Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 70 (2014) 369 – 378

Procedia Engineering

www.elsevier.com/locate/procedia

12th International Conference on Computing and Control for the Water Industry, CCWI2013

Low level hybrid procedure for the multi-objective design of water distribution networks

E. Creaco[a,]*, M. Franchini[a]

[a]*Dipartimento di Ingegneria, Università degli Studi di Ferrara, Via Saragat 1, 44100 Ferrara, Italy*

Abstract

This paper presents a procedure for the multi-objective design of looped water distribution systems. The main block of the procedure encompasses four sub-algorithms. Since one sub-algorithm co-ordinates the others (which then operate in a subordinate way), the procedure can be inserted into the category of low level hybrid procedures. The results of the algorithm are optimal solutions in the cost-reliability space, with reliability being compactly expressed through the network resilience metric. The application to four case studies shows the benefits of the new algorithm in terms of numerical and computational efficiency with respect to a multi-objective genetic algorithm.

Keywords: water supply, multi-objective design, hybrid procedure.

1. Introduction

One of the most challenging problems to test the efficiency of optimization techniques is, no doubt, the design of water networks, since it features numerous decisional variables to be considered and numerous constraints to be satisfied.

In the last decades, network design has been more and more frequently faced through the multi-objective approach (Todini, 2000; Prasad et al., 2003; Farmani et al., 2006 to name a few contributions to the field in the scientific literature). This approach makes it possible to obtain a Pareto front of optimal solutions in the trade-off

* Corresponding author. Tel.: +39-(0)532-974151; fax: +39-(0)532-974850.
E-mail address: enrico.creaco@unife.it

doi:10.1016/j.proeng.2014.02.042

between cost and reliability, with the latter being often expressed through compact indexes, such as the pressure head surplus (Gessler and Walski, 1985), the resilience index (Todini, 2000) or the network resilience index (Prasad and Park, 2004), representative of network redundancy in terms of pressure heads. In order to face this problem, simply heuristic (Todini, 2000) and heuristic evolutionary (Prasad et al., 2003; Farmani et al., 2006) techniques have been adopted yielding good results in the case of small case studies; however, when the complexity increases, the growth of the computation burden due to the increase in the number of decisional variables reduces significantly the efficiency of these optimization techniques.

A first strategy that may be adopted to obtain an improved computational efficiency in tackling the network design problem has recently been proposed by Wang et al. (2013) and consists of the use of procedures, such as AMALGAM (Vrugt and Robinson, 2007) and MOHO (Moral and Dulikravich, 2008), made up of various inner algorithms which cooperate; the objective of the combination of algorithms is to combine the power of different methods and thus to obtain a better final solution than that which would be obtained if only one algorithm were adopted. According to the classification proposed by Talbi (2002), AMALGAM and MOHO can be considered as a high-level hybrid procedures since the various algorithms which compose them collaborate in parallel. Wang et al. (2013) showed the benefits of their high level hybridization with respect to the performance of the NSGAII (Deb et al., 2002) algorithm in many case studies of small to medium size. Nevertheless, the Authors state that in case studies of large size the high-level hybrid procedures lose their adaptive capabilities.

On the other hand, Creaco and Franchini (2012) proposed a hybrid procedure which combines the multi-objective genetic algorithm NSGAII and linear programming; the role of NSGAII in this procedure is to provide linear programming with the instructions for the design of a group of branched networks (each one fed by a single source point) concealed inside the original looped network layout and then to assign a single diameter to the pipes that have to be re-inserted in order to re-close network loops. These instructions are encoded in a very small number of genes, i.e. 3, in all the kinds of case study (small, average and large networks) and then the adaptive capability of the procedure is not affected significantly by a growth of the network complexity. The merits of the procedure in terms of computational and numerical efficiency were highlighted by the Authors by comparing it with the traditional approach, which consists in considering in NSGAII so numerous decisional variables as the number of pipes that have to be sized. According to the classification proposed by Talbi (2002), the Creaco and Franchini (2012) procedure can be considered as a low-level hybrid procedure since its two inner algorithms (NSGAII and linear programming) do not cooperate at the same level and in fact the latter is embedded in the former. However, a drawback in this effective and efficient procedure lies in the fact that it does not consider explicitly any pipe flow velocity constraints and it does not make it possible to obtain diameter uniformity in the network, which is a key ingredient of reliability. These weaknesses have been corrected in the present work. The following sections first describe the structure of the upgraded procedure; then, the applications to four case studies, the analysis of the results and the conclusions follow.

