Scientia Iranica A (2014) 21(5), 1591–1607

Sharif University of Technology
Scientia Iranica
Transactions A: Civil Engineering
www.scientiairanica.com

An improved firefly algorithm with harmony search scheme for optimization of water distribution systems

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Received 1 October 2013; received in revised form 17 December 2013; accepted 5 February 2014

KEYWORDS
Meta-heuristics;
Firefly algorithm;
Harmony search;
Optimum design;
Water distribution systems.

Abstract. In this study, a new hybrid method based on Firefly Algorithm (FA) and Harmony Search (HS) techniques is presented for solving the least-cost design problem of Water Distribution Systems (WDS). This algorithm is designed to improve the performance of the FA as a recently developed meta-heuristic that mimics the natural behaviour of fireflies. The use of such a nature-inspired optimization method to solve the optimal design problem of WDS needs particular modifications to produce high quality solutions. Therefore, a modification is proposed to the movement stage of artificial fireflies, and based on the HS strategy a memory is utilized to save a number of the best solutions. Another improvement in this algorithm includes the addition of pitch adjustment operation in the FA as a mutation operator. The presented method is applied to the optimal design of some well-known benchmark problems taken from literature, and the results confirm its validity. In addition, a sensitivity analysis is performed on the parameters of the algorithm.

1. Introduction

The term meta-heuristic, first introduced by Glover [1], is a set of concepts that can be used to define heuristic methods applicable to a wide set of different problems with relatively few modifications to adapt them to a specific problem. These meta-heuristic algorithms are mainly based on natural phenomena comprising stochastic search techniques [2]. Design and implementation of such optimization methods is the origin of a multitude of contributions to the literature over the last 50 years.

For example, in 1966, Fogel et al. [3] proposed evolutionary programming. Holland [4] proposed the first Genetic Algorithm (GA) in 1975. Smith [5] described genetic programming. Kirkpatrick et al. [6] conceived Simulated Annealing (SA). Cerný [7] proposed a similar algorithm for another problem considering it a thermo-dynamical approach. Glover [1] proposed Tabu Search algorithm (TS). Farmer et al. [8] worked on Artificial Immune systems (AI). Reynolds [9] introduced the flocking algorithm and the three flocking rules of Reynolds: flock centering (cohesion), collision avoidance (separation) and velocity matching (alignment). Moyson and Manderick [10] worked on the collective behaviour of ants and found an application in artificial intelligence. Moscato [11] proposed the term memetic algorithm. Koza [12] registered his first patent on genetic programming. Dorigo [13] proposed ant colony algorithms (ACO) in his PhD thesis. Kennedy and Eberhart [14] conceived the Particle Swarm Optimization algorithm (PSO). Storn and Price [15] proposed a Differential Evolution algorithm (DE). Rubinstein [16] worked on the Cross Entropy (CE) method. Geem et al. [17] proposed Harmony Search (HS). Abbass [18] proposed Marriage in the

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Honey Bee Optimization algorithm (MHBO). Nakrani and Tovey [19] described the Honey Bee Algorithm (HBA). Karaboga [20] described the Artificial Bee Colony algorithm (ABC). In 2006, Erol and Eksin [21] proposed a novel optimization algorithm, the so-called big Bang-Big Crunch (BB-BC), as an efficient meta-heuristic optimization method based on the BB-BC theory of the universe evolution.Yang [22] developed the Firefly Algorithm (FA). Recently, Kaveh and Khayatazad [23] developed a new meta-heuristic, so-called, Ray Optimization (RO), and examined its capability through some well-known benchmark problems. Kaveh and Zolgadr [24] improved the PSO and presented the democratic PSO. In 2011, a general model was presented to unify the explanation of different meta-heuristic algorithms by Kaveh and Talatahari [25]. This model is based on the concept of fields of forces from physics and is called the Fields Of Forces (FOF) model. The FOF model covers many meta-heuristic algorithms and provides efficient means to improve, expand, modify and hybridize the meta-heuristics. The advantage of such a model consists of an easy explanation of different algorithms. The FOF model can easily predict the deficiency of some existing meta-heuristics, and can suggest ways for their improvement.

Unlike exact methods, these meta-heuristics allow one to tackle large-size problems by delivering satisfactory solutions in a reasonable time. Application of meta-heuristics falls into a large number of real-world problems; one of them is the cost optimization of Water Distribution Systems (WDS). Optimal design of WDS has been the focus of many researchers over the past three decades. In the WDS design problems, it is usually assumed that the pipe layout, nodal elevations, and demands are known in advance and the task is to find the combination of pipe sizes that can satisfy the required hydraulic head value at the demand nodes with least-cost. Obtaining the least-cost design of a WDS is a combinatorial problem. A set of solutions must be selected from a discrete set of feasible solutions where the functions representing the hydraulic behaviour of the network are nonlinear [26]. The solution process involves simultaneous consideration of the continuity equation, energy conservation, and head-loss function that makes the analytical solution of the problem rather complicated. From a mathematical point of view, significant difficulties are involved due to the discrete nature of the pipe diameters and the nonlinearity of the head-loss relationship. These lead to a large-scale, mixed integer, and nonlinear problem, corresponding to the NP-hard class.

In the present study, the cost optimization of different types of WDS are carried out using a new hybrid meta-heuristic, so-called, improved, firefly algorithm with the harmony search scheme (IFA-HS). The IFA-HS can be considered an improved version of the recently developed FA algorithm. The improvements consist of utilizing a memory (**HM**) that contains some information extracted online during the search, adding of the pitch adjustment operation in FA, serving as the mutation operator during the process of the firefly updating, and modifying the movement phase of the FA. As mentioned before, in this study, the WDS design is formulated as a least-cost optimization problem with a selection of pipe diameters as the decision variables, while network layout and its connectivity, nodal demand, and minimum requirements are imposed. Since the literature on the optimization of WDSs has traditionally dealt with an idealized problem, this form of the optimization of WDSs is used in this paper. The above formulation results in a mixed integer nonlinear programming problem (MINLP), which is non-convex, because of the existence of integer variables and the nature of the continuity equations. On the other hand, the problem constraints are not smooth and, hence, the application of smooth algorithms cannot be appropriate. Therefore, using new meta-heuristic optimization techniques is an interesting, if not the best, way of treating this problem. Historically, as a result of comprehensive analyses performed by many authors in recent decades, starting from the 1970s, a large number of methods have been applied to solving this optimization problem, including linear programming techniques, non-linear optimization models, global optimization methods and meta-heuristic algorithms. The main contribution of this study is to develop a new hybrid algorithm for minimum-cost design of WDSs, in which some components of HS are incorporated into an improved version of the FA. The detailed implementation procedure of this hybrid meta-heuristic method is also presented.

The hybridization of HS with other meta-heuristic has been carried out previously in different forms which can be grouped into two types. The first approach is the integration of some components of other meta-heuristic algorithms into HS, while the second approach is the integration of some HS components into other meta-heuristic algorithms. In Ref [27], the authors improved the performance of PSO, which is used in the designing of optimal pin-connected structures, by handling the particles that fly outside the variables' boundary. This improvement was based on the use of the **HM** concept. Kaveh and Talatahari [28] proposed a new framework based on a modified version of PSO, ACO and the HS scheme. In this framework, the HS was used to control the variable constraints. Li et al. [29] proposed a modified version of GA using HS. Their proposed modification mimics the HS improvisation method, where the new generated vector is selected from all vectors stored in the **HM**, which is contrary to the GA method of generating new vectors. Moeinzadeh et al. [30] used HS to improve the performance of the Linear Discriminate Analysis (LDA) classification algorithm. Lee and Zomaya [31] proposed a parallel algorithm, where HS was considered its key component. In this method, three meta-heuristics, GA, SA, and AI, were utilized to enhance the solutions stored in the **HM** as an extra step to speed up the convergence and, at the same time, to avoid being trapped in local optima.

