genetic operators and constraint handling for pipe network
31 optimization. *In: Evolutionary Computing, AISB Workshop*, 154–165.
- 32 Savić, D.A. and Walters, G.A., 1997. Genetic algorithms for least cost design of water distribution
33 networks. *J. Water Res. Plan. Manag.*, 123 (2), 67–77.
- 34 Shi, X. H., Liang, Y.C. et al., 2007. Particle swarm optimization-based algorithms for TSP and
35 generalized TSP. *Information Processing Letters*, In Press, Corrected Proof.
- 36 Shi, Y. and Eberhart, R.C., 1998. A modified particle swarm optimizer. *In: IEEE international*
37 *conference on evolutionary computation*, Piscataway, NJ 69-73.
- 38 Smith, R.E., Forrest, S. and Perelson, A.S., 1993. Searching for diverse, cooperative populations with
39 genetic algorithms. *Evolution Computation*, 1 (2), 127–49.
- 40 Wu, Z.Y. and Simpson, A.R., 2001. Competent genetic-evolutionary optimization of water
41 distribution systems. *Journal of Computing in Civil Engineering*, 15 (2), 89–101.
- 42 Wu, Z.Y. and Walski, T., 2005. Self-adaptive penalty cost for optimal design of water distribution
43 systems. *Journal of Water Resources Planning and Management*, 131 (3), 181–192.
- 44 Yoo, J. and Hajela, P., 1999. Immune network simulations in multicriterion design. *Struct.*
45 *Multidisciplinary Optimization*, 18 (2–3), 85–94.
- 46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

- 1
2 Zecchin, A., 2003. Max-min ant system applied to water distribution system optimisation. *In:*
3 MODSIM 2003: International Congress on Modelling and Simulation.
4 Zecchin, A.C., Simpson, A.R., Maier, H.R. and Nixon J.B., 2005. Parametric study for an ant
5 algorithm applied to water distribution system optimization. *IEEE Trans. Evolutionary*
6 *Computation*, 9 (2), 175–191.
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