2. Methods

2.1. Overview

The solution of the network multi-objective design problem (Todini, 2000; Prasad et al., 2003) leads to a curve of optimal solutions (Pareto front) being defined in the minimum cost-reliability space. These solutions feature growing values of cost and reliability. The total cost C of the network can be calculated as the sum of the costs of the n_p pipes:

$$C = \sum_{j=1}^{n_p} c_j \cdot L_j \,, \tag{1}$$

where c_j and L_j represent the unit cost associated with diameter D_j and the length of the generic j-th pipe.

As to reliability, the network resilience proposed by Prasad and Park (2004) is adopted as a measure of network redundancy in terms of pressure heads with respect to the minimum values which ensure full demand satisfaction.

Its relationship with performance index in the context of network design is clearly highlighted by Creaco et al. (2013). If no pumping station is present in the network, it can be expressed by the following formula:

$$I_n = \frac{\sum_{k=1}^{n_1} C_k q_k \left(H_k - H_{des,k}\right)}{\sum_{r=1}^{n_0} Q_{res,r} H_{res,r} - \sum_{k=1}^{n_1} q_k H_{des,k}}, \tag{2}$$

where, for the generic k-th demanding node, q_k and H_k represent the demand and the head (the latter evaluated by means of a simulation model) and $H_{des,k}$ is the sum of node elevation z_k and $h_{des,k}$ (Tanymboh et al., 2001), minimum value of the pressure head which ensures full demand satisfaction at the k-th demanding node. H_{res} and Q_{res} are the head and the outgoing water discharge from the generic r-th source point. Finally, C_k represents the uniformity of the diameters $D_{i,k}$ of the $n_{p,k}$ pipes connected to the generic k-th demanding node and is calculated through the following relationship:

$$C_k = \frac{\sum_{i=1}^{n_{p,k}} D_{i,k}}{n_{p,k} \max_i \left(D_{i,k}\right)}. \tag{3}$$

where $D_{i,k}$ is the i-th pipe in the k-th node and $n_{p,k}$ is the number of pipes related to the k-th node. The latter coefficient takes on values in between $1/n_{p,k}$ and 1, where values tending to $1/ n_{p,k}$ are associated with not uniform diameters whereas a value equal to 1 indicates that the diameters of all the pipes connected to a node are equal. If only one pipe is connected to a certain node, the values $1/n_{p,k}$ and 1 then coincide.

The resilience index of eq. (2), instead, takes on values within the range 0-1, where lower and higher values correspond to networks with small diameters and high energy dissipations and large diameters and small energy dissipations respectively. In this context, it is also worth highlighting that, since in the numerator of eq. (2) diameter uniformity coefficient C_k is multiplied by q_k (H_k-$H_{des,k}$), it is clear that diameter uniformity gives real benefits in terms of I_n only for nodes with high demand and high pressure head excess with respect to $H_{des,k}$. In other words, if a node has low demand and/or low pressure head excess, an increase in the diameter uniformity is not paid back by a significant growth of network resilience I_n.

The Prasad and Park (2004) resilience index is a generalization of the Todini (2000) resilience index IR; as a matter of fact, the latter parameter, which does not consider explicitly the uniformity of pipes connected to each node, can be re-obtained by assuming C_k=1 in eq. (2); it then holds that:

$$\mathrm{IR} = \frac{\sum_{k=1}^{n_1} q_k \left(H_k - H_{des,k}\right)}{\sum_{r=1}^{n_0} Q_{res,r} H_{res,r} - \sum_{k=1}^{n_1} q_k H_{des,k}}, \tag{4}$$