The remaining sections of this article are organized as follows: A review of FA and HS is presented in Section 2, and then the proposed method is introduced in Section 3. In Section 4, optimal design of WDS is described in detail using the proposed method, and, in Section 5, the performance of the algorithm is evaluated utilizing typical design examples. The sensitivity analysis is also carried out in this section. Finally, Section 6 concludes the paper.

2. A review on FA and HS

In order to make the paper self-explanatory, before proposing the new hybrid algorithm, the characteristics of FA and HS are briefly explained in the following two subsections.

2.1. Firefly algorithm

Among the phenomenon-mimicking methods, algorithms inspired from the collective behavior of species such as ants, bees, wasps, termite, fish, and birds are referred to as swarm intelligence algorithms [32]. Recently, Yang [22] proposed the Firefly Algorithm (FA) as a new swarm intelligence algorithm which mimics the natural behaviour of fireflies. In some articles, [33,34] the efficiency of FA based optimization methods is compared to that of the PSO and GA based approaches, through different test functions. Recently, various applications of the FA in different research areas are reported. In the field of optimal structural design, there is limited work available in the literature based on the application of FA. Gandomi et al. [35] used a FA based approach for solving mixed continuous/discrete structural optimization problems. This study revealed the efficiency of the FA algorithm in structural optimization. Gomez [36] employed the FA for the sizing and shape optimization of truss structures with dynamic constraints. Also, Kazemzadeh Azad and Kazemzadeh Azad [37] employed an Improved FA (IFA) algorithm for optimum design of planar and spatial truss structures with both sizing and shape design variables, and reported promising results.

As mentioned before, the FA is a nature-inspired heuristic search technique based on the natural behaviour of fireflies. According to [33] who developed the FA, the natural flashing characteristics of fireflies can be idealized using the following three rules:

- **Rule 1.** All fireflies are unisex; therefore, one firefly will be attracted to other fireflies regardless of their gender.
- **Rule 2.** The attractiveness of each firefly is proportional to its brightness. Thus, for any two flashing fireflies, the less bright firefly will move towards the brighter one. The attractiveness is proportional to brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly.
- **Rule 3.** The brightness of a firefly is determined according to the nature of the objective function.

The attractiveness of a firefly is determined by its brightness or light intensity which is obtained from the objective function of the optimization problem. However, the attractiveness, β, which is related to the judgment of the beholder, varies with the distance between two fireflies. The attractiveness, β, is defined by [38]:

$$\beta = \beta_0 \exp(-\gamma r^2), \tag{1}$$

where r is the distance of two fireflies, β_0 is the attractiveness at $r = 0$, and γ is the light absorption coefficient. The distance between two fireflies, i and j, at x_i and x_j, respectively, is determined using the following equation:

$$r_{ij} = ||x_i - x_j|| = \sqrt{\sum_{k=1}^{k=d} (x_{i,k} - x_{j,k})^2}, \tag{2}$$

where $x_{i,k}$ is the kth parameter of the spatial coordinate, x_i, of the ith firefly. In the firefly algorithm, the movement of a firefly, i, towards a more attractive (brighter) firefly, j, is determined by the following equation [38]:

$$x_i = x_i + \beta_0 \exp(-\gamma r_{ij}^2)(x_j - x_i) + \alpha \varepsilon_i, \tag{3}$$

where the second term is related to the attraction, while the third term is randomization with the vector of random variables, ε_i, using a normal distribution.

The performance of the IFA was investigated using optimal design of truss structures, and satisfactory results were reported. In the present study, the IFA is employed for optimum design of WDS. Here, considering the nature of the optimization problem, the following equation is utilized for the movement stage of the FA:

$$x_i = x_j + \beta_0 \exp(-\gamma r_{ij}^2)(x_j - x_i) + \alpha \varepsilon_i. \tag{4}$$

In the original FA, the movement of firefly i towards brighter firefly j was determined by Eq. (3). Since x_j is brighter than x_i, in Eq. (4) instead of moving firefly i towards j, searching the vicinity of firefly j, which is a morereliable area, is proposed to update the position of firefly i, based on the current position of firefly j. To do this, x_i is replaced by x_j and the above equation is employed for the movement stage of the FA. In Eq. (4), ε_i is a randomly generated number using a normal distribution and α is a scaling parameter. Normal distribution has two parameters: a mean value and a standard deviation. In this study, the mean value of the normal distribution is set to zero and the standard deviation is taken as the standard deviation of the kth parameter of all fireflies in each generation.

In the IFA, to avoid missing the brighter fireflies of the population, the position of a firefly is updated only if the new position found is better than the old one. Therefore, in the process of optimization, each candidate design is replaced only with a better design. It is apparent that Eq. (3) may generate fireflies outside the bounds of design variables. In order to remove this difficulty, the parameters of fireflies that are not created within the bounds of design variables are rounded into the boundary values [37].

2.2. Harmony search technique

When musicians improvise a harmony, they usually try various possible combinations of the music pitches stored in their memory. This kind of effective search for a perfect harmony is analogous to the procedure of finding an optimal solution in engineering problems. The HS method is inspired by the working principles of harmony improvisation. Similar to the GA and PSO, the HS method is a random search technique. It does not require any prior domain knowledge, such as the gradient information of the objective function. However, different from those population-based approaches, it only utilizes a single search memory to evolve. Therefore, the HS method has the distinguished feature of algorithmic simplicity [39]. HS is a meta-heuristic search technique without the need for derivative information, and with reduced memory requirements. In comparison with other meta-heuristic methods, HS is computationally effective and easy to implement for solving various kinds of engineering optimization problems. There are four principal steps in this algorithm [40].

Step 1. Initialize a Harmony Memory (**HM**). The initial **HM** consists of a certain number of randomly generated solutions for the optimization problem under consideration. For an n dimensional problem, a **HM** with the size of HMS can be represented as follows:

$$\mathbf{HM} = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_n^1 \\ x_1^2 & x_2^2 & \dots & x_n^2 \\ \dots & \dots & \dots & \dots \\ x_1^{\mathrm{HMS}} & x_2^{\mathrm{HMS}} & \dots & x_n^{\mathrm{HMS}} \end{bmatrix}, \tag{5}$$

where $x_1^i, x_2^i, .., x_n^i$ ($i = 1, 2, ..., \mathrm{HMS}$) is a candidate solution. HMS is typically set to be between 10 and 100.

Step 2. Improvise a new solution $(x'_1, x'_2, .., x'_n)$ from the **HM**. Each component of this solution, x'_j, is obtained based on the Harmony Memory Considering Rate (HMCR). The HMCR is defined as the probability of selecting a component from the **HM** members, and 1-HMCR is, therefore, the probability of generating it randomly. If x'_j comes from the **HM**, it can further be mutated according to the Pitching Adjust Rate (PAR). The PAR determines the probability of a candidate from the **HM** to be mutated.

Step 3. Update the **HM**. First, the new solution from Step 2 is evaluated. If it yields a better fitness than that of the worst member in the **HM**, it will replace it. Otherwise, it is eliminated.

Step 4. Repeat Steps 2 and 3 until a termination criterion (e.g., maximal number of iterations) is met.

The usage of harmony memory (**HM**) is important because it ensures that good harmonies are considered as elements of the new solution vectors. In order to use this memory effectively, the HS algorithm adopts a parameter, HMCR$\in$ (0,1), called the harmony memory considering (or accepting) rate. If this rate is too low, only few elite harmonies are selected and it may converge too slowly. If this rate is extremely high, near 1, the pitches in the harmony memory are mostly used, and others are not explored well, leading not into good solutions. Therefore, typically, we use HMCR $= 0.7 \sim 0.95$ [40]. Note that a low PAR with a narrow bandwidth (bw) can slow down the convergence of HS because of the limitation in the exploration of only a small subspace of the whole search space. On the other hand, a very high PAR with a wide bw may cause the solution to scatter around some potential optima as in a random search. Furthermore large PAR values with small bw values usually cause the improvement of best solutions in final generations in which the algorithm is converged to an optimal solution vector.

