Application of Genetic Algorithms for Designing Micro-Hydro Power Plants in Rural Isolated Areas—A Case Study in San Miguelito, Honduras

A. Tapia, D. G. Reina, A. R. del Nozal and P. Millán

Abstract The use of Micro-Hydro Power Plants (MHPP) has established itself as a fundamental tool to address the problem of energy poverty in rural isolated areas, having become the most used renewable energy source not just in this field but also in big scale power generation. Although the technology used has made important advances in the last few decades, it has been generally applied to big scale hydro-power systems. This fact has relegated the use of isolated MHPPs to the background. In this context, there is still a vast area of improvement in the development of optimization strategies for these projects, which in practice remains limited to the use of thumb rules. It results in a sub-optimal use of the available resources. This work proposes the use of a Genetic Algorithm (GA) to assist the design of MHPP, finding the most suitable location of the different elements of a MHPP to achieve the most efficient use of the resources. For this, a detailed model of the plant is first developed, followed by an optimization problem for the optimal design, which is formulated by considering the real terrain topographic data. The problem is presented in both single (to minimize the cost) and multi-objective (to minimize cost while maximizing the generated power) mode, providing a deep analysis of the potentiality of using GAs for designing MHPP in rural isolated areas. To validate the proposed approach, it is applied to a set of topographic data from a real scenario in Honduras. The achieved results are compared with a baseline integer-variable algorithm and other meta-heuristic algorithms, demonstrating a noticeable improvement in the solution in terms of cost.

A. Tapia · A. R. del Nozal · P. Millán
Departamento de ingeniería, Universidad Loyola Andalucía, Seville, Spain
e-mail: atapia@uloyola.es

A. R. del Nozal
e-mail: arodriguez@uloyola.es

P. Millán
e-mail: pmillan@uloyola.es

D. G. Reina (✉)
Departamento de ingeniería electrónica, University of Seville, Seville, Spain
e-mail: dgutierrez@us.es

M. Rout et al. (eds.), *Nature Inspired Computing for Data Science*,
Studies in Computational Intelligence SCI 871,
https://doi.org/10.1007/978-3-030-33820-6_7

Keywords Genetic algorithms · Micro-Hydro Power Plants · Optimization · Rural electrification

1 Introduction

The growth of the energy demand around the world constitutes a big challenge that must be addressed in the coming years [1]. As population and industrialization grow, global access to energy expands, playing a fundamental role. Nevertheless, in 2017 there were still 1.06 billion people who lacked access to electricity and 2.6 billion who used biomass to meet their basic needs, in accordance with the World Data Bank [2]. Although urban areas tend to be more electrified (4% lack access to electricity), rural areas are the most affected by this problem (27% lack access to electricity). Furthermore, these statistics are more critical in developing countries, and thus the expansion of the electricity supply constitutes an area of special interest in these countries [3], which tends to promote rural electrification programs to improve life quality of the rural population.

Renewable Energy Sources (RES) play a fundamental role [4] in this context, having demonstrated to constitute an effective way to guarantee the increasing need of energy supply (some works predict that by 2050 RES could provide half of the world's energy needs [5]) without compromising the natural resources, while mitigating CO_2 emissions. Although a wide range of options have been demonstrated to be adequate to provide an effective reduction of greenhouse gas emissions, such as nuclear energy or carbon capture and storage (CCS), the use of RES is praised as one of the most suitable choices [6]. In contrast with the limitations of nuclear and fossil fuel availability, RES do not deplete over time, and (with a few exceptions, such as certain bio-energy production methods and bio-energy life-cycle) are carbon-free. Nevertheless, the major disadvantages of these systems lie in the uncertainty implied by the stochastic nature of the natural sources, which translates into a limitation to high levels of electricity production [7]. Nevertheless, these limitations have no noticeable effects on small generation systems, making RES ideal candidates to meet the energy supply requirements for rural areas [8, 9], where due to geographical or economic reasons, national grid supply are not accessible.