Here we propose that the Pareto front of optimal solutions in the space cost C (eq. 1) – network resilience I_n (eq. 2) should be obtained by an efficient hybrid procedure made up of two blocks (Fig. 1) and based on the combination of various algorithms; the first preliminary block makes it possible to detect one or more decompositions of the looped network each one generating a set of single source branched networks. The second main block encompasses a cascade of four different algorithms for the network multi-objective design: the first and main algorithm (A1) is the NSGAII multi-objective genetic algorithm. The individuals of the population of this algorithm are made up of only five genes: the first makes it possible to detect time by time which of the decompositions detected in the preliminary block has to be applied to the looped network; the second and third genes are parameters that have to be supplied to the second algorithm, i.e. to the linear programming (A2) performing the branched network design; the fourth and fifth genes are parameters that have to be supplied to the third algorithm (heuristic algorithm A3), which re-closes network loops with the smallest diameter considered in the design phase and then improves the uniformity of the diameters of the pipes connected to each network node; the fourth algorithm (heuristic algorithm A4) modifies some pipe diameters in order that maximum flow velocity constraints are respected all over the network. The final network configuration is assessed in terms of cost (eq. 1) and network resilience (eq. 2), which are the objective functions of A1.

In this context, it is worth highlighting that, naturally, the rationale behind the procedure herein presented (based on the design of the branched networks concealed inside the looped network, loop re-closure and diameter modification) comes from a significant simplification of the design problem and may thus lead to a reduction in the research space. However, this weakness is balanced by its simplicity, which leads to the procedure easily converging and finding good solutions, as will be shown in the next sections.

In the next subsections the description of the two blocks and of the various algorithms follows.

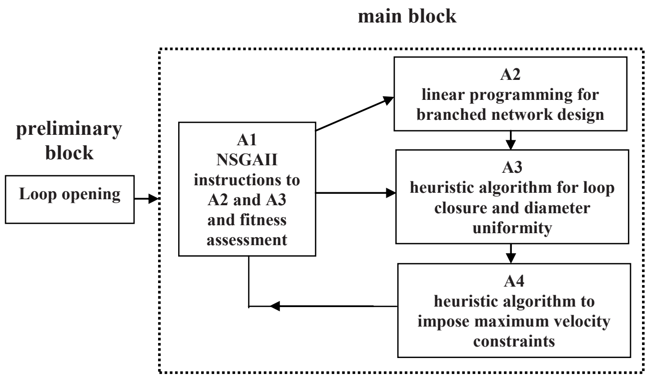

Fig. 1. Logic flux of the procedure proposed.

2.2. Preliminary block

The procedure proposed in this paper features a preliminary block for the decomposition of the looped network into different groups of branched networks, where each branched network is fed by a single source. As already shown by Stephenson (1984), Ciaponi and Papiri (1985) and Creaco and Franchini (2012), this can be accomplished by solving the minimum cost-flow problem, i.e. by minimizing, while preserving the continuity equations at network demanding nodes, the following function C_s, surrogate of network cost:

$$C_s = \sum_{j=1}^{n_p} L_j \left|Q_j\right|^n \tag{5}$$

where exponent n takes on values ≤ 1; Q_j, water discharge of the generic j-th pipe, is the decisional variable of the minimization problem. The solution of the previous minimization problem makes it possible to detect low cost branched structures (each one related to a selected value of n) even in topologically complex networks featuring multiple source points.

When n=1, the previous minimization problem is successfully solved by linear programming if each network pipe is transformed into a couple of oriented arcs, in each of which flow must respect a pre-fixed direction (Orlin, 1997). As a matter of fact, the solution will feature a series of Q values for the various arcs of the network; the pipes for which the two corresponding arcs feature values of Q equal to 0 in the final solution represent the pipes that have to be removed in order to transform the looped network into the lowest cost group of branched networks (see Creaco and Franchini, 2012 for further details).

When n<1, the problem becomes concave and the application of typical line-search methods does not ensure that a global minimum is reached which is however not important at this level of the procedure. In order to obtain the global minimum, algorithms for the exploration of the whole collection of possible branched networks concealed inside the looped network can be used (Read and Tarjan, 1975). However, the latter algorithms can be applied only to small networks because they become computationally burdensome in the case of medium-large networks.

Summing up, by solving the minimization problem of eq. (5) for various values of exponent n, it is possible to obtain various decompositions of the looped network into different groups of single source branched networks.