3. The present algorithm

In this section, we propose a new version of the firefly algorithm called the IFA-HS algorithm. The hybrid IFA-HS algorithm combines the optimization capabilities of HS and IFA. There are various hybrid models of HS with other meta-heuristics in the literature. Alia and Mandava [41] categorized this hybridization into two types. The first type consists of algorithms which are an integration of some components of the

Improved Firefly Algorithm with Harmony Search Scheme (IFA-HS)
- Initialize the problem parameters:
  Objective function $f(\mathbf{X})$, $\mathbf{X} = (x_1, x_2, ..., x_n)^T$
  Number of design variables (n)
- Initialize the algorithm parameters:
  Population size (popsize)
  Harmony Memory Size (HMS)
  Harmony Memory Considering Rate (HMCR)
  Pitch Adjustment Rate (PAR)
  Maximum allowed number of evaluation (maxevaluation)
- Randomly generate initial population of fireflies $\mathbf{X}_i\,(i = 1, 2, ..., popsize)$
- Evaluate fitness of the population
- Construct the vectors of the harmony memory $\mathbf{HM} = \mathbf{X}_k(k = 1, 2, ..., HMS)$

While evaluation < maxevaluation (stopping criterion not met)
  For $i = 1$: popsize
    For $j = 1$: popsize
      Search the vicinity of the brighter firefly
      Move firefly i, (apply Eq.(4))
      Vary attractiveness with distance r via exp $(-\gamma r^2)$
      Evaluate new solutions and update light intensity
      Include the best solution to the **HM**
      Exclude the worst solution from the **HM**
      With probability HMCR
        Select a new solution randomly from the **HM**
      With probability 1-PAR
        Do nothing
      With probability PAR
        Choose a neighboring value
      With probability 1-HMCR
      Select a new solution from the possible value set
      Evaluate new solution and update the **HM**
    End for j
  End for i
End while

Figure 1. The outline of the proposed IFA-HS method.

other meta-heuristic algorithms within HS, while the second type consists of methods that integrate some HS components within other meta-heuristic algorithms, such as the IFA-HS algorithm.

In the HS algorithm, the diversification is controlled by random selection. Random selection explores global search space more widely and efficiently, while pitch adjustment makes the new solution good enough and near existing good solutions. The intensification in the HS algorithm is controlled by memory consideration, leading the searching process toward the searching space of good solutions [42]. Also, the use of the **HM** in HS allows the selection of the best vectors that may represent different regions in the search space. On the other hand, the disadvantages of the basic FA algorithm are premature convergence and sometimes efficacious experiences between solutions in a population are not obtained. In order to obtain a high quality solution, we combine the above mentioned strategies. Since FA algorithms are memory less, there is no information extracted dynamically during the search, while the hybrid IFA-HS uses a memory that contains some information extracted online during the search. In other words, some history of the search stored in a memory can be used in the generation of the candidate list of solutions and in selection of the new solution. Using the original configuration of the IFA, we generate the new harmonies based on the newly generated firefly each iteration after firefly's position has been updated. The updated harmony vector substitutes the newly generated firefly only if it has better fitness. This selection scheme is rather greedy which often overtakes original HS and FA. The proposed IFA-HS algorithm involves two phases of optimization: (a) The IFA algorithm using the heuristic search technique, (b) The HS algorithm using memory consideration, random selection and pitch adjustment. Figure 1 shows the outline of the proposed IFA-HS method.

The hybrid IFA-HS algorithm has another beneficial feature; it iteratively explores the search space by combining multi-search space regions to visit a single search space region. The IFA-HS iteratively recombines the characteristics of many solutions in order to make one solution. It is able to fine-tune this solution, to which the algorithm converges, using neighbourhood structures. Throughout the process, recombination is represented by memory consideration, randomness by random consideration, and neighbourhood structures by pitch adjustment and variation of the firefly's attractiveness. Therefore, the IFA-HS algorithm has the advantage of combining key components of population-based and local search-based methods in a simple optimization model. The framework of the algorithm is illustrated in Figure 2.

In order to further clarify how the IFA-HS can solve optimization problems, let us consider the following mathematical minimization problem:

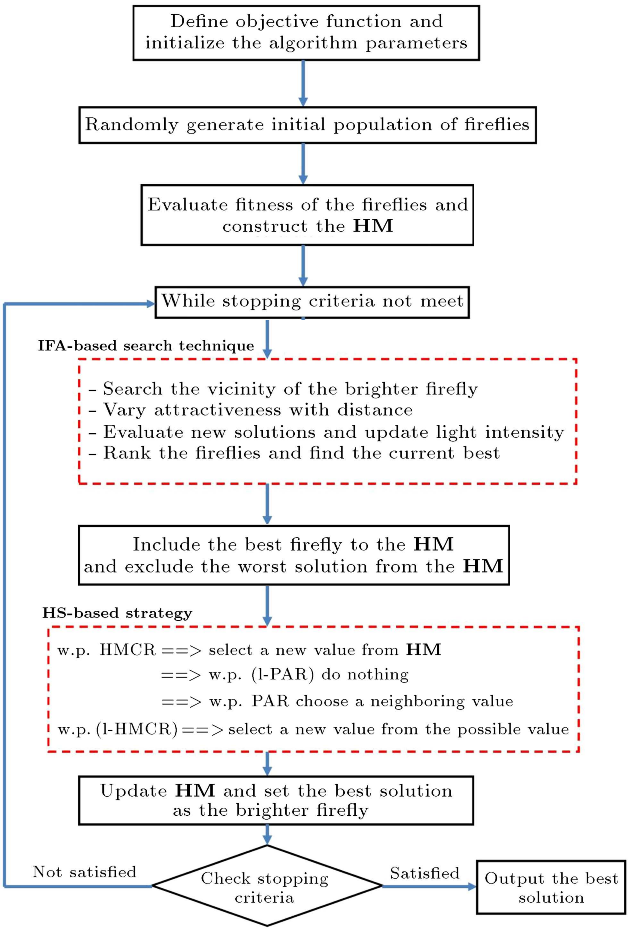


Figure 2. Flowchart of the IFA-HS algorithm developed in this research.

$$f(x) = \frac{1}{4}x_1^4 - \frac{1}{2}x_1^2 + \frac{1}{10}x_1 + \frac{1}{2}x_2^2. \tag{6}$$