Although there are several alternatives among RES that have been demonstrated to be suitable to supply electric power to remote isolated areas [10–12], hydro-power has established itself as the most frequently used [13] since it is capable of reaching the highest efficiency rates [14] with low investment costs [15]. Given its versatility and stable projection [16], hydro-power plants represent a suitable and efficient option to supply rural isolated areas [17].

Nevertheless, despite of the goodness of MHPPs, the precariousness of the context of rural communities usually represents a challenge for the adequate use of RES. The lack of qualified manpower, together with the limitations of the resources constitute big barriers to the optimal development of these installations. Within this context, the study of robust and efficient design strategies is essential to guarantee that the resources are used in the most efficient way, without compromising the limited resources.

1.1 *Micro-Hydro Power Plants*

Micro-Hydro Power Plants (MHPPs) are hydro-power plants with generation capacities inferior to 100 kW [18]. These systems have small power source requirements and their ease of installation makes them suitable to supply small communities by means of an independent electrical grid [19].

Unlike big-hydro plants, where advance architectures, equipment and expensive civil works are required, MHPPs have both minimal equipment and labour requirements. The water flow is directly extracted from its natural flow without the installation of a reservoir dam. Although a small dam is generally built, its purpose is to guarantee a smooth and clean entrance of the water into the piping. The water is driven downhill through a long pipe (penstock) that ends in the powerhouse, a small building where the generation equipment is installed (a typical scheme is shown in Fig. 1). Inside the powerhouse, the water flow is driven into a turbine, being its kinetic energy

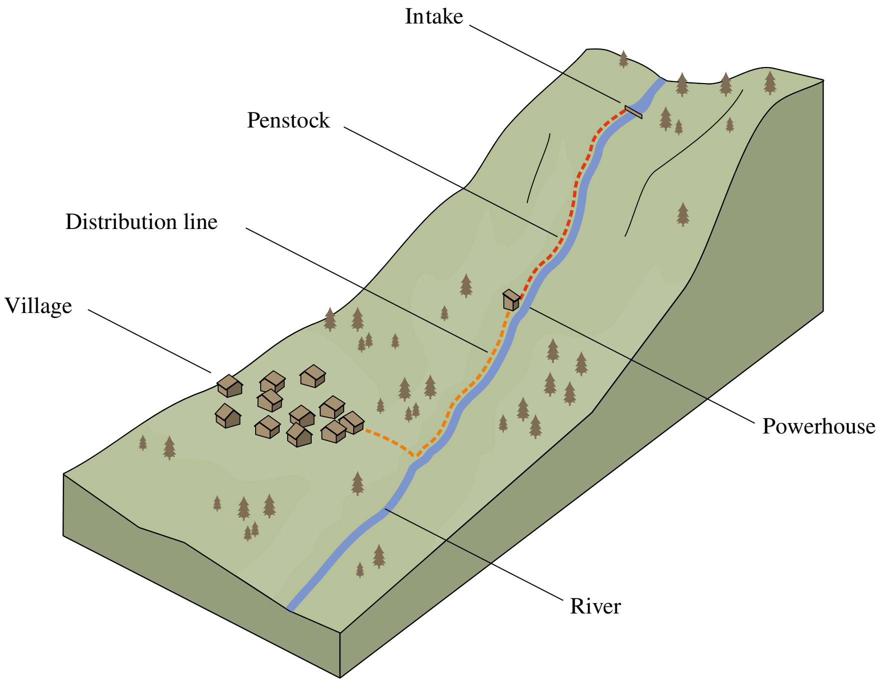

Fig. 1 Basic scheme of a MHPP supplying an isolated village

transformed into mechanical. This last is finally converted into electrical energy by means of a generator, while the water flow is returned to its natural course. Although non-traditional alternatives are frequently used as a turbine, such as locally made systems or pumps working as turbines (PAT) [20], Pelton and Turgo wheels [21] are the usual choices, given their suitability to low flow rates emplacements [22].