2.3. Main block

Multi-objective genetic algorithm (A1)

The first algorithm (A1) of the main block of the procedure is the multi-objective genetic algorithm NSGAII . In this algorithm, the population is made up of individuals featuring only five genes: the first gene g_1 makes it possible to select time by time which of the decompositions detected as described in section 2.2 has to be considered for network design: it takes on integer values within the range 1-n_o, where n_o is the total number of decompositions detected in the preliminary block. The second gene g_2 is a real number, which takes on real values around 1 and represents the ratio of the minimum pressure head $h_{des\_b,k}$ to be considered for branched network design to the minimum pressure head $h_{des,,k}$ required for the design of the network with closed loops (here we assume that each node can have its own minimum pressure constraint). The third gene g_3 is a real number variable within the range 0-1 and encodes parameter IR_b, which represents the minimum resilience index (see eq. 4) for the branched network design. The fourth and fifth genes, g_4 and g_5, whose suitable range of values have to be searched for, by trial and error, during the application of the procedure, refer to the uniformity that has to be prescribed to the diameters of the pipes connected to each network node. In particular, as better clarified in section A3, g_4 yields the average value of uniformity associated with the network nodes whereas g_5 (which is a weight) makes it possible to calculate the uniformity degree corresponding to the generic k-th node of the network on the basis of the value of the product q_k (H_k-$H_{des,k}$) that the node itself features.

The encoding of the individuals of the genetic algorithm is very simple because it involves only five genes for networks of whatever size. Hence comes the easiness for the procedure to quickly converge towards good solutions. The higher computational efficiency with respect to the traditional approach, which requires the use of one gene for each pipe that has to be sized in the network (see, for instance, Prasad et al., 2003), becomes more evident for the complex networks, made up of numerous pipes; this advantage will be clearly highlighted in the application section.

For each population individual the two objective functions, network cost C (eq. 1) to be minimized and network resilience I_n (eq. 2) to be maximized, are evaluated on the network with reclosed loops, that is obtained after applying the cascade of algorithms shown in Fig.1, which are useful to design the branched network(s) concealed inside the looped network (A2), to re-close network loops with the smallest diameter and modify the diameters of some pipes in order to improve diameter uniformity in the k-th node (A3), and to slightly increase the diameters of those pipes which do not respect the maximum velocity constraint. In particular, network resilience I_n (eq. 2) is evaluated on the basis of the results of a demand driven simulation (Todini and Pilati, 1988), performed with reference to peak demand and old pipe operation conditions. Penalties are applied to objective functions C and I_n in order to penalize network configurations which do not respect nodal minimum ($h_{des,k}$) and maximum ($h_{max,k}$) pressure head constraints.

Linear programming for branched network design (A2)

The optimal design of the branched network(s) can be carried out for prefixed values of minimum pressure head ($h_{des\_b,k}$) and resilience index IR_b constraints, derived from genes g_1 and g_2 of the genetic algorithm (A1). In this problem, given a set of n_D diameters D_i for each pipe of the branched network(s), the unknown variables are, with reference to the j-th network pipe, the lengths $l_{j,i}$ of the sub-pipes fitted with diameter D_i. The objective of this design is to minimize the overall cost of the branched network while satisfying the minimum acceptable pressure and resilience constraints for the pre-selected configuration of nodal demands. The design entails solving a linear programming problem, with the following cost function to be minimized:

$$cost_b = \sum_{j=1}^{n_{pb}} \sum_{i=1}^{n_D} c_i l_{j,i} \quad , \tag{6}$$

where c_i is the unit cost associated with diameter D_i and n_{pb} is the number of pipes in the branched network(s)

For each network pipe j, the constraint that the sum of sub-pipe lengths $l_{j,i}$ is equal to the length L_j of the whole pipe needs to be considered:

$$L_j = \sum_{i=1}^{n_D} l_{j,i} \quad , \tag{7}$$

For the path leading from the reservoir (with head H_{res}) supplying the k-th node (with elevation z_k) to the k-th node itself, the sum of the head losses in the n_k pipes belonging to the path has to be so low as to allow the minimum acceptable pressure $h_{des\_b,k}$ constraint to be satisfied at node k. This can be expressed as:

$$\sum_{j=1}^{n_k} \sum_{i=1}^{n_D} J_{j,i} l_{j,i} \le H_{res} - H_{des\_b,k} \quad , \tag{8}$$

where $J_{j,i}$ is the energy friction slope relative to sub-pipe $l_{j,i}$ of pipe L_j; $H_{des\_b,k}$ is the desired total head at node k for full demand satisfaction, being the sum of node elevation z_k and prefixed minimum pressure $h_{des\_b,k}$ of the branched network.