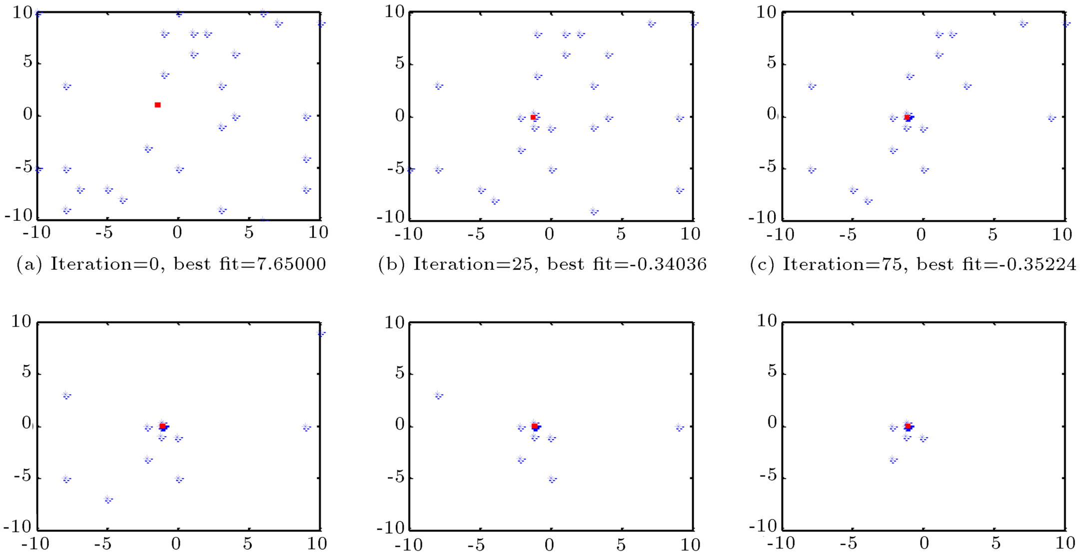
The objective function is the Aluffi-Pentiny function, which is one of the standard test functions in optimization. This function has global optima with a corresponding function value equal to -0.352386. Possible value bounds between -10.0 and 10.0 are used for the two decision variables, x_1 and x_2, shown in Eq. (6). The total number of fireflies is 30, and the HMS is equal to 15. Also, PAR $= 0.40$ and HMCR $= 0.98$. Figure 3 is prepared to show the positions of the fireflies during the optimization for this problem. The proposed method is similar to other meta-heuristics in respect to creating an initial population randomly where the candidate solutions are spread all over the search space in a stochastic manner. Figure 3(a) is plotted to give an idea of how the candidate solutions are spread in the optimization problem of the Aluffi-Pentiny function. It can be seen that in the first iterations, the fireflies investigate the entire search space to discover a promising region (exploration). When this promising region containing a global optimum is discovered, the movements of the fireflies are limited to this space in order to provide more local search (exploitation). In Figure 3(f), nearly all 30 fireflies lie on the optimal point, but there still exist some fireflies far beyond the optimal solution. In Eq. (4), the third term ($\alpha\varepsilon_i$) will reach zero as iterations go to infinity. Thus, we can conclude that there will always be an offspring that will be located far from the best firefly with decreasing probability but never equal to zero, bearing the potential to affect the so-found best firefly towards itself if it has a higher fitness value than the remaining fireflies. This is one of the key features of the IFA-HS that promises the global convergence of the algorithm.

4. Statement of WDS design optimization problems

A hydraulic network is a system containing pipes, reservoirs, pumps, and valves of different types, which are connected to each other to provide water to consumers. It is an important component of an urban infrastructure or agricultural landscape as an irrigation project and requires significant investment. Therefore, researchers are constantly searching for new ways to create more economical and efficient designs. A general strategy for solving the optimal design problem of a WDS involves the balancing of several factors: finding the lowest costs for layout and sizing using new components, reusing or substituting existing components, creating a working system configuration that fulfils all water demands, adhering to design constraints, and guaranteeing a certain degree of reliability for the system [43]. On the other hand, water network dimensioning is mathematically undetermined, thus, allowing for innumerable solutions. A typical design problem of a hydraulic network consists of sizing, i.e. determining the size of as many of the pipes as the equations allow to meet the specified pressures and discharges throughout the network. From a mathematical point of view, significant difficulties are involved due to the discrete nature of the pipe diameters and the nonlinearity of the head-loss relationship. Here, the WDS design is formulated as a least-cost optimization problem with a selection of pipe sizes as the decision variables, while network layout and its connectivity, nodal demand, and minimum head requirements are imposed. The optimization problem can be stated mathematically as [44]:

$$\text{Minimize} f_{\text{cost}} = \sum_{i=1}^{n_p} C(D_1) \times L_i, \tag{7}$$

where f_{cost} is the cost of the design; $C(D_i)$ is the cost per unit length of pipe diameter, D_i; L_i is the length of pipe i; and n_p is the number of pipes in the network.



(a) Iteration=0, best fit=7.65000
(b) Iteration=25, best fit=-0.34036
(c) Iteration=75, best fit=-0.35224
(d) Iteration=125, best fit=-0.35226
(e) Iteration=142, best fit=-0.35231
(f) Iteration=150, best fit=-0.35231

Figure 3. Collection of the fireflies around the global optima after the 150th iteration.

The above objective function is subjected to the following constraints,

$$\begin{cases} \text{1–Mass conservation constraint:} \quad \sum Q_{\text{in}} - \sum Q_{\text{out}} = \sum Q_e \\ \text{2–Energy conservation constraint:} \ \sum H_f - \sum E_p = 0 \\ \text{3–Minimum pressure constraint:} \quad H_j \geq H_j^{\min} \\ \text{4–Pipe size availability constraint:} \ D_i \in \Phi_D, \ \forall i \in n_p \end{cases} \tag{8}$$

In the continuity constraint, Q_{in} is the flow rate to the node; Q_{out} is the flow rate out of the node; and Q_e is the external inflow rate at the node. In the energy constraint, h_f is the head loss computed by the Hazen-Williams or Darcy-Weisbach nonlinear formulae; and E_p is the energy added to the water by a pump. Also, H_j is the pressure head and $H_j^{\min}$ is the minimum required pressure head at node j in which $j = 1, 2, ..., n_n$, with n_n being the number of nodes in the network. In the pipe size availability constraint, D_i is the diameter of pipe i; and Φ_D denotes the set of commercially available pipe diameters.

The constraints of the optimal design problem of WDS can be grouped into the following: size limitation, minimum required pressure head, and hydrodynamic constraints. Size limitation constraints reduce the parameter space to a discrete one. The IFA-HS based model has an alternative to fix the resolution of the parameter space to be searched. This can be adjusted to the number of commercially available pipe diameters and each parameter can take values from one to the number of commercial pipe sizes. This number is used as an index for the choice of diameters. Therefore, the IFA-HS algorithm will search for the optimal set of pipe indices instead of the optimal set of diameters. In order to handle minimum nodal head constraints, a penalty approach is utilized. If the constraints are between the allowable limits, the penalty is zero; otherwise, the amount of penalty is obtained by dividing the violation of the allowable limit to the limit itself. After analyzing a model, the pressure of each node is obtained, then, these values are compared to the allowable limits to calculate the penalty functions as:

$$\begin{cases} H_j^{\min} \leq H_j \implies \Delta_j = 0 \\ H_j^{\min} > H_j \implies \Delta_j = \frac{H_j^{\min} - H_j}{H_j^{\min}} \quad j = 1, 2, ..., n_n \end{cases} \tag{9}$$

In this method, the aim of the optimization is redefined by introducing the cost function as:

$$F_{\text{cost}} = \varepsilon_1 . f_{\text{cost}} + \varepsilon_2 . \sum (\Delta_j)^{\varepsilon_3}, \quad j = 1, 2, ..., n_n. \tag{10}$$

The penalty function method has certain drawbacks. For example, penalty parameters are problem dependent and require proper parameter tuning to converge to the feasible domain. Here, for better control of the parameters, ε_1 is set to 1. Investigations have shown that when the magnitudes of the second term of the above function (penalty function with coefficients) are in balance with the first term (cost function), better results are obtained. Therefore, the coefficient, ε_2, is taken as the cost of the WDS and the coefficient, ε_3, is set in such a way that the penalties decrease. The values of the penalty function, defined for infeasible designs, increase as the exponent ε_3 increases. The value of the penalty function exponent is important because it governs the rate of increase in the cost of infeasible designs, which directly effects exploration of the fireflies by adjusting the brightness or light intensity values, and, thus, selection probabilities. In the first iterations, if ε_3 has a large value, the fireflies tend to narrow the search space to designs that, while feasible, are more expensive than the optimal design and reduce the exploration of the solution space. However, within the last iterations, if ε_3 has a small value, the fireflies have an undesirable tendency to converge to least-cost, but infeasible, designs that have a very small penalty. Setting a large value for ε_3 in the last iterations may help to prevent convergence to infeasible designs by increasing the applied penalty. Therefore, in the first iterations of the search process, ε_3 is set to 1.05 but is gradually increased to 1.5. Then, Eq. (10) can be redefined as:

$$F_{\text{cost}} = f_{\text{cost}} + f_{\text{cost}} \cdot \sum (\Delta_j)^{\varepsilon_3}$$

$$= (1 + \sum (\Delta_j)^{\varepsilon}) \times f_{\text{cost}}, \quad j = 1, 2, ..., n_n. \quad (11)$$

In other words, this approach has the property of allowing highly infeasible solutions early in the search, while continually increasing the penalty imposed to eventually move the final solution to the feasible region.

