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Comparing Low and High-Level Hybrid Algorithms on a Two-Objective Optimal Design of Water Distribution Systems

Qi Wang[a], Enrico Creaco[b], Marco Franchini[b], Dragan Savić[a], Zoran Kapelan[a]

[a]Centre for Water Systems, University of Exeter, Exeter, Devon, UK, EX4 4QF

[b]Dipartimento di Ingegneria, University of Ferrara, Via Saragat 1, 44100 Ferrara, Italy

Abstract

This paper presents the comparison of two hybrid methodologies for the two-objective (cost and resilience) design of water distribution systems. The first of them is a low level hybrid algorithm (LLHA), in which a main controller (the non-dominated genetic algorithm II, NSGA-II) coordinates various subordinate algorithms. The second methodology is a high level hybrid algorithm (HLHA), in which various sub-algorithms collaborate in parallel. Applications to four case studies of increasing complexity enable the performances of the hybrid algorithms to be compared with each other and with the performance of the benchmark NSGA-II. In the case study featuring low/intermediate complexity, the hybrid algorithms (especially the HLHA) successfully capture a more diversified Pareto front, although the NSGA-II shows the best convergence. When network complexity increases, instead, the hybrid algorithms (especially the LLHA) turn out to be superior in terms of both convergence and Pareto front diversification. With respect to both the HLHA and the NSGA-II, the LLHA is capable of detecting the final front in a single run with a small computation burden; the HLHA and the NSGA-II, which are more affected by the initial random seed, require, instead, numerous runs with an attempt to reach the definitive Pareto front, as the envelope/tangle of the Pareto fronts obtained at the end of the various runs. On the other hand, a drawback of the LLHA lies in its reduced ability to deal with general problem formulations, i.e., those not relating to water distribution optimal design).

Keywords: low-level hybrid algorithm; high-level hybrid algorithm; multi-objective design; water distribution system

1. Introduction

The optimal design of a Water Distribution System (WDS) is a difficult problem to solve as it represents a discontinuous, highly nonlinear, constrained and multi-modal combinatorial optimisation problem (di Pierro et al., 2009; Sedki and Ouazar, 2012) featuring non-deterministic polynomial-time hard (NP-hard) characteristics (Papadimitriou and Steiglitz, 1998). In the context of network design, the multi-objective approach (Cheung et al., 2003; Farmani et al., 2003; 2004; 2005; Fu et al., 2012; Halhal et al., 1997; McClymont, 2012; Perelman et al., 2008) has recently been gaining more and more favour than the single-objective approach (Babayan et al., 2005; Cisty, 2010; Savic and Walters, 1997), which may lead to network solutions featuring poor hydraulic performance since it is only based on economic concerns (Walski, 2001; Fu et al., 2012). Various multi-objective evolutionary algorithms (MOEAs), which are capable of approximating the trade-off among different objectives (Pareto front-PF) in a single run (Zitzler and Thiele, 1999), have then been applied to solve small-to-medium sized benchmark problems and some large problems based on the real-world networks. Among these algorithms, it is worth mentioning the NSGA-II (Deb et al., 2002), the Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler et al., 2002), the cross entropy (Perelman et al., 2008), the multi-objective particle swarm optimisation (PSO) (Montalvoa et al., 2010), and the multi-objective cuckoo search (Wang et al., 2012).

Among the various MOEAs, the NSGA-II is that which is more often used by researchers and engineers in order to solve optimization problems of different kinds and involving complex water distribution network configurations (for instance, it was adopted by most teams in The Battle of the Water Networks II – Marchi et al., 2013).

Despite the features of flexibility and robustness, the MOGAs algorithms are often (Kollat and Reed, 2006; Hadka and Reed, 2012; Creaco and Franchini, 2013a) criticised due to the issue of parameterisation and extensive function evaluations to reach a near-optimal PF (Fu et al., 2012). In order to overcome their limits and then to obtain a better numerical performance, hybrid algorithms that combine different components and strategies have then been proposed in the scientific literature of water supply systems (Jourdan et al., 2004; Olsson et al., 2009; Raad et al. 2009; Raad et al. 2011; Creaco and Franchini; 2012; 2013a; Wang et al., in press). According to Talbi's (2002) classification, these algorithms can be subdivided into two categories: the low-level hybrid algorithms (LLHA), in which the component metaheuristics are embedded in other metaheuristics as functional parts, and the high-level hybrid algorithms (HLHA), in which the component metaheuristics work on their own without mutual dependence. In particular, Jourdan et al. (2004) presented a LLHA by integrating a Learnable Evolution Model (Michalski, 2000; Michalski et al., 2000), which was based on Quinlan's (1993) *C4.5* program for machine learning, with NSGA-II. They compared this LLHA with NSGA-II on the two-objective design of three benchmark problems, concluding that the proposed LLHA was superior to NSGA-II by finding better solutions in reliably fewer evaluations. Olsson et al. (2009) tested three probabilistic methods within the structure of NSGA-II and compared their performance with NSGA-II on three design and rehabilitation problems, including one large problem based on a real-world system. Although the PFs obtained by these LLHAs suffer from the problem of satisfactory diversity, they offered significantly better solutions than NSGA-II in terms of convergence for the case of large systems. Raad et al. (2009) addressed three benchmark problems as well as a real case in South Africa using a HLHA for the first time. This HLHA was based on the framework of a multi-algorithm, genetically adaptive multi-objective method (AMALGAM) (Vrugt and Robinson, 2007) and introduced two new sub-algorithms which differed from those within the original AMALGAM. They also conducted a comparative study extensively by testing up to 23 alternative algorithms for the multi-objective design of 9 small-to-large sized WDS benchmarks (Raad et al., 2011). Three novel variants based on the structure of AMALGAM and NSGA-II turned out to be the four top-performing algorithms according to various metrics. Wang et al. (in press) compared two HLHAs (including the original AMALGAM) with NSGA-II on a wide range of benchmark problems and found that AMALGAM outperformed its competitor for small-to-medium sized cases. However, both HLHAs deteriorated for larger problems due to the loss of their adaptive capabilities. Creaco and Franchini (2012) proposed a LLHA as a fast tool dedicated for the multi-objective design of large WDSs. This method embedded a Linear Programming in the NSGA-II. Unlike the traditional definition of decision variables (the diameter option for each single pipe), only three genes were considered for individuals of a population (independent from the number of pipes), thus yielding significant computational efficiency especially on larger networks. When compared with the traditional approach (i.e., NSGA-II), the hybrid approach demonstrated convincing benefits in terms of quality of solutions and CPU time. In a more recent work, Creaco and Franchini (2013a) presented an upgraded version of LLHA (with number of individual genes extended to five), able to consider more complex objective functions (network resilience) and constraints (maximum flow velocity) within the WDS design.