At the same time, starting from the definition of resilience proposed by Todini (2000) of eq. (4), the minimum resilience constraint can be expressed as follows in terms of $l_{j,i}$:

$$\sum_{k=1}^{n_1} \sum_{j=1}^{n_k} \sum_{i=1}^{n_D} q_k J_{j,i} l_{j,i} \le \mathrm{IR_b}\left(\sum_{k=1}^{n_1} q_k H_{des\_b,k} - \sum_{r=1}^{n_0} Q_{res,r} H_{res,r} \right) + \sum_{k=1}^{n_1} q_k \left(H_{res} - H_{des\_b,k} \right), \tag{9}$$

where q_k and $Q_{res,r}$ are the demand at the k-th node (among the n_1 demanding nodes) and the water discharge leaving the r-th reservoir respectively. $\mathrm{IR_b}$ is the minimum prefixed value of the resilience index for the branched network(s) (derived from genes g_2).

Though the sub-pipes featuring all the diameters D_i in the set are simultaneously considered for each pipe in the linear programming problem, the solution generally yields lengths greater than 0 only for one or two sub-pipes. However, since the objective of the design is generally to assign a single diameter to each pipe, the diameter of the longest sub-pipe is extended to the whole pipe length. This entails considering the branched network configuration with undivided pipes closest to the optimal solution furnished by linear programming, which, as stated above, may potentially feature multiple diameters for some pipes.

<u>Heuristic algorithm for loop closure and diameter uniformity (A3)</u>

After the design of the branched network(s) has been performed through linear programming (A2), network loops are reclosed using the smallest diameter considered within the design problem. Then, an iterative algorithm (A3) is performed in order to improve, for each node, the uniformity of the pipes connected. Since the uniformity to be imposed at the generic k-th node must depend on the value of the product q_k (H_k-$H_{des,k}$) for the node itself (see section 2.1), a demand driven simulation is performed on the network in order to assess the head H_k values at the various network nodes prior to the application of A3 and then to evaluate, for the various network nodes, the products q_k (H_k-$H_{des,k}$), on the basis of which the diameters D_i of the pipes connected to the generic node are modified in order to respect the following pipe diameter uniformity constraint:

$$D_i \geq U_k \frac{\sum_{i=1}^{n_{p,k}} D_i}{n_{p,k}}, \tag{10}$$

where U_k is a uniformity parameter derived for the k-th node from genes g_4 and g_5 of algorithm A1 through the following formula:

$$U_k = g_4 \left[1 + g_5 \left(\frac{W_k - \overline{W}}{\overline{W}} \right) \right], \tag{11}$$

where quantity W_k comes from the following manipulation made on the products q_k (H_k-$H_{des,k}$), in order to avoid the presence of any negative values:

$$W_k = q_k \left(H_k - H_{des,k} \right) - \min_k \left[q_k \left(H_k - H_{des,k} \right) \right] \quad , \tag{12}$$

where $\overline{W}$ is the average value of W_k.

As a matter of fact, prescribing eq. (10) at each node makes it possible to correct the diameters of those pipe connected, which turn out to be smaller than a certain fraction of the (average) mean value of the diameters connected to the node itself. If at the k-th node the generic i-th diameter does not respect the constraint of eq. (10), this diameter is replaced with the smallest diameter considered in the design problem which respects the constraint itself. The fraction U_k is calculated through eq. (11), which is a linear relationship whose parameters are related to the genes g_4 and g_5 of the genetic algorithm. Eq. (11) entails that the fraction U_k is high at those nodes which feature a high value of W_k (i.e. where the product q_k (H_k-$H_{des,k}$) is high).

Algorithm A3 is applied iteratively. During each iteration, the constraint in eq. (10) is verified at all network nodes. Iterations go on as long as corrections are made on pipe diameters. Incidentally, when U_k>1 eq. (10) cannot be verified. As a consequence the diameters of the pipes linked to the k-th node increase up to their maximum possible value.

Heuristic algorithm to impose maximum velocity constraints (A4)

Algorithm A4 is iterative and makes it possible to impose an eventual maximum velocity constraint to network pipes. At each iteration, a demand driven simulation is performed in order to detect pipes whose velocity is higher than the threshold value V_{max}. In particular, the pipe with the highest excess from V_{max} can be detected and its diameter can be replaced with the immediately larger diameter. Iterations (inside the global cycle controlled by the NSGAII) go on as long as there are pipes which feature velocity values higher than V_{max}.