The hydrodynamic constraints are handled by the network simulation model. Water network simulation models have become everyday tools for planners, designers, maintainers and operators. Due to accurate hydraulic analysis calculation methods, WDS models have found applicability in design, optimization, performance evaluation, rehabilitation, risk management, and operation, among others. In this study, the IFA-HS is coupled with the widely used water distribution network software, EPANET 2 [45], and applied to WDS designs. Here, the IFA-HS optimization model is the outer driver model and simulation is the inner model. The EPANET programmer's toolkit was provided by the United States Environmental Protection Agency (USEPA) that is a Dynamic Link Library (DLL) of functions that allow developers to customize EPANET's computational engine for the user's specific needs. Thus, a computer programming code is written for IFA-HS in MATLAB, and EPANET2 is linked using the EPANET toolkit. A brief description of the steps in the implementation of the IFA-HS optimization model can be outlined as follows:

Step 1. Generate N (N=popsize) population of points randomly in the solution space. Each of the N populations represents a possible combination of pipe indices.

Step 2. Compute the network cost (f_{cost}) for each of the N solutions after converting the randomly generated pipe indices to the pipe sizes available on the market.

Step 3. Update the input file of the simulator (only the diameters are changed).

Step 4. Perform hydraulic analysis of each network. EPANET2 is used to analyze the network and check the pressure at some nodes which are required to meet certain nodal pressures.

Step 5. Compute penalty function ($\sum \Delta$), if the nodal head at any node is less than the required minimum.

Step 6. Calculate the total cost of the network (F_{cost}) using the network cost and the penalty found in Steps 2 and 5, respectively.

Step 7. The total cost found in Step 6 is utilized as the fitness value for each of the trial networks.

5. Test problems

In this section, the IFA-HS algorithm is applied to four well-known networks: GoYang (small size), Hanoi (small size), double Hanoi (medium size), and Balerma network (large size). On the other hand, any meta-heuristic algorithm involves a set of parameters. In many cases, we would be interested in knowing the sensitivities or derivatives of the optimum design with respect to these parameters, because it is very useful to the designer to know which data values are more influential on the design. The sensitivity of optimal responses to these parameters is an important issue in the optimum cost design of WDS. As a result, here, a sensitivity analysis is performed for the parameters of the IFA-HS algorithm. The algorithm parameters used in this study include HMS, HMCR, PAR, and popsize (population size). In order to avoid the possible randomness of the search process due to the use of different initial solutions, the GoYang problem is solved 10 times for different parameter configurations. Due to the large computational time, the sensitivity analyses of the other networks are not carried out for this reason; the best parameter configuration obtained for the GoYang network is used for them.

After the sensitivity analysis described in subsection 5.1, for each of the above problems, a population size of 200 and harmony memory size of 70 are utilized. The HS parameters are set to HMCR = 0.95, and PAR = 0.35 for all the examples. The maximum number of evaluations is taken as 20,000 for GoYang, Hanoi, and double Hanoi problems, and 100,000 for the Balerma network. Note that for these parameters, the IFA-HS algorithms exhibited good performance in solution

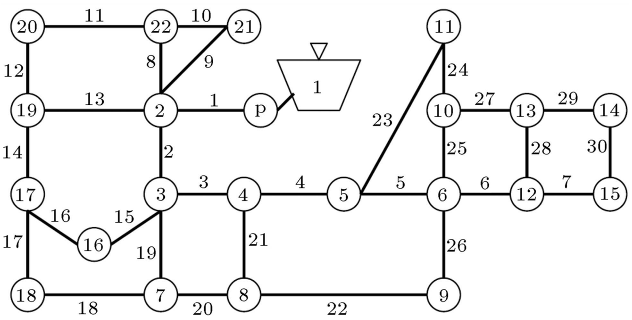


Figure 4. Network layout for the GoYang problem.

quality and required a reasonably small amount of computational overhead.

5.1. GoYang water distribution network

The optimum design problem of the GoYang network was presented by Kim et al. [46] in South Korea. It consists of 22 nodes, 30 pipes, and 9 loops, and is fed by a pump (4.52 kW) from a reservoir with a 71 m fixed head. The pipeline deployment of the GoYang network, shown in Figure 4, is derived from a water distribution network in South Korea. The data of nodes and pipes, also, IFA-HS optimal diameters, are shown in Table 1. The cost of commercially available pipe sizes {80, 100, 125, 150, 200, 250, 300, 350; in mm} is {37,890; 38,933; 40,563; 42,554; 47,624; 54,125; 62,109; 71,524; in won/meter} respectively, which have a Hazen-Williams coefficient of 100. Therefore, the search space of this optimization problem is $8^{30} = 1.24 \times 10^{27}$ possible designs. The minimum head limitation is 15 m above ground level.

In order to tune the utilized parameters for the proposed IFA-HS, a sensitive study on two parameters of the algorithm is performed while fixing other parameters (HMS = 50 and HMCR = 0.9). For various values of popsize and PAR, this example is solved several times (10 times for each value of popsize and PAR) and the average cost of the designs is shown in Table 2. This table shows that when the values of PAR and popsize increase, the optimum cost of WDS decreases. From Table 2, it can be concluded that small PAR and popsize values can cause the poor performance of the algorithm and a considerable increase in the iterations needed to find an optimum solution. On the other hand, a very large PAR may cause the solution to scatter around some potential optima, as in a random search. As shown in the table, PAR = 0.35 and popsize = 200 are suitable values for the IFA-HS algorithm. These parameter values are used for all other presented examples.

The result of sensitivity analysis of HMS and HMCR (HMS = {30, 40, 50, 60, 70}, and HMCR = {0.80, 0.85, 0.90, 0.93, 0.95}) while fixing other parameters (popsize = 200 and PAR = 0.35) are shown in Table 3. The original cost of the GoYang network was

Table 1. GoYang network data.

Node & pipe	Demand (m^3/day)	Ground level (m)	Length (m)	IFA-HS optimal diameter (mm)
01	Reservoir	71.0	165.0	200
02	153.0	56.4	124.0	125
03	70.5	53.8	118.0	125
04	58.5	54.9	81.0	100
05	75.0	56.0	134.0	80
06	67.5	57.0	135.0	80
07	63.0	53.9	202.0	80
08	48.0	54.5	135.0	80
09	42.0	57.9	170.0	80
10	30.0	62.1	113.0	80
11	42.0	62.8	335.0	80
12	37.5	58.6	115.0	80
13	37.5	59.3	345.0	80
14	63.0	59.8	114.0	80
15	445.5	59.2	103.0	80
16	108.0	53.6	261.0	80
17	79.5	54.8	72.0	80
18	55.5	55.1	373.0	80
19	118.5	54.2	98.0	80
20	124.5	54.5	110.0	80
21	31.5	62.9	98.0	80
22	799.5	61.8	246.0	80
23		71.0	174.0	80
24		56.4	102.0	80
25		53.8	92.0	80
26		54.9	100.0	80
27		56.0	130.0	80
28		57.0	90.0	80
29		53.9	185.0	80
30		54.5	90.0	80

Table 2. Results from various PAR and popsize values.

PAR	Popsize	Cost (won)	Number of analyses
0.10	50	179,832,124	16,200
0.20	100	179,100,561	12,000
0.25	150	178,050,300	10,820
0.35	200	177,015,450	8,450
0.45	250	177,093,324	6,000
0.55	300	177,100,025	4,200
0.85	350	177,075,020	3,800

Table 3. Sensitivity analysis of HS parameters (HMS and HMCR).