For Peer Review Only

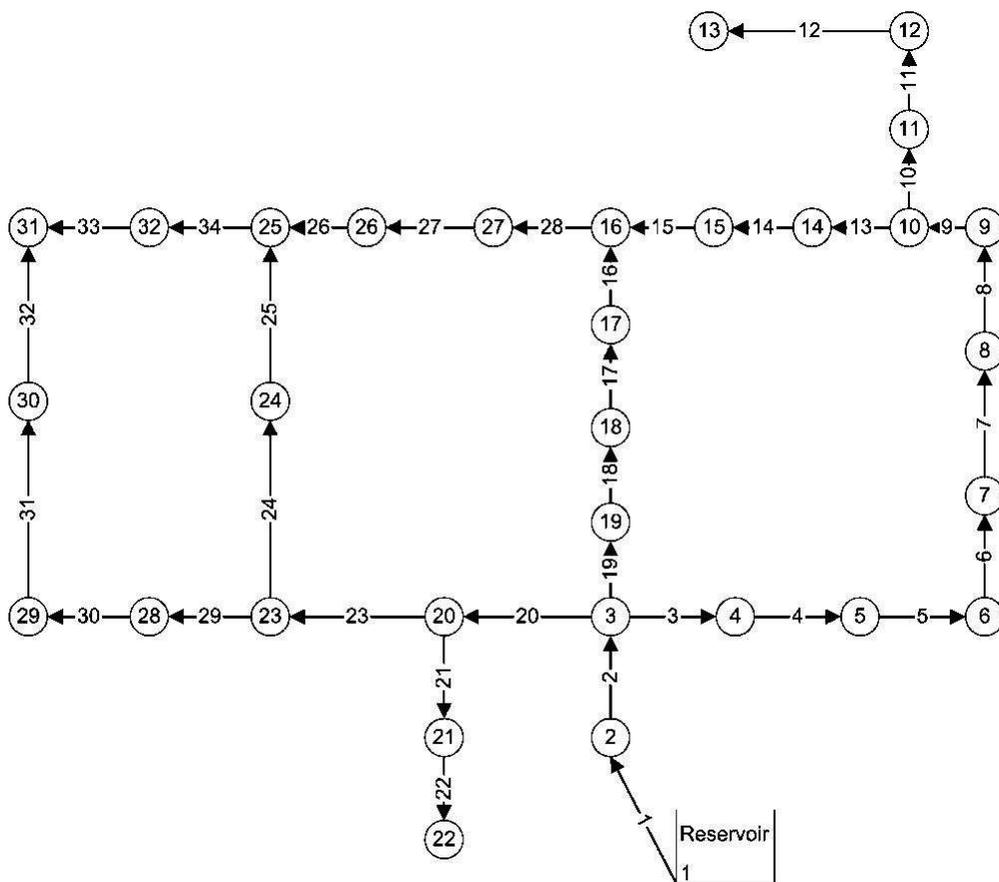


Figure 1. Hanoi network
264x232mm (96 x 96 DPI)

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

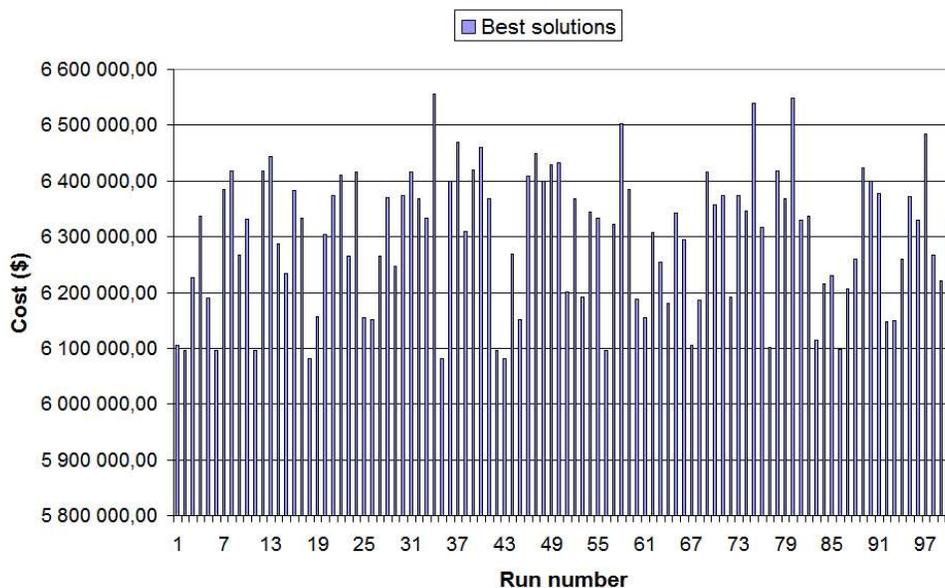


Figure 3. Best solutions for Hanoi's network with the proposed re-generation option (100 runs)
256x159mm (96 x 96 DPI)