3. Applications

The applications concerned the design of all the network pipes in four case studies drawn from Bragalli et al. (2012), i.e. the networks of Blacksbourgh, Fossolo, Pescara and Modena (main characteristics reported in the following Table 1). In these case studies design has to be performed in the peak demand and old pipe scenario. Furthermore, in each case study, constraints concerning minimum and maximum pressure heads at nodes and maximum flow velocities in network pipes *are prescribed* (even though not reported here) and optimizations have to be performed considering the network cost (see eq. 1) and resilience (see eq. 2) as objective functions to minimize and maximize respectively.

The applications described in this section were performed using a single processor of a 2.70GHz Pentium® Dual-Core CPU. All the algorithms used were implemented in the Matlab2011b environment.

Prior to the application of the hybrid procedure proposed in this paper, optimizations were performed as benchmark using the traditional approach (algorithm NSGAII with individuals made up of so numerous genes as the number of network pipes to be sized). Unlike the hybrid procedure, in which constraint respect comes directly from the application of algorithms A3 and A4, penalizations in the objective functions are made in the traditional approach in order to encourage the survival of those individuals which satisfy the constraints and to hinder the survival of those individuals which do not satisfy them. In the optimizations carried out through the traditional approach, the numbers of individuals and generations considered, along with the computation time required, are reported in Table 1.

Table 1. For each case study, numbers n_0 of source points, n_1 of demanding nodes, p of pipes and total demand D_{tot}. As to the application of the traditional approach and of the new hybrid procedure, numbers of individuals and of generations and computation time.

case study	n_0	n_1	p	D_{tot} (L/s)	traditional approach			hybrid procedure		
					individuals	generations	comp. time (min)	individuals	generations	comp. time (min)
Blacksbourgh	1	30	35	98	100	250	1	50	20	2
Fossolo	1	36	58	34	100	500	3	50	20	3
Pescara	3	68	99	498	100	1000	10	50	50	7
Modena	4	268	317	407	100	1000	45	50	50	91

As to the preliminary block of the hybrid procedure proposed in this paper, useful to find optimal decompositions of the original network into branched networks, an algorithm for the exploration of the whole collection of possible branched networks concealed inside the looped network was used for the Blacksbourgh and Fossolo networks. This made it possible to find 7 and 6 optimal decompositions associated with values of the exponent coefficient n of eq. (5) within the range 0.7-1.0. Since the application of the algorithm was too burdensome for the two other case studies, only the optimal decomposition derived by the Orlin (1997) method for n=1 was taken into account; the application of methods aimed at searching for approximate solutions in the case of n<1 was not considered in this context.

The main block of the hybrid procedure was then applied. To this end, the genes of algorithm A1 of the procedure were generated considering the lower and higher values reported in the following Table 2. Ranges for genes g_4 and g_5 were defined after some attempts. The numbers of individuals and generations adopted for the hybrid procedure (see Table 1) were assessed in order to ensure the convergence of the procedure and to have the same order of computation time as the benchmark optimizations performed using the NSGAII.

The results of the hybrid procedure in terms of Pareto front are reported and compared with the results of the traditional approach in the graphs in Fig.2. The comparison shows that the Pareto fronts obtained by the new hybrid procedure dominate the corresponding fronts obtained by using the traditional approach under all conditions. It is also worth highlighting that the Pareto fronts obtained by the new hybrid procedure are also better in terms of extension, since the new procedure always seems to be able to detect the extreme solutions (i.e. those featuring the lowest and highest values of cost and I_n respectively). Furthermore, as expected, the largest distance between the Pareto front obtained by the hybrid procedure and that obtained by using the traditional approach is noticed in the last case study, the Modena network (Fig. 2d), which is the most burdensome from the computational viewpoint and then better highlights the computational and numerical efficiency of the hybrid procedure presented herein, which is not affected significantly by the growth of the size in the design problem.