The aforementioned studies only compared the performance of hybrid algorithms with other popular MOEAs (like NSGA-II). Therefore, there is a lack of comparative studies in the literature between LLHAs and HLHAs, which motivated the work carried out in this paper. The LLHA developed by Creaco and Franchini (2013a) and the original AMALGAM (Vrugt and Robinson, 2007) were tested and compared between each other and with the NSGA-II benchmark on four medium-to-large sized design problems based on the real-world networks in Italy.

The remainder of this paper is arranged as follows. Section 2 provides the two-objective formulation of a WDS and the concise introduction to the LLHA and the HLHA considered. Section 3 briefly describes the cases used for the comparative study. The results and discussion is given in Section 4. Section 5 concludes the whole paper.

2. Methodology

2.1. Two-Objective Design of a WDS

The optimal WDS design is aimed at determining the size and location of different components (e.g., pipes, pumps and tanks) in order to convey the treated water in a safe and efficient manner, with respect to a number of constraints, such as conservation of mass and energy as well as other service standards (e.g., quantity and quality). More often, only the size of pipes is considered under a single demand loading condition given the configuration of the network system. This is also known as a pipe sizing problem (Kahler et al., 2003). The task is to choose the best combination of pipe diameters from within a number of discrete options, which are available in the market or from the manufacturers. Minimising the cost (mainly the capital cost) is one of the main concerns during the process as the design and construction of a WDS usually require a great amount of expenditure. The capital cost is, then, the first objective function (to minimise) in the WDS design. In the present work, it takes on the following form:

$$\min C = \sum_{i=1}^{np} c_i(D_i) \times L_i \tag{1}$$

Where C=total cost (monetary units problem dependant); c_i=unit cost of pipe i depending on the specific diameter; np=number of pipes; D_i=diameter of pipe i; L_i=length of pipe i.

Besides the economic considerations, hydraulic performance should also be well addressed to ensure the reliability and service standard of a WDS. A compact measure of the hydraulic performance has then to be considered as the second objective of the WDS design. In this context, variants of pressure surplus to maximise (Gessler and Walski, 1985) or pressure deficit to minimise (Cheung et al., 2003; Farmani et al., 2005; Olsson et al., 2009) were initially used. However, these aforementioned formulations did not necessarily lead to looped networks, which are reliable configurations under abnormal conditions (e.g., pipe burst). On the other hand, Todini (2000) introduced a resilience index formulation as a surrogate measure for hydraulic benefits. The index is based on the concept that the total input power into a network consists of the power dissipated in the network and the power delivered at demand nodes. A high value of the index, which takes place in the case of low power consumed internally to overcome the friction, thus results in more surplus power at demand nodes, which will then be less affected by the lowering of network service pressure during such critical network operation scenarios, as those related to segment isolation or hydrant service. Later on, an improved version of resilience indicator, called network resilience, was proposed by Prasad and Park (2004) in order to take also the uniformity of pipes around each demand node into account and thus to better characterise the redundancy of a network. Since various studies (Prasad and Park, 2004; Raad et al., 2010; Creaco et al., 2013b) proved that a network featuring a high value of the network resilience is robust under pipe failure conditions, this index is considered in the present work as the second objective (to maximise) during the WDS design problem:

$$\max I_n = \frac{\sum_{j=1}^{nn} C_j Q_j (H_j - H_j^{req})}{\sum_{k=1}^{nr} Q_k H_k - \sum_{j=1}^{nn} Q_j H_j^{req}} \tag{2}$$

$$C_j = \frac{\sum_{i=1}^{np_j} D_i}{npj \times \max\{D_i\}} \tag{3}$$

Where I_n=network resilience; nn=number of demand nodes; C_j, Q_j, H_j and H_j^{req}=uniformity coefficient, demand, actual head (evaluate by means of a hydraulic simulator, e.g. EPANET software, Rossman 2000) and minimum head of node j; nr=number of reservoirs; Q_k and H_k=discharge and actual head of reservoir k; np_j=number of pipes connected to node j; D_i=diameter of pipe i connected to demand node j.