1.2 Motivation of the Research

Despite of the cited benefits of MHPP for rural electrification, the precariousness context in which these solutions are developed causes that their true potential is not generally achieved, due to the use of inefficient traditional design methodologies. These methodologies can be generally divided in the following steps:

- Measurement of available flow rate (Q) and height (H_g).
- Estimation of power generation (P).
- Decision-making of dam and powerhouse location.
- Sizing of the equipment.

This traditional process begins with an evaluation of the emplacement, that consists in measuring the available water flow rate and height difference. As flow rate records are not usually available for small rivers and streams, in-situ measurements are generally required (for example, using gauging weirs [23]). Regarding the gross height, its estimation is done by means of traditional methods such as height maps or Topographic Abney levels. With the measurement of flow and gross height, a gross estimation of the obtainable power can be made, in terms of which the feasibility of the plant is evaluated. If the estimations satisfy the requirements considered for the project, the hydro-power professionals proceed to determine the precise location of the water intake (where a small concrete dam is installed) and the powerhouse, on the basis of an initial site visit and know-how. This decision is focused on minimizing the pipe length, L_P, as this variable will strongly condition the cost and the final performance of the MHPP, as will be seen later. In terms of this, the generation system (pipe, turbine and generator) is sized using thumb rules [24], and thus the work labours are planned.

Although it is clear that this routine provides a reasonable approach to design the system, it is clear that the final performance is far from the optimal one. The feasible layout, considering the terrain height, is not evaluated, and the effects on the performance is not considered in the determination of the location of the dam and the powerhouse. For this reason, the estimation of the obtainable power represent is far from the optimal. In sight of these issues, the need of developing practical and efficient design methodologies to improve the use of the natural resources is evidenced.

1.3 Contributions

In order to improve the design of MHPPs to rural electrification projects, this work proposed the application of evolutionary computational approach to address the problem of optimizing the design of a MHPP by finding the most suitable layout, considering the real terrain profile. Although the optimization of MHPP to supply remote areas has been extensively approached in the literature [25–28], most of the studies generally aim at developing general guidelines, while the study of particular design strategies to assist the implementation of MHPP considering the real scenario remains a matter of study. In addition, the complex nonlinear nature of the MHPP performance in a particular location constitutes a high complexity, that has generally been addressed in the literature by simplifying either the domain (approximating the river profile by a straight line [29]), or the problem formulation (fixing certain parameters, such as the pipe diameter [30]). Although it is clear that the existing approaches lead to a better usage of the resources, the cited simplifications imply that the obtained solutions may differ from the optimal solutions of the real problem. In this work, a Genetic Algorithm (GA) is developed to find the most suitable layout of a MHPP, on the basis of the topographic characteristics of the emplacement. To this end, the terrain profile is obtained through a topographic survey, in terms of which the problem is formulated. The paper aims to find the optimal location of the main elements, this is, the powerhouse, the dam and the distribution of pipe lengths along the terrain, including the selection of the most adequate penstock diameter, in accordance to a set of performance criteria. In addition, to obtain a deeper understanding of the potential of the emplacement, the multi-objective problem is also studied, being three competitive objectives of the model optimized simultaneously. With this, the influence of the different parameters in the performance of the MHPP is studied. A real river profile scenario in Honduras is applied to verify the benefits of the proposed approach.

This chapter is organized as follows: A general overview of the related work in the literature is presented in Sect. 2, where the main advantages of the proposed within the actual state of the art approach are presented. In Sect. 3, a detailed description of the problem set-up and the main variables is made. For this, a model of the MHPP is developed in terms of the decision variables, being the model used then to define the problem of optimally designing the MHPP layout. In Sect. 4, a GA is developed to address the optimization problem proposed. In Sect. 5, the proposed GA is applied to a real scenario in Honduras, where the results are summarized and the performance of the approach is validated. Finally, the conclusions of this work, together with the concluding remarks, are summarized in Sect. 7.