Table 2. For each case study, range of values considered for the generation of the five genes of the individuals of algorithm A1 of the hybrid procedure.

gene	Blacksburgh		Fossolo		Pescara		Modena	
	lower value	higher value	lower value	higher value	lower value	higher value	lower value	higher value
1 (network decompositions)	1	7	1	6	1	1	1	1
2 (minimum pressure)	0.05	1.3	0.05	1.3	0.05	1.3	0.05	1.3
3 (resilience)	0	1	0	1	0	1	0	1
4 (diameter uniformity)	0	1.5	0	1.5	0	1.5	0	1.5
5 (uniformity variation)	0	2	0	0	0	2	0	2

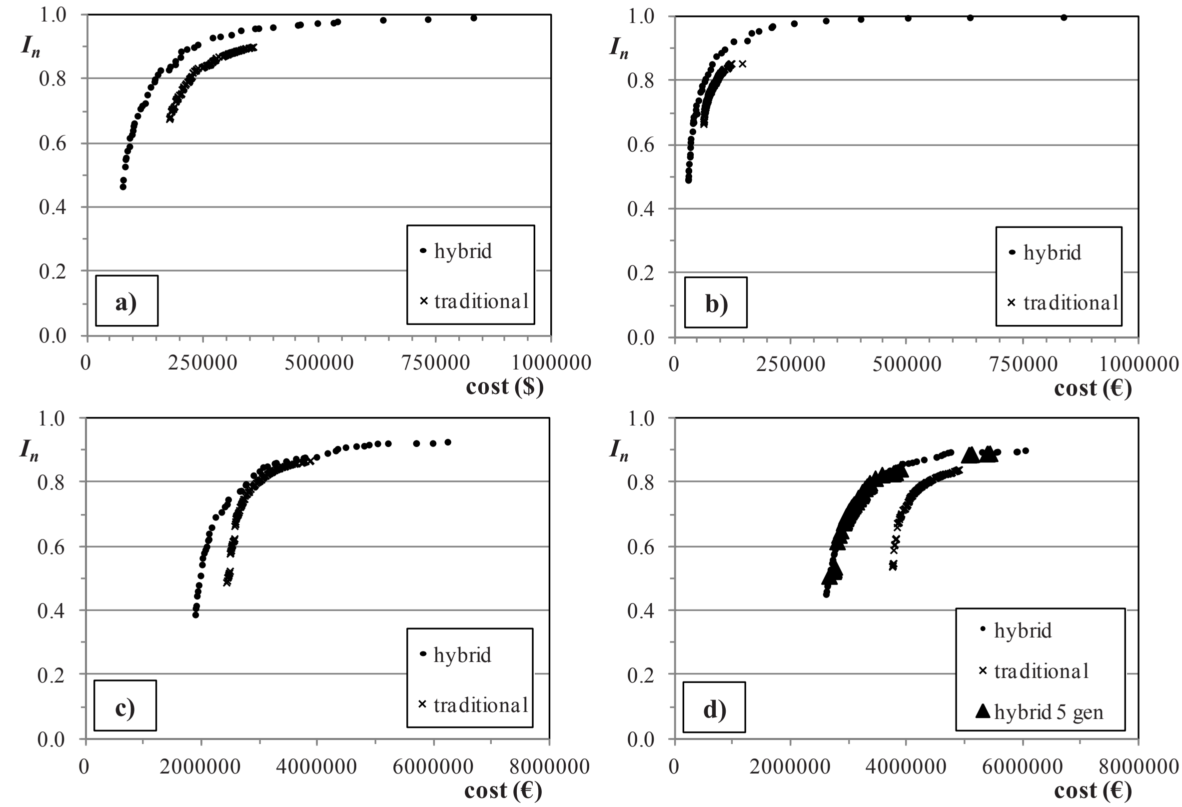

Fig. 2. Final Pareto fronts obtained by the new hybrid procedure and the traditional for the networks of a) Blacksbourgh, b) Fossolo, c) Pescara and d) Modena. In graph d) the Pareto front obtained by the hybrid procedure after 5 generations is also shown.

The last analysis that is worth conducting in this study concerns how the results of the hybrid procedure optimization vary during generations. To this end the Pareto front obtained after 5 generations (only 9 min of computation time) is also reported in graph d) in Fig. 2, with reference to Modena network. The analysis shows that the Pareto front obtained after 5 generations is very close to that obtained after 50 generations in terms of position and still dominates the Pareto front obtained by using the traditional approach. The only difference with respect to the front obtained after 50 generations lies in the fact that it comprises much less solutions. Nevertheless, the closeness of the fronts highlights the capability of the hybrid procedure to detect quickly good solutions in the trade-off between cost and network resilience.