EPANET software (Rossman, 2000) is taken to run the hydraulic simulation, in which the variables required for the evaluation of network resilience are obtained.

2.2. Hybrid Optimisation Algorithms

Low-level Hybrid Algorithm

Creaco and Franchini (2013a) proposed an efficient LLHA dedicated for the two-objective design of a WDS considering the cost and network resilience. This LLHA is made up of two blocks (see Figure 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 NSGA-II 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) for the branched network design, and relate to the minimum pressure head and resilience constraints respectively; 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, which entails that the design of a looped network comes from the design of a system of branched networks concealed inside the network itself and from the correction of the generic network solution by the application of two heuristic algorithms. This significant simplification may then result in 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.

More details about this low-level hybrid algorithm can be found in Creaco and Franchini (2013a).

High-level Hybrid Algorithm: AMALGAM

AMALGAM is a high-level hybrid optimisation framework which employs simultaneously four sub-algorithms within its structure, including NSGA-II, adaptive metropolis search (Haario et al., 2001), particle swarm optimisation (Kennedy and Eberhart, 2001) and differential evolution (Storn and Price, 1997). It is designed to overcome the drawbacks of using an individual algorithm and to be suitable for a wide range of problems. The strategies of global information sharing and genetically adaptive offspring creation are implemented in the process of population evolution. Each sub-algorithm is allowed to produce a specific number of offspring based on the survival history of its solutions in the previous generation.

The pool of current best solutions is shared among sub-algorithms for reproduction. Figure 2 illustrates the general process of AMALGAM and a brief description of this algorithm is provided as follows. Firstly, an initial population P_0 of individuals ,with a number N of genes equal to the number of pipes to be designed, is generated using Latin hypercube sampling (LHS). Then, P_0 is ranked via the fast non-dominated sorting (FNS) procedure (Deb et al., 2002). The offspring Q_0 of size N is yielded from P_0 using four sub-algorithms simultaneously, with each algorithm contributing the same number of individuals (i.e., $N/4$). Next, a combination of the parents (P_0) and the offspring (Q_0), namely R_0 (size $2N$), is produced and ranked via the FNS. A number of N members from R_0 are selected based on their rank and crowding distance (CR), forming the population in the next generation. The latest population is then taken to create the offspring using the adaptive multi-method search technique, which is detailed in the subsequent paragraph. The aforementioned procedure is repeated until the stopping criteria are met (e.g., number of function evaluations and/or prescribed precision).

The basic idea of adaptive multi-method search is to take full advantage of the most efficient sub-algorithm and to keep a balance in using diverse methods. That is, each algorithm is allowed to produce a number of children according to the reproductive rate (ratio of the children alive to the children created) in the previous generation. However, if one fails to contribute even a single individual in the latest population, a minimum number of individuals (5 here as the bottom line) are consistently maintained for it to generate the offspring. Therefore, the most successful algorithm (with highest reproductive rate) is favored by giving more slots in the process of reproduction, but no one is completely discarded even though it exhibits the worst performance.

In addition, AMALGAM provides a general template which is flexible and extensible, and can easily accommodate any other population-based algorithm (Raad et al. 2009; 2011).

3. Applications

3.1 Case Studies

Four WDS design problems were used to compare the performance of the aforementioned hybrid optimisation algorithms. These problems are based on different WDSs in Italy with varied complexity in terms of the size of search space. The first three cases were originally introduced in Bragalli et al., (2008), while the last case was taken from a WDS of a city in Northern Italy. A brief summary of these WDSs is provided subsequently.

The first, Fossolo network includes 58 pipes, 36 demand nodes, and 1 reservoir with a fixed head of 121 m, while the average ground elevation for the nodes is 64.2 m. The material for all the pipes is polyethylene. There are 22 pipe sizes in total to choose from, hence, the search space is as big as 22^{58}≈$7.25\text{x}10^{77}$. Due to the feature of polyethylene, a relatively high Hazen-Williams roughness coefficient of 150 is applied to all the pipes. The minimum pressure of all the demand nodes should be maintained at 40 m, while the maximum allowed pressure of each node is specified individually. In addition, the flow velocity in each pipe is enforced to be less than or equal to 1 m/s.

The second, Pescara network includes 99 pipes, 68 demand nodes, and 3 reservoirs with fixed head within 53.08 m to 57.00 m, while the average ground elevation for the nodes is 5.0 m. The pipe material is cast iron. There are 13 pipe sizes and thus the extent of search space is as big as 13^{99}≈$1.91\text{x}10^{110}$. A uniform Hazen-Williams roughness coefficient of 130 is applied to all pipes. The minimum pressure of all the demand nodes should be maintained at 20 m, while the maximum allowed pressure of each node is specified individually. In addition, the flow velocity in each pipe is enforced to be less than or equal to 2 m/s.