2 Related Work

During the last years, the optimization of MHPP has received a big attention in the literature [31–34]. A deep analysis of the current state of the art in computational optimization methods applied to RES can be found in [34]. In this relevant work, the latest research advances, regarding he different optimization strategies applied to the design of RES systems, are summarized. A similar more recent work is [33], where the authors review the main optimization methods for the deployment and operation of RES generation units. In general, the complexity of reliably modeling RES systems, especially hydro-power plants [26, 35], has motivated the decomposition of the problem on the basis of specific aspects, such as determining the most suitable operation strategies [36, 37] or sizing the equipment [28]. The main reason lies in the use of analytical approaches, whose performance is strongly conditioned by the complexity of the problems addressed. For this reason, it is usual to simplify the problems formulation as much as possible. For example, the authors in [29]study the optimization of penstocks in MHPPs in order to minimize the energy cost, simplifying the river by means of an average slope. This same approximation is considered in [38], where the optimal flow discharge and penstock diameter are determined by means of a dimensional analysis. In this approach the problem aims to minimize the water usage, being also a set of dimensionless relationships between the relevant design variables derived. It is important to note that the flow rate respond to a stochastic nature, and thus a stochastic approach can be proposed to improve the design of MHPPs. For example, the authors in [39] consider the Flow Duration Curves (FDC) and the environmental requirements to develop an analytical framework to determine the performance and profitability of a MHPP, being it validated in a real case. Although the use of FDC has been relevant in the literature, its application to small scale plants is not generally relevant, being its potential generally focused in bigger scales. An example of this is [40], where the authors present a toolbox to optimize the design of hydro-power plants by means of performance simulations in terms of FDC.

Although traditional optimization approaches such as Linear Programming (LP) [41], Integer Linear Programming (ILP) [30] or Mixed-Integer Non-Linear Programming (MINLP) [41] have been proven useful to address these problems, metaheuristic algorithms are gaining relevance in several areas of engineering [42, 43], and especially in the field of systems optimization [44–46]. An illustrative example of this can be found in [45], where the authors develop a numerical sizing tool on the basis of simulations of the plant performance (production and cost) during the year. In terms of these simulations, a parametric study is developed to evaluate the effects of the different factors, by means of a stochastic evolutionary algorithm implemented. In [46], the authors propose three different to optimize reservoir operation and water supply operations. Similarly, a strategy for the optimal design, control and operation of MHPPs is proposed in [27], where the authors present a Honey Bee Mating Optimization (HBMO) algorithm. This algorithm determines the turbine type and number, and the penstock diameter, in addition to scheduling the operation that maximizes the benefit for a given set of FDC. Nevertheless, this approach does not consider particular characteristics of the plant location. Similar to the present work but taking into account this last issue, the MHPP layout is optimized in [47], where the authors develop a Genetic Algorithm (GA) to find the most adequate locations for the different parts of the plant, including powerhouse, dam and penstock layout, in order to reach a certain power rate with the minimal cost, satisfying a set of constraints related to flow usage and feasibility of the layout for a certain terrain profile.

This work proposes the use of a GA [48] to find the optimal layout of MHPP in a certain location, which is considered as an input by means of a topographic survey. The problem is formulated on the basis of the framework proposed in [30]. An improved cost function is proposed, and the generated power, flow usage and physical feasibility constraints are considered. To verify the benefits of the proposed approach, it is applied to optimize a real MHPP project in a rural community of Honduras.

3 Problem Statement

The layout of a MHPP constitutes a strong conditioning to its performance, and thus finding its optimal configuration represents a challenge itself, as requires a compromise between different parameters, such as the gross height and the length of the penstock. The higher the gross head is, the bigger the amount of obtainable power is. Nevertheless, a long penstock implies negative effects due to the friction losses, especially for small penstock diameters [49]. For this, a model of the plant is required to be developed.

3.1 Model of the System

The objective of modeling the MHPP is based on finding the relation between the variables that result from the plant layout (this is the gross head H_g and the penstock length L_P) and the variables that determine the performance of the plant (this is the generated power P, the water flow rate Q and the cost C).