Review Only

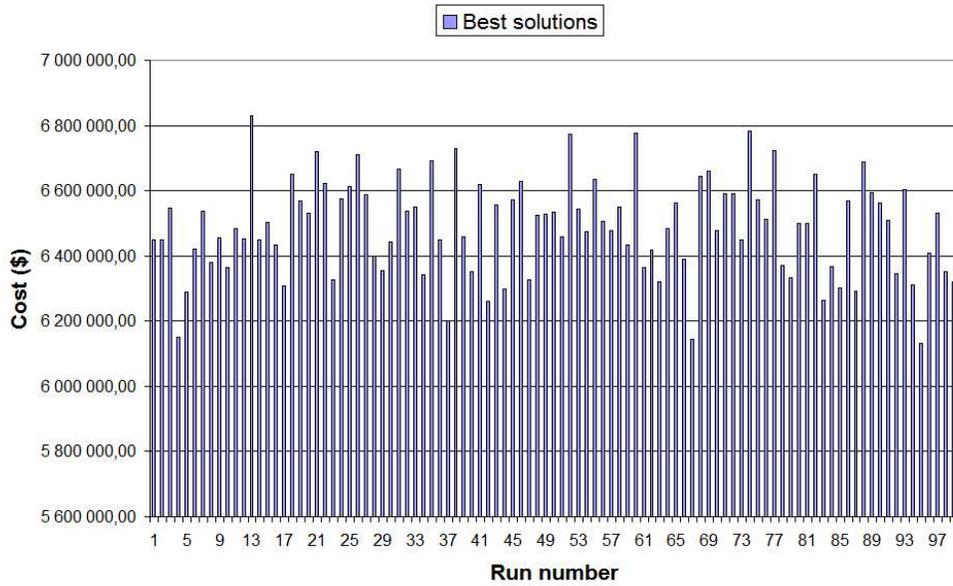


Figure 4. Best solutions for Hanoi's network with standard discrete PSO (100 runs)
256x159mm (96 x 96 DPI)

Review Only

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

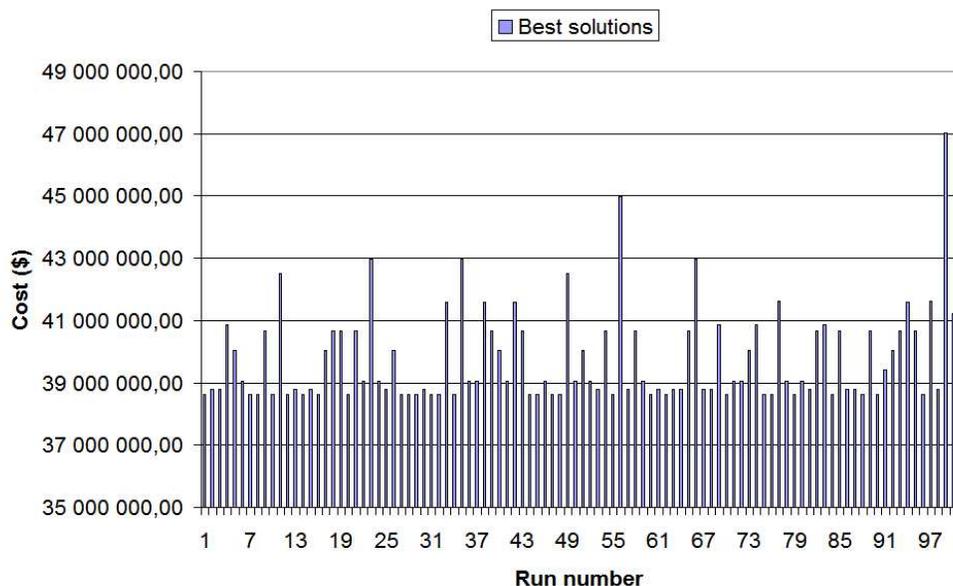


Figure 5. Best solutions for NYT's network with the proposed re-generation option (100 runs)
256x159mm (96 x 96 DPI)