The third, Modena network includes 317 pipes, 268 demand nodes, and 4 reservoirs with fixed head within 72.0 m to 74.5 m, while the average ground elevation for the nodes is 35.4

m. The pipe material is the same as Pescara network. There are 13 pipe sizes and thus the extent of search space is as big as $13^{317} \approx 1.32 \times 10^{353}$. A uniform Hazen-Williams roughness coefficient of 130 is applied to all pipes. The minimum pressure of all the demand nodes and the upper bound of flow velocity in each pipe are the same as those specified for Pescara network.

For more details about the aforementioned networks, readers can refer to Bragalli et al. (2008), including available pipe diameters, unit price of pipes and maximum pressure requirement of each demand node.

Finally, the fourth, Town X network has 825 pipes, 536 demand nodes and 2 reservoirs with fixed head at 30 m, while the average ground elevation for the nodes is 0 m. The pipe material is the same as Pescara network. A uniform Hazen-Williams roughness coefficient of 130 is applied to all pipes. There are 13 pipe sizes and thus the extent of search space is as big as $13^{825} \approx 1.01 \times 10^{919}$. The pressure head of all the demand nodes should be maintained within 25 m and 30 m. In addition, the flow velocity in each pipe is enforced to be less than or equal to 2 m/s. Due to the issue of authorisation, the data of this network is not available in the public domain.

3.2. Benchmarking Setup

The LLHA, HLHA and the NSGA-II were run on a 2.70 GHz CPU. In the experiments, no parallel computing was used and thus each optimisation run was executed on a single core.

In order to investigate the performance of the hybrid algorithms and compare it with that of the NSGA-II under low and high computational burdens, short and long runs on each benchmark problem were applied concurrently. To this end, the general optimisation parameter settings in the algorithms were set in such a way as to keep the execution of the single optimization run performed by the LLHA and the HLHA as close as possible. The details of the computational budgets in terms of CPU time for each design problem and single run are given in Table 1. Table 2 and Table 3 show, instead, the general parameter settings, i.e., population size (PS) and number of function evaluations (NFE), of the LLHA and the HLHA, respectively for the low and high computational burdens.

The analysis of Table 2 shows that in the LLHA the population size (PS) is always the same (equal to 50 individuals) and number of function evaluations (NFE) does not vary significantly as the network complexity increases (from case study 1 to case study 4). This is a direct consequence of the fact that the number of individual genes used in the LLHA (equal to 5 – see section 2.2) does not depend on the network size. Furthermore, the simple genetic structure entails that the Pareto front obtained in a single optimization run is definitive.

In the HLHA, instead, the influence of the initial random seed is much stronger. In order to obtain a definitive Pareto front, each problem was then solved independently 30 times using three varied population sizes (see Table 3) (10 times for ach population size). The idea of such a plan for the HLHA is to capture a Pareto front as widespread as possible in the objective space of *Cost* against I_n. In this context, it is worth stressing that the computation time indicated in Table 2 for the HLHA refers to the single of the 30 optimization runs.

A comparison between Tables 2 and 3 proves that the PS and NFE required by the LLHA are smaller than those featured by the HLHA for pre-fixed computation time (of a single run). This is due to the fact that in the LLHA each objective function evaluation requires linear programming and various hydraulic simulations to be performed (see algorithms A2, A3, A4 and A5 in section 2.2); in the AMALGAM HLHA, instead, each objective function evaluation simply requires a single hydraulic simulation to be performed.

4. Results & Discussion

The results of the optimisations carried out by means of the LLHA and the HLHA and of the NSGA-II as benchmark are reported in Figures 3 and 4. The first analysis was made for pre-fixed computational burden. In Figure 3, graphs on the left and right correspond to the small and large computational burdens respectively.

For the Fossolo problem (low complexity case study) the positions of the Pareto fronts obtained by the LLHA and the HLHA, considering both the small and large computational burden, are close. The Pareto fronts are slightly dominated by those obtained by the NSGA-II, which shows a higher convergence performance on a reduced front length. The only remarkable difference between the LLHA and the HLHA lies in the fact that the LLHA lends itself better to detect the solutions featuring both low cost and resilience (left side of the front). The fact that the LLHA procedure performs better for low cost solutions and worse for high cost solutions than the HLHA can be ascribed to its basic assumptions: the design based on the looped network decomposition (basic assumption of the LLHA) is more effective to yield solutions featuring low cost and resilience rather than solutions featuring high cost and resilience. In the case of high cost and resilience solutions, the simplifications contained in the LLHA structure can, instead, endanger its performance. Results in graph (a) on the left of Figure 3, obtained considering a small computational burden, indicate a slight predominance of the HLHA in detecting solutions featuring high cost and resilience.

The better performance of the LLHA in detecting low cost solutions seems to vanish for the Pescara problem of intermediate complexity (above all in the case of large computational burden). On the other hand, in the latter case study, the superiority of the HLHA in the case of high cost and resilience solutions is highlighted; the HLHA seems to be capable of detecting the right part of the front much better than the LLHA. In the second case study, the comparison with the Pareto front of the NSGA-II shows that the latter yields very close results to the LLHA, with a slightly higher convergence performance for the high computation burden.