3.1.1 Generated Power

The power obtained in a MHPP can be expressed as

$$P = Qh\eta, \tag{1}$$

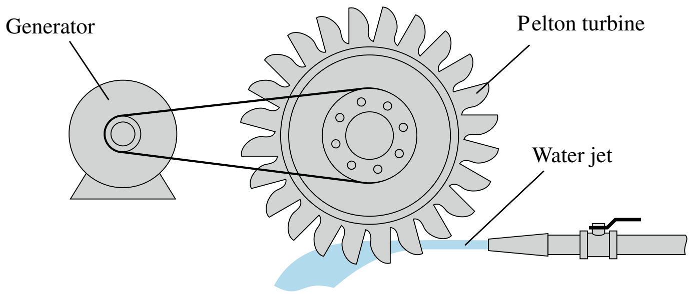

Fig. 2 Working scheme of a typical Pelton microturbine

being η the efficiency of the generation equipment (turbine and generator) and h the water height at the entrance of the turbine. The difference between the gross height, H_g, and this last relies in the heigh losses, h_L, that appear due to the friction. This is

$$h = H_g - h_L. \tag{2}$$

As the turbines considered are action micro-turbines [26], the energy conversion is made by means of an atmospheric jet (see Fig. 2), and thus the energy of the flow at the entrance of the turbine is entirely kinetic. Following this, using v_{jet} to denote the water speed of the jet, it can be written that

$$h = \frac{1}{2g} v_{jet}^2. \tag{3}$$

Given the incompressibility of water, the speed of the jet v_{jet}, can be expressed in terms of the flow Q, and the sectional area of the nozzle injector S_{noz} as

$$v_{jet} = \frac{Q}{c_D S_{noz}}, \tag{4}$$

where the coefficient of discharge c_D models the formation of a jet contraction after the water leaves the nozzle [24]. Using this last expression, the height at the entrance of the turbine h can be written in terms of the flow as

$$h = \frac{1}{2g c_D^2 S_{noz}^2} Q^2. \tag{5}$$

With respect to the friction loss h_L, it can be modeled by using several approaches proposed in the literature. In this work, the same expression used in [30] is used, yielding that

$$h_L \approx k_{fric} \frac{L_P}{D_P^5} Q^2, \tag{6}$$

where k_{fric} is a constant that depends on the material, D_P is the pipe diameter. Introducing expression (4) in (5), and the resultant expression, together with (6), in (3), the following expression for the flow Q can be obtained:

$$Q = \left[\frac{H_g}{\frac{1}{2gc_D^2 S_{noz}^2} + \frac{k_{fric}}{D_P^5} L} \right]^{\frac{1}{2}}. \tag{7}$$

Finally, an expression for the obtainable power P, in terms of the height H_g and length of the penstock L_P can be obtained by substituting (7) and (5) in (1), resulting

$$P = \frac{\eta\rho}{2S_{noz}^2} \left[\frac{H_g}{\frac{1}{2gS_{noz}^2} + k_{fric}\frac{L}{D_P^5}} \right]^{\frac{3}{2}}. \tag{8}$$

3.1.2 Cost of the Plant

Given the context of precariousness presented in Sect. 1, the cost of the installation constitutes the main limitation for the success of the project of developing a MHPP for rural electrification. It is relevant to note that the overall cost of the installation includes not just the penstock, the dam, and the powerhouse, but also the distribution line, the turbine, and the generator. Despite of this, the sizing of the turbine and generator is usually conditioned by the order of the power estimation at each location. The device selection is made for a wide margin of operation points, and thus its dependency on the nominal point does not present a significant difference in the manufacturing process, as the cost is approximately constant. For this, the location of the dam and the powerhouse, together with the layout of the penstock and the power line represent the main conditioning factors regarding the problem of optimizing the use of the funding resources. As the cost of the generating equipment is considered constant in this work, it is then not considered in the optimization problem.