Review Only

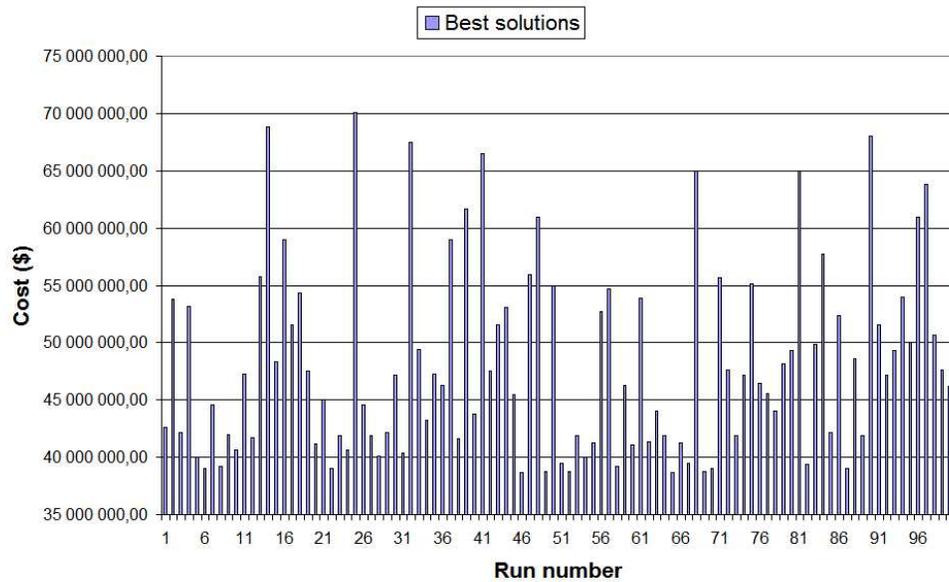


Figure 6. Best solutions for NYT's network with standard discrete PSO (100 runs)
256x159mm (96 x 96 DPI)

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

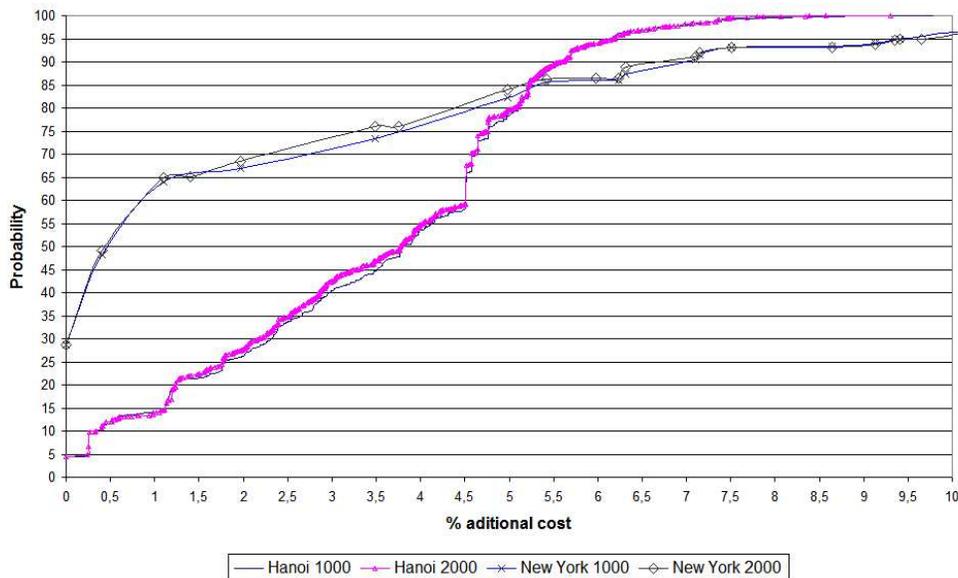


Figure 7. Probability of one-run 'good' solution for Hanoi and NYT systems 256x159mm (96 x 96 DPI)

Review Only

Table 1. Optimal design cost for Hanoi's network according to several researchers

Reference	Used method	Cost $\times 10^6$ \$
Matías, 2003	Genetic Algorithms	6.093
Wu et al., 2001	Genetic Algorithms	6.182
Savic and Walters, 1997	Genetic Algorithms	6.195
Zecchin et al., 2005	$AS_{i\text{-best}}^a$	6.367
Iglesias et al., 2006	Genetic Algorithms	6.081
Montalvo et al., 2007	Particle Swarm Optimization	6.133
This work	PSO + re-generation	6.081

^a $AS_{i\text{-best}}$ is an ACO-based algorithm that uses a different scheme for pheromone updating.

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Table 2. Optimal design cost for NYT’s network according to several researchers

Referente	Used method	Cost × 10⁶\$
Matías 2003	Genetic Algorithms	38.64
Dandy et al., 1996	Genetic Algorithms	38.80
Maier et al., 2003	Ant Colony Optimization	38.64
Savic and Walters, 1997	Genetic Algorithms	40.42
Montalvo et al., 2007	Particle Swarm Optimization	38.64
This work	PSO + re-generation	38.64

Peer Review Only