The applications to the Modena problem of intermediate complexity yield similar interpretations to the Pescara problem as regards both the comparison of the hybrid procedures and the comparison between the hybrid procedures and the NSGA-II. The incapacity of the LLHA to detect high cost and resilience solutions in these two cases is due to the fact that when large pipes are yielded by the genes of the LLHA in the case of multi-source networks, some water transfers may take place between the various sources. These transfers lead to a decrease in the network resilience index (see Eq. 2), because of the increase in the denominator of the formula. In the LLHA, no expedients are taken in order to prevent these transfers from occurring and then, high cost solutions, which entail large size pipes in the network and are eventually born inside the LLHA, are discarded being dominated in terms of resilience by the low cost solutions of the Pareto front. On the other hand, within the HLHA the genes of the high cost solutions naturally evolve in order to prevent inter-source water transfer from taking place by means, for instance, of the local installation of small size pipes. The incapacity of the NSGA-II to detect high cost and resilience solutions, instead, has to be ascribed to the fact that it is generally able to yield high convergence performance in a reduced front length (see also case study 1).

For the Town X problem of high complexity, the LLHA yields better results than HLHA in the case of both low and high computational burden and for either side of the Pareto front (low cost and resilience solutions on the left and high cost and resilience solutions on the right). This better performance is ascribed to the fact that, when network topology complexity increases, the reduction in the search space due to the many assumptions made inside LLHA, is counterbalanced by the easiness to find the best solution in this context; on the other hand, the HLHA, though potentially more suitable to reach the real optimal solution due to the absence of research space limitations, has the drawback of the complexity in the search space, which is made up of numerous possibilities which are "scanned" by the procedure with difficulty. Unlike case studies 2 and 3, in case study 4 high cost and resilience solutions are also present in the Pareto fronts yielded by the LLHA; this happens because the elevation of the two sources and their mutual distance spontaneously hinder the formation of inter-source water transfer. The comparison between the hybrid algorithms and the NSGA-II in case study 4 highlights that, for high network complexity, the hybrid procedures turn out to have a much better performance in terms of both convergence and front diversification.

In Figure 4, another viewpoint of the optimisation results, which is different from the one showed in Figure 3, is reported. In particular, graphs on the left report the Pareto fronts obtained by the LLHA considering small and large computational burdens; those on the right report, instead, the results obtained by the HLHA considering small and large computational burdens. The comparison of the results obtained by the LLHA with small and large computational burden in each case study showed that the fronts obtained with the small computational burden are almost coincident with those obtained with the large computational burden. This means that only a small computational burden is needed to obtain the best results achievable by means of the procedure. In the case of the HLHA, instead, the increase in computational burden improves the effectiveness of the results significantly since the fronts obtained using the large computational burden dominate those obtained using the small computational burden; the latter effect becomes more and more evident when network complexity increases, i.e. moving from graph (a) to graph (d) in Figure 4.

5. Conclusions

The comparison of two different types of hybrid procedures was presented in this paper. The comparison was made under the framework of water distribution network multi-objective design, aimed at simultaneously minimising cost and maximising network resilience. The first type of hybrid procedure considered was a low-level hybrid algorithm, where various inner algorithms are embedded within a coordinating multi-objective genetic algorithm. The second type of hybrid procedure was a high-level hybrid algorithm, where various multi-objective algorithms co-operate in parallel.

Applications to case studies of increasing complexity showed that performances of the LLHA and HLHA are complementary. As a matter of fact, due to the fact that optimizations with LLHA are not significantly affected by the initial random seed and they are computationally efficient in obtaining the best Pareto front; the LLHA can be successful used when limited computation capabilities are available. Furthermore, as the size of the search space of LLHA does not increase with the growth in network complexity, selecting LLHA is recommended for the case of high complexity networks. On the other hand, when computation efficiency is not a concern (i.e., it is possible to consider a large number of individuals as well as to repeat optimization several times in order to eliminate the influence of the initial random seed), selecting HLHA improves the accuracy of the results as much as required under the various circumstances. However, this approach may not always be possible in practice. Overall, the comparison between the hybrid algorithms and the NSGA-II demonstrates the advantage of using the hybrid algorithms in order to obtain a more diversified Pareto front. ~~considered as the benchmark algorithm for optimization problems, points out a certain convenience, in terms of front diversification, of making use of the hybrid algorithms~~. Their superiority in terms of convergence also emerges when network complexity increases.

In the future, more objectives should be taken into account for the optimal design of a WDS, transforming the task from two-objective to many-objective (four or more) optimisation. As indicated by Fu et al. (2012), the optimal solutions obtained in a lower dimensional formulation often tend to have a worse performance in other objectives considered in a higher dimensional formulation. Although it supports more informed and transparent decision making in the design stage, the many-objective formulation will greatly challenge the capabilities of the current algorithms, including both LLHAs and HLHAs, in approximating the Pareto front in higher (thus more complex) dimensional space. Furthermore, more complex benchmark problems, not only based on large networks with/without multiple loading conditions, but also the ones associated with operational cost (typically requiring extended period simulation), should also be considered for the comparison.