HMS	HMCR	Cost (won)	Number of analyses
30	0.80	177,783,950	10,400
40	0.85	177,072,511	9,800
50	0.90	177,014,772	6,371
60	0.93	177,010,359	4,961
70	0.95	177,010,359	3,631

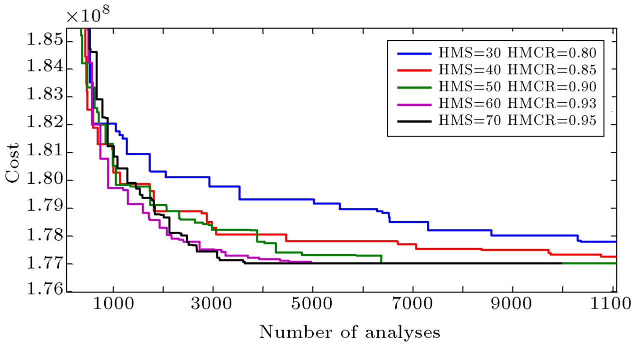


Figure 5. Convergence rate comparison for each parameter configurations (GoYang problem).

179,428,600 won. Kim et al. [46] solved this problem using a projected Lagrangian algorithm (NLP) supported by GAMS/MINOS, and then converted the continuous diameters to discrete commercial diameters. They obtained the optimal cost of 179,142,700 won. Also Geem [47] found a solution of 177,135,800 won using the Harmony Search algorithm (HS) after 10,000 function evaluations, which is the current best known solution for the GoYang network. The best solution found by the proposed IFA-HS for the GoYang case study was 177,010,359 won, spending 3,631 function evaluations when the HMS = 70 and HMCR = 0.95, which is less than the original cost, NLP and HS based-models.

As shown in Table 3, the IFA-HS algorithm with a larger HMS and HMCR performed better for this case study. The best cost of 177,010,359 won was obtained when HMS = {60, 70} and HMCR = {0.93, 0.95}. However, they require different computational overheads to reach the same final solution. Figure 5 displays the convergence history of each parameter configuration. This figure shows that it takes about 10,400, 9,800, 6,371, 4,961, and 3,631 function evaluations for {HMS = 30, HMCR = 0.80}, {HMS = 40, HMCR = 0.85}, {HMS = 50, HMCR = 0.90}, {HMS = 60, HMCR = 0.93}, and {HMS = 70, HMCR = 0.95} In considering both solution quality and efficiency, the HMS of 70 and HMCR of 0.95 were selected as the best configuration.

5.2. Hanoi water distribution network

The second problem is proposed by Fujiwara and Khang [48]. This network consists of 32 nodes, 34 pipes

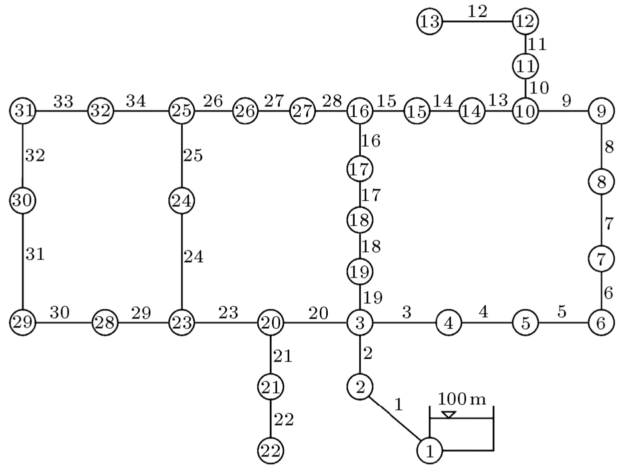


Figure 6. Network layout for the Hanoi problem.

and 3 loops. The network has no pumping station as it is fed by gravity from a reservoir with a 100 m fixed head. For this example, the system data are presented in Table 4. The Hanoi network (Figure 6) requires the optimal design of 34 pipes, allowing a minimum hydraulic head of 30 m, for all its 32 nodes, by means of 6 available diameters. The total solution space is then equal to $6^{34} = 2.87 \times 10^{26}$. The cost of commercially available pipe sizes {12, 16, 20, 24, 30 and 40 in inches} is {45.73, 70.40, 98.38, 129.30, 180.80 and 278.30 in dollar/meter}, respectively.

Table 5 reports the best results and the required number of evaluation for convergence in the present algorithm and some of the other heuristic methods. The IFA-HS found the best feasible solution of 6.2237×10^6 \$ after 15,200 function evaluations while the IFA found the best solution of 6.580×10^6 \$ spending 17,800 evaluations, which is a 5.41% more expensive design. Also, the best cost of the BLIP (Binary Linear Integer Pogramming), MSATS (Mixed Simulated Annealing and Tabu Search), SSSA (Scatter Search using Simulated Annealing as local searcher), [49], SCE (Shuffled Complex Evolution) [50], BB-BC (Big Bang-Big Crunch algorithm) [26], HBA (Heuristic Based Approach) [51], and MGA (Modified GA) [52] is 6.363, 6.352, 6.273, 6.220, 6.224, 6.232, and 6.190 million dollars, respectively. In addition the BLIP, MSATS, and SSSE found the best feasible solution after 26,457 and BB-BC, HBA, and MGA after 26,000, 259, and 18,000 function evaluations, respectively. A comparison with the hybrid meta-heuristics, such as BLIP, MSATS, and SSSA, demonstrates the effectiveness and efficiency of the proposed method. Also, the optimal design obtained using the IFA-HS algorithm showed good agreement with the previous designs reported in the literature.

In order to illustrate the performance of the constraint handling approach, Figure 7 is plotted, which shows the rate of reduction on infeasibilities

Table 4. Hanoi network data.

Node number	Demand (m^3/h)	Pipeline	Length (m)	IFA-HS optimal diameter (in)
01	-	01	100	40
02	890	02	1350	40
03	850	03	900	40
04	130	04	1150	40
05	725	05	1450	40
06	1005	06	450	40
07	1350	07	850	40
08	550	08	850	30
09	525	09	800	30
10	525	10	950	30
11	500	11	1200	24
12	560	12	3500	24
13	940	13	800	12
14	615	14	500	12
15	280	15	550	16
16	310	16	2730	30
17	865	17	1750	30
18	1345	18	800	30
19	60	19	400	30
20	1275	20	2200	40
21	930	21	1500	20
22	485	22	500	12
23	1045	23	2650	30
24	820	24	1230	24
25	170	25	1300	20
26	900	26	850	16
27	370	27	300	24
28	290	28	750	24
29	360	29	500	16
30	360	30	2000	16
31	105	31	1600	12
32	805	32	150	16
		33	860	20
		34	950	24

with the number of analyses. As it is clear from this figure, after about 1,200 function evaluations, the fireflies are forced to fly-back to feasible space. In this figure, the Vio (constraint violation) parameter is defined as:

$$\text{Vio} = \sum \max\left[0, (H_{\min} - H_j)\right],$$
$$j = 1, 2, ..., n_n. \tag{12}$$

Table 5. Performance comparison for the Hanoi network.

Method	Cost (10^6\$)	Number of analyses
BLIP [49]	6.363	26,457
MSATS [49]	6.352	26,457
SSSA [49]	6.273	26,457
SCE [50]	6.220	25,402
BB-BC [26]	6.224	26,000
HBA [51]	6.232	259
MGA [52]	6.190	18,000
IFA-HS (present work)	6.224	15,200

5.3. Double Hanoi network

The third design example is the double Hanoi network. Because this network is derived from the basic Hanoi network, its optimal cost is known. All the parameters for the reservoir, nodes and lines in the double Hanoi water distribution network are the same as in the original Hanoi network on both mirrored parts, except for the first pipe (from the reservoir to node 2), which is shortened from the original 100 to 28.9 m. This change was made for the sake of obtaining the same head in node 2 (with a diameter of 40 in, which will certainly be proposed here by any optimization method) as in the original Hanoi network. The total solution space is then equal to $6^{67} = 1.37 \times 10^{52}$. Network layout for this problem is shown in Figure 8. The reference optimal solution (global) could be evaluated as follows [53]:

$$C_{\text{DH}} = 2C_H - 2L_1C_1 + 28.9C_1, \tag{13}$$

in which C_{DH} is the optimal cost of the double Hanoi network; C_H is the reference optimal cost of the Hanoi network; L_1 is the length of the first pipe on the original network (100 m); and C_1 is the unit price of diameter 40 in (278.28 \$).