4. Conclusions

The results of this study point out that *low level hybrid optimization procedures* are computationally and numerically efficient in the context of multi-objective water network design, even when constraints concerning nodal pressure heads and pipe flow velocities are prescribed in the network. As a matter of fact, these procedures proved to be able to detect quickly good solutions in the trade-off between cost and network resilience in case studies of various complexity.

A further development of this study could be represented by the comparison with *high level hybrid optimization procedures*, in a bid to understand which is the most suitable choice depending on the size of the network to be designed.

Acknowledgements

This study was carried out as part of the PRIN project and under the framework of Terra&Acqua Tech Laboratory, Axis I activity 1.1 of the POR FESR 2007–2013 project funded by Emilia-Romagna Regional Council (Italy) (htp://fesr.regione.emilia-romagna.it/allegati/comunicazione/la-brochure-dei-tecnopoli).

References

Bragalli, C., D'Ambrosio, C., Lee, J., Lodi, A., Toth, P., 2012. On the optimal design of water distribution networks: a practical MINLP approach. Optimization and Engineering, 13(2), 219-246.

Ciaponi, C., Papiri, S., 1985. Contributo al dimensionamento ottimale delle reti di condotte in pressione a maglie chiuse. Ingegneria Sanitaria, 4, 209-217.

Creaco, E., Franchini, M., 2012. Fast network multi-objective design algorithm combined with an a-posteriori procedure for reliability evaluation under various operational scenarios. Urban Water Journal 9(6), 385-399.

Creaco, E., Fortunato, A., Franchini, M., Mazzola, M.R., 2013. Comparison of entropy and resilience as inirect measures of reliability in the framework of water distribution network design, Proceedings of CCWI 2013, Perugia, Italy.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm NSGA-II. IEEE Transactions on Evolutionary Computation 6(2), 182-197.

Farmani, R., Walters, G., Savic, D., 2006. Evolutionary multi-objective optimization of the design and operation of water distribution network: total cost vs. Reliability vs. Water quality. Journal of Hydroinformatics 8(3), 165-179.

Gessler, J., Walski, T.M., 1985. Water distribution system optimization, US Army Corps of Engineers' Waterways Experimentation Station, Technical Report TREL-85-11, Vicksburg.

Moral, R.J., Dulikravich, G.S., 2008. Multi-Objective Hybrid Evolutionary Optimization with Automatic Switching Among Constituent Algorithms. AIAA Journal 46(3), 673-681.

Orlin J.B., 1997. A polynomial time primal network simplex algorithm for minimum cost flows. Mathematical Programming 78, 109-129.

Prasad, T.D., Park, N.S., 2004. Multiobjective Genetic Algorithms for Design of Water Distribution Networks. Journal of Water Resources Planning and Management 130(1), 73-82.

Prasad, T.D., Sung-Hoon, H., Namsik, P., 2003. Reliability based design of water distribution networks using multiobjective genetic algorithms. KSCE Journal of Civil Engineering 7(3), 351-361.

Read, R.C., Tarjan, R.E., 1975. Bounds on Backtrack Algorithms for Listing Cycles, Paths and Spanning Trees. Networks 5, 237-252.

Stephenson, D., 1984. Pipeflow Analysis, Elsevier.

Talbi, E.G., 2002. A Taxonomy of Hybrid Metaheuristics. Journal of Heuristics 8, 541-564.

Tanyimboh, T.T., Tabesh, M., Burrows, R., 2001. Appraisal of Source Head Methods for Calculating Reliability of Water Distribution Network. Journal of Water Resources Planning and Management 127(4), 206-213.

Todini, E., Pilati, S., 1988. A gradient algorithm for the analysis of pipe networks, in *"Computer Application in Water Supply"*. In: Coulbeck B. and Choun-Hou O. eds, Vol I – System Analysis and Simulation, John Wiley & Sons, London, pp. 1-20.

Todini, E., 2000. Looped water distribution networks design using a resilience index based heuristic approach. Urban Water Journal 2(3), 115–122.

Vrugt, J.A., Robinson, B.A., 2007. Improved Evolutionary Optimization from Genetically Adaptative Multimethod Search, Proceedings of the National Academy of Sciences 104(3), 708-711.

Wang Q., Savic D.A., Kapelan Z., 2013. Hybrid Metaheuristics for Multi-Objective design of Water Distribution Systems. Journal of Hydroinformatics, in press.