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Figures

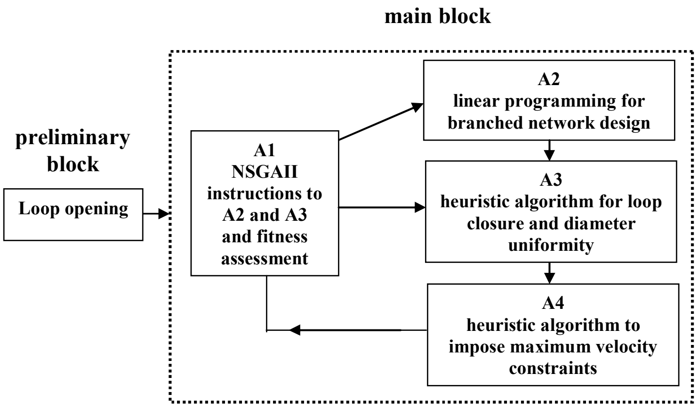


Figure 1 Flowchart of the LLHA

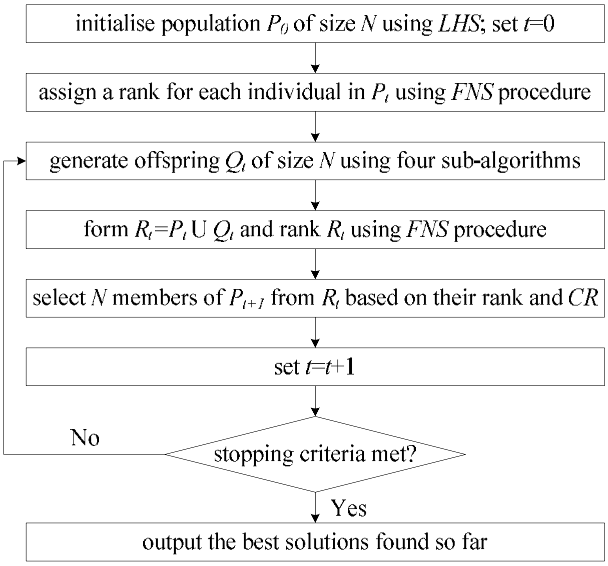
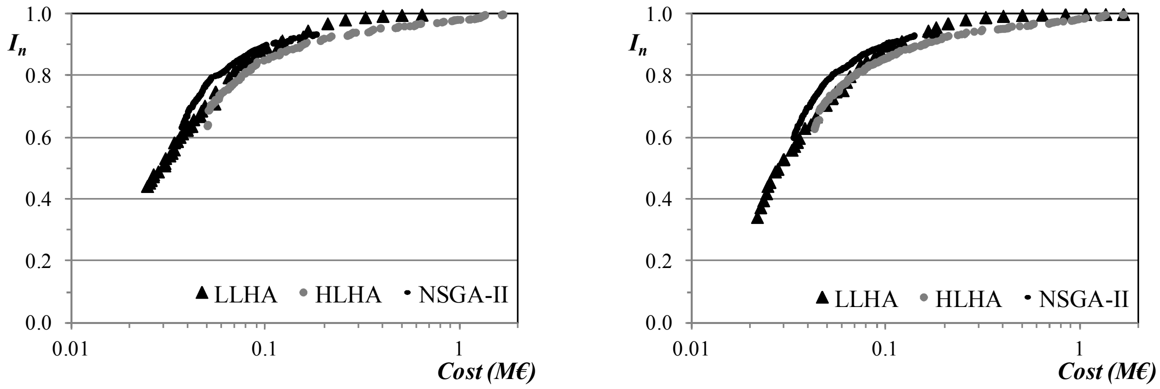
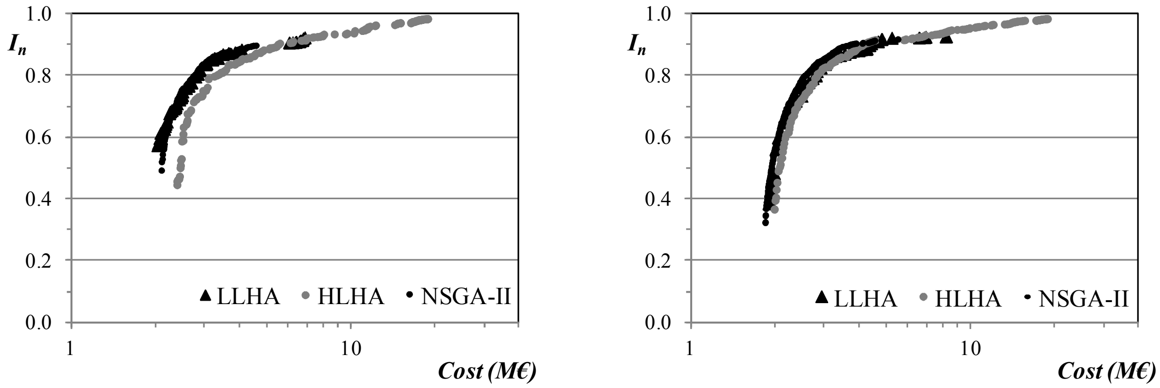