For our solution described in the previous example (6.2237×10^6 \$), according to Eq. (13), the global optimum solution of the double Hanoi network should be 12.400×10^6 \$. The best results obtained with the IFA-HS, BB-BC [26], GA, OptiDesigner, and the HS [53] are summarized in Table 6. The reference optimal cost of the Hanoi network for the GA and HS is 6.081×10^6 \$ and it is 6.115×10^6 \$ for the OptiDesigner. The IFA-HS found the best feasible solution of 12.611×10^6 \$ after 18,000 analyses, as given in Table 7, while the best cost for the IFA, HS, GA, and OptiDesigner are 14.118, 12.405, 12.601 and 12.795 million dollars, respectively. Therefore, deviation from the reference optimal solution for the IFA-HS algorithm is 1.70%, and it is 2.00%, 2.39%, 4.01%, 5.62% and 7.27% for the BB-BC, HS, GA, OptiDesigner and IFA, respectively. This result demonstrates that the IFA-HS algorithm is better in terms of closeness to the global

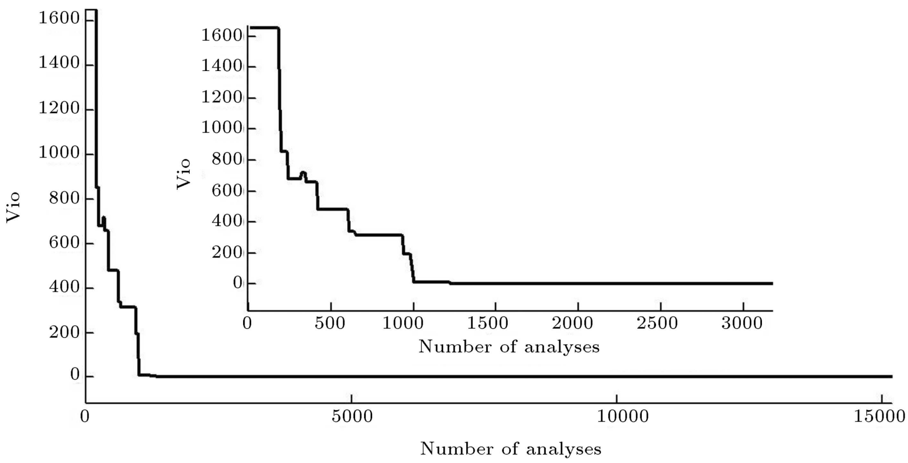


Figure 7. Variation of constraint violation (Vio) with the number of function evaluations (Hanoi problem).

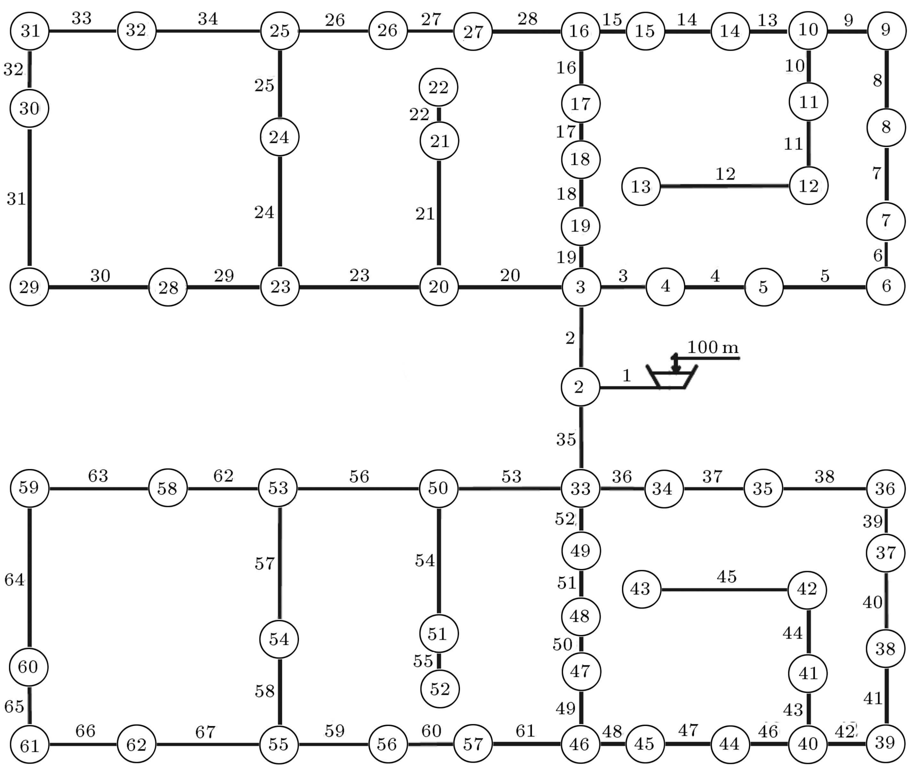


Figure 8. Network layout for the double Hanoi problem.

minimum. The hydraulic head for each node is shown in Figure 9. As shown in this figure, the minimum value for the pressure head is equal to 30.0179 m (in node 60).

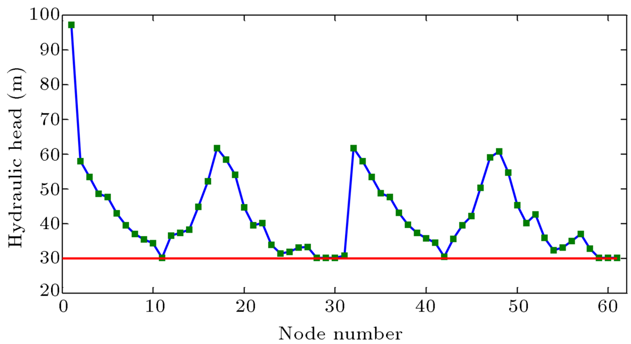


Figure 9. Existing hydraulic head for the double Hanoi network using IFA-HS.

5.4. Balerma irrigation network

Balerma is a water irrigation distribution network in the Sol-Poniente County in Almeria Province, Spain (Figure 10). There are 454 pipes, arranged in 8 loops, which are to be designed using a set of 10 PVC pipes with diameters between 125 and 600 mm, and an absolute roughness coefficient of $k = 0.0025$ mm. In this design example, total enumeration reaches an

Table 6. Performance comparison for the double Hanoi network.

Method	Hanoi network (10^6\$)	Double Hanoi network (10^6\$)	Deviation from reference global optimum (%)
OptiDesigner [53]	6.1150	12,795,541	5.62
GA [53]	6.0811	12,600,624	4.01
HS [53]	6.0811	12,404,680	2.39
BB-BC [26]	6.2240	12,647,789	2.00
IFA-HS (present work)	6.2237	12,611,176	1.70

Table 7. The optimum design of IFA-HS for the double Hanoi network.

Pipeline	Diameter (in)	Pipeline	Diameter (in)	Pipeline	Diameter (in)
01	40	24	24	47	12
02	40	25	24	48	16
03	40	26	16	49	30
04	40	27	20	50	30
05	40	28	20	51	40
06	40	2	916	52	40
07	30	30	16	53	40
08	30	31	12	54	20
09	30	32	20	55	12
10	30	33	20	56	30
11	30	34	30	57	20
12	24	35	40	58	16
13	16	36	40	59	20
14	16	37	40	60	20
15	20	38	40	61	20
16	30	39	40	62	20
17	30	40	30	63	20
18	30	41	30	64	20
19	30	42	30	65	20
20	40	43	30	66	12
21	20	44	30	67	20
22	12	45	24		
23	30	46	12		

impressive amount of 10^{454}. Also, the Darcy-Weisbach equation has been adapted to calculate the head losses, using EPANET 2. The minimum required pressure head is 20 m for each node.