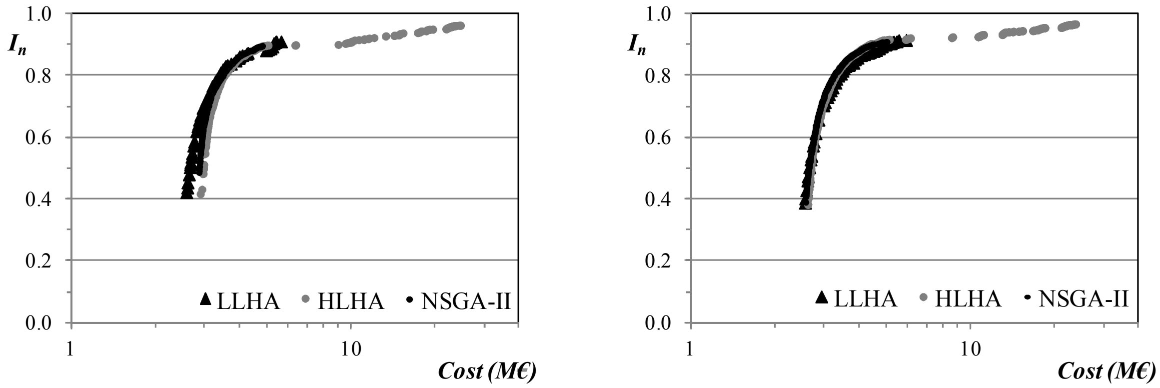
Figure 2 Flowchart of AMALGAM



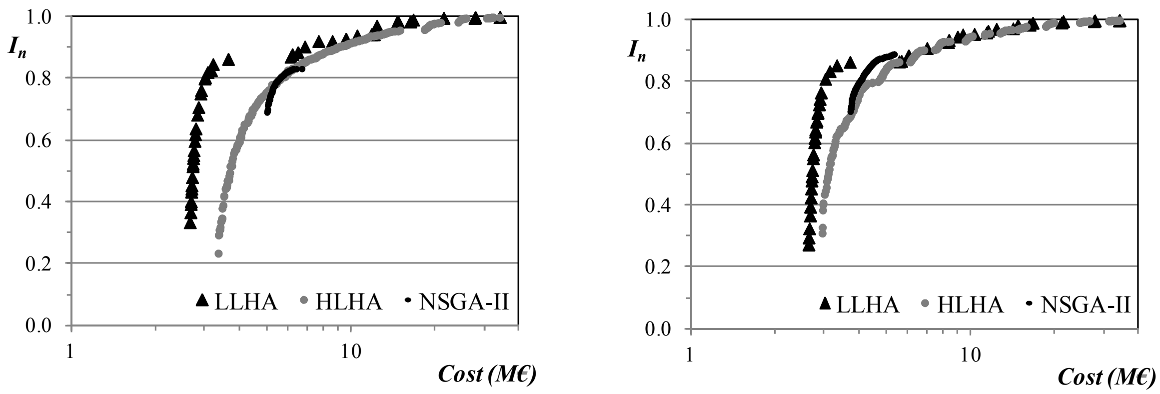
(a) Fossolo problem under low computational burden (left) and high computational burden (right)



(b) Pescara problem under low computational burden (left) and high computational burden (right)

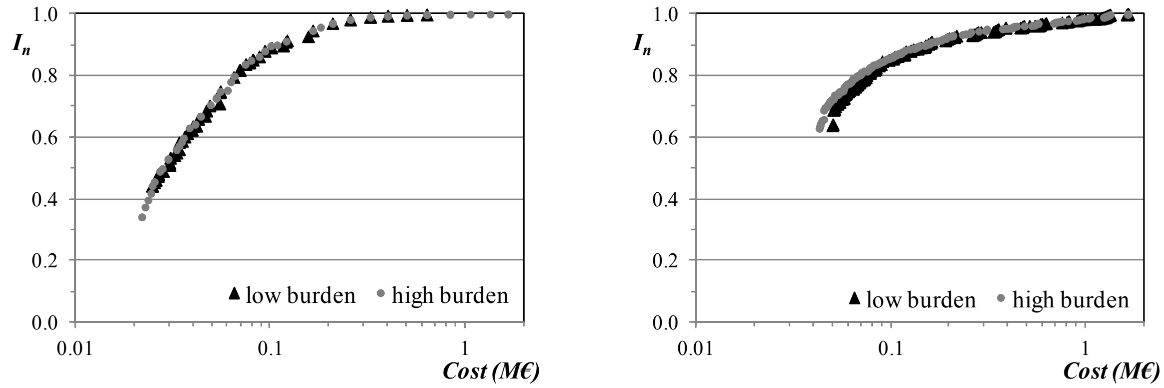


(c) Modena problem under low computational burden (left) and high computational burden (right)

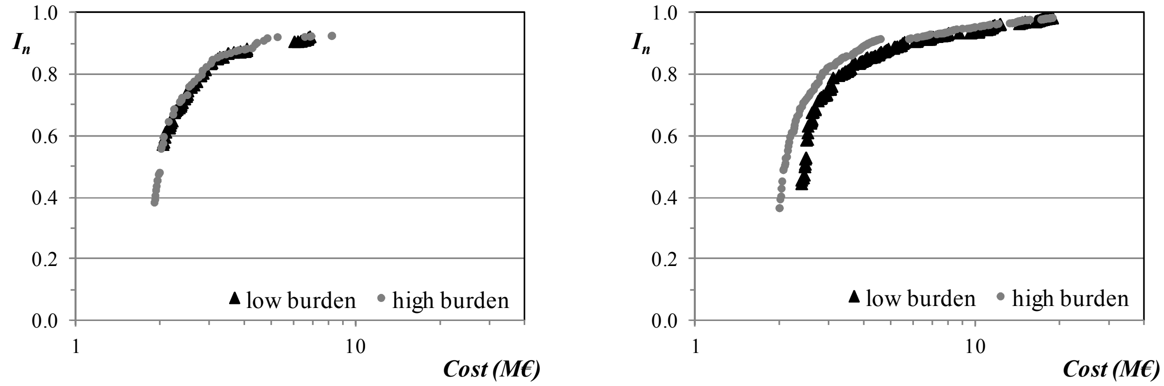


(d) Town X problem under low computational burden (left) and high computational burden (right)

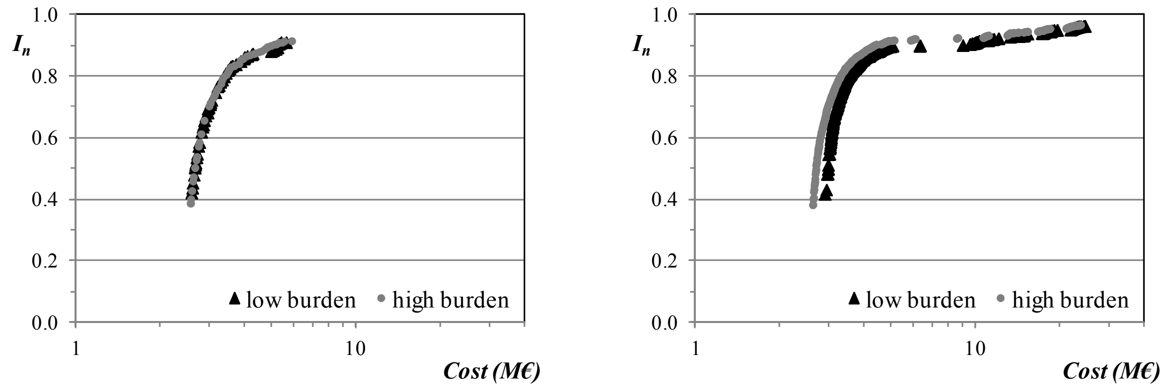
Figure 3 Comparison of LLHA, HLHA and NSGA-II using low and high computational burdens (Cost axis in logarithmic scale)



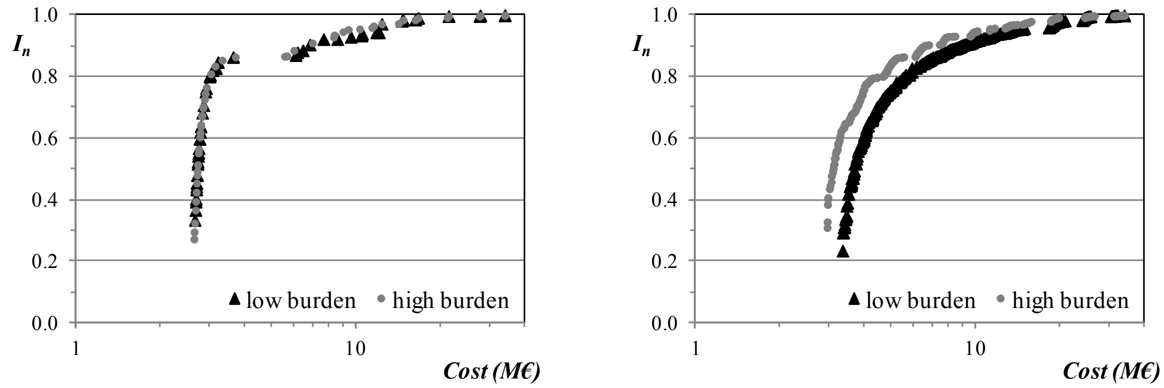
(a) Fossolo problem by LLHA (left) and HLHA (right) using low and high computational burden



(b) Pescara problem by LLHA (left) and HLHA (right) using low and high computational burden



(a) Modena problem by LLHA (left) and HLHA (right) using low and high computational burden



(a) Town X problem by LLHA (left) and HLHA (right) using low and high computational burden

Figure 4 Comparison of low burden with high burden for LLHA and HLHA (Cost axis in logarithmic scale)

Tables

Table 1 Computational times Used in Analyses

Case Study	Computational Budget (minutes)					
	Short Run			Long Run		
	LLHA	HLHA	NSGA-II	LLHA	HLHA	NSGA-II
Fossolo	0.7	0.8	0.8	3	3	3
Pescara	0.7	0.7	0.7	5	7	7
Modena	9	9	9	55	58	58
Town X	17	18	18	100	90	90

Table 2 Parameter settings of LLHA

Case study	Population Size	Computational Budget in Terms of NFE	
	PS	Low Burden	High Burden
Fossolo	50	500	2000
Pescara	50	500	3000
Modena	50	800	3000
Town X	50	500	3000

Table 3 Parameter settings of HLHA and NSGA-II

Case Study	Population Size (PS)			Computational Budget in Terms of NFE	
	Group1	Group2	Group3	Low Burden	High Burden
Fossolo	100	200	400	50,000	80,000
Pescara	100	200	400	40,000	150,000
Modena	200	400	800	200,000	800,000
Town X	400	800	1600	113,600	454,400