Table 8 shows the best cost and the required number of analyses for convergence of the present algorithm and some other meta-heuristics. For this large-size network, Reca and Martinez [54] (GA) reached a best feasible solution of 2.302×10^6 € spending 10^7 EPANET 2 calls, while Geem [55] (HS) found a solution of 2.018×10^6 € with 10^7 calls. The best feasible solution obtained by Bolognesi et al. [56] (GHEST) is 2.002×10^6 €, spending 290,500 evaluations, and Cisty et al. [57] (DEPSO) found the best solution of 1.934×10^6 € after 500,000 calls. The best solution found by Zheng et al. [58] (SADE) for the Balerma network case study was 1.983×10^6 €, which is higher than the best solution (1.940×10^6 €) reported by Tolson et al. [59] (HD-DDS). However, the HD-DDS yielded the best solution requiring 30 million evaluations, while the SADE algorithm used only 1.3 million average evaluations to finally converge. The IFA-HS based method obtained the new best solution of 1.969×10^6 € after 90,800 function evaluations. It

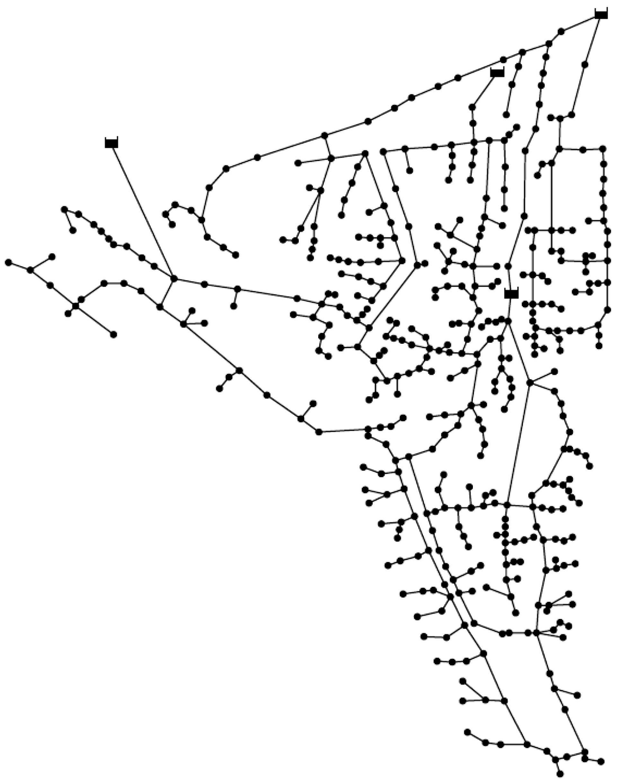


Figure 10. Balerma network [54].

Table 8. Performance comparison for the Balerma network.

Method	Cost (10^6 €)	Number of analyses
GA [54]	2.302	10×10^6
SA [60]	3.476	45,400
MSATS [60]	3.298	45,400
PSHS [55]	2.633	45,400
HS [55]	2.018	10×10^6
GHEST [56]	2.002	290,500
HD-DDS [59]	1.940	30×10^6
SADE [58]	1.983	1.3×10^6
DEPSO [57]	1.934	550,000
IFA-HS (present work)	1.869	90,800

means that the IFA-HS algorithm performed really fast, since the required number of analyses is the best performance published to date. The convergence history for the Balerma network using the IFA-HS algorithm and the hydraulic head for each node is shown in Figures 11 and 12, respectively. As shown in Figure 12, the minimum value for the pressure head is equal to 22.9577 m (in node 295). The table of diameters is not specified here because it is too lengthy, and can be obtained from the authors.

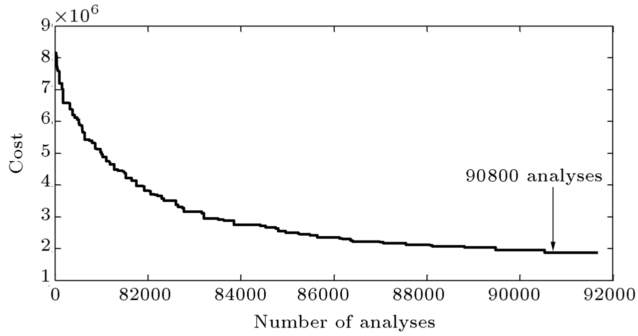


Figure 11. The convergence for the Balerma network obtained by the IFA-HS.

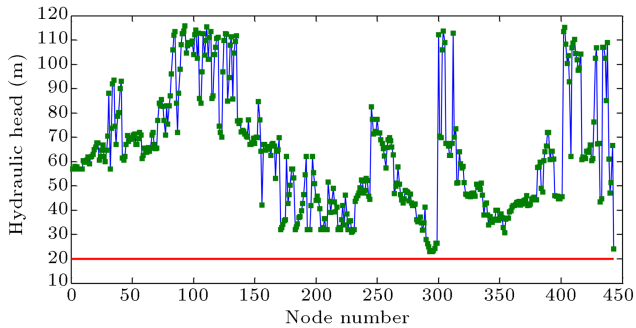


Figure 12. Existing hydraulic head for the nodes of the Balerma network using IFA-HS.

6. Conclusions

In this paper, a new hybrid swarm intelligence algorithm, namely; the improved firefly algorithm with the harmony search scheme (IFA-HS), is proposed to solve the design problems of water distribution systems based on the combined concepts of the Firefly algorithm and Harmony Search technique. It is found that the proposed algorithm is a promising method for solving pipe network design problems as it outperforms some advanced algorithms previously presented in the literature for the case studies considered. The main idea of the hybrid IFA-HS algorithm is to integrate the HS operators into the FA algorithm, and, thus, increase the diversity of the population and the ability to have the FA to escape the local minima. Here, an improved FA is used for fine-tuning of the vectors stored in the harmony memory. Actually, harmony memory vectors become as the FA population, and then the evolving process is performed as the usual improved FA procedure. Another improvement in this algorithm is adding a pitch adjustment operation in the FA as a mutation operator with the aim of speeding up the convergence of the algorithm, thus, making the approach applicable to a wider range of practical applications, while preserving the attractive characteristics of the basic FA.

The performance of the proposed IFA-HS is demonstrated using four well-known case studies and the results are compared to those of the standard and previously applied optimization methods consisting of GA, HS, BB-BC, FA, SCE and some hybrid methods such as BLIP, MSATS, SSSA, DEPSO, and PSHS. The IFA-HS algorithm found the best feasible solutions of 1.969 € (90,800 analyses), 12.611 $ (18,000 analyses), 6.224 $ (15,200 analyses) million and 177,010,359 won (3,631 analyses) for the Balerma, double Hanoi, Hanoi and GoYang network, respectively. Also, a sensitivity analysis is performed for the IFA-HS algorithm parameters in which population size, pitch adjustment rate, harmony memory size, and harmony memory considering rate are concerned.

As can be observed from the results, the proposed algorithm exhibits good performance in terms of solution quality, and for almost all examples, the IFA-HS method found the best solution in fewer numbers of function evaluation than the other nature-inspired algorithms. This means that the proposed method can find good results in a shorter time. For the third design example, the numerical results demonstrate that the IFA-HS algorithm is better in term of closeness to the global minimum. The IFA-HS efficiency can be valuable in large-scale optimization problems as evidenced by results on the optimization of the Balerma network, where a new optimal cost has (1.869×10^6 €) been set by 90,800 function evaluations, since the optimal cost and required number of analyses are the best between other methods up to date.

Acknowledgement

The second author is grateful to the Iran National Science Foundation for its support.

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