The cost function considered is defined as the sum of the cost of the penstock, C_P and the cost of the distribution line C_E. This is

$$C = C_P + C_E. \tag{9}$$

The price of a piping installation typically varies in proportion to the total weight of the pipes, which depends not only on the length but also on the diameter D_P and the wall width. Following [29], a simple expression for the cost of the pipe has the form of

$$C_P = k_P L_{P,eq} D_P^2,$$

being K_P a constant that must be defined in terms of the pipe material and its geometry, and $L_{P,eq}$ is the equivalent length of the penstock, which is defined as the physical length plus a virtual length to consider the drawbacks of installing and deploying the connections between the pipe lengths. Using λ to model the equivalent cost of installing each elbow, it can be written

$$L_{P,eq} = L_P + \lambda n_c,$$

and thus the cost of the penstock is

$$C_P = k_P(L_P + \lambda n_c)D_P^2. \tag{10}$$

With respect to the cost of the distribution line, it can be modeled as

$$C_E = k_E L_E, \tag{11}$$

being k_E the linear cost of the wiring. Introducing (10) and (11) in (12), the cost function is

$$C = k_P(L_P + \lambda n_c)D_P^2 + k_E L_E. \tag{12}$$

The distribution line of the MHPP is assumed to consist of two intervals. The first interval connects the village with the closest point of the river, named s_c, while the second connects this point to the powerhouse along the river. This scheme is followed by the difficulties of access that the rough terrain imply, easing its installation and maintenance. As the first interval is not conditioned by the layout of the plant, only the second one is considered in the optimization problem. Note that the location of this point s_c must be determined in advance.

3.2 Model of the Layout

The possible feasible layouts are modeled by using the method proposed in [30], where the domain of the problem is defined as a $N-$discretization of the topographic profile of the river, in the form of

$$\{s_i,\ z_i\}, \qquad i = 1 \ldots N, \tag{13}$$

Variables s_i and z_i are the coordinates of the i-th point belonging to the profile of the river, represented in the plane $s - z$ that results from the 2D-development of the real profile. This 2D development (schematically represented in Fig. 3) is made on the basis of several assumptions. First, given the mountainous geography related to the remote nature of the studied areas, the water sources are upper-course rivers, typically formed in V-shaped valleys with very low or negligible curvature. This, in addition with the short length of the required penstocks, implies that neglecting the 3D nature of the layout will have no noticeable implications on the formulation of the problem.

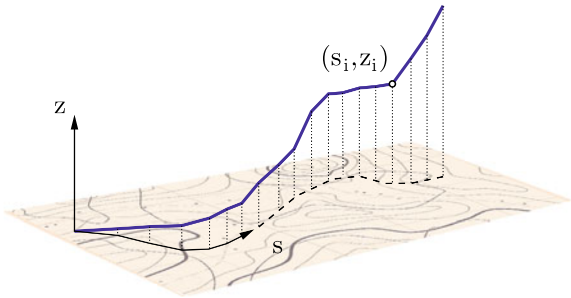

Fig. 3 Scheme of the 2D simplification of the 3D real river profile

The solutions are modeled by means of a variable Δ is defined as a set of N binary variables δ_i in the form of

$$\Delta = [\,\delta_i\,]_{1\times N} \qquad i = 1 \ldots N, \tag{14}$$

These variables δ_i are defined in such a way that each combination of them (resulting in an array Δ) defines a layout of the MHPP as follows:

- A value $\delta_i = 1$ represents the deployment of an elbow in point (s_i, z_i).
- The minimal index i satisfying $\delta_i = 1$ represents the location of the powerhouse.
- The maximum index i satisfying $\delta_i = 1$ represents the location of the dam.

For a better understanding of the proposed scheme, an illustrative example of this scheme is represented in Fig. 4 for a discretization with $N = 10$ and an arbitrary Δ. Note that the number of combinations for Δ is 2^N. With this in mind, it must be noted that even a low sampled set of data with a $N \sim 100$ (this corresponds to a 1 km river with a height measurement each 10m) represents an intractable problem for brute-force algorithms, justifying the use of meta-heuristic approaches.

Using this scheme, the variables H_g, L_P and L_E can now be defined in terms of the solution Δ. The gross head is defined as the height difference of the locations of the dam and the powerhouse, and thus it can be determined as the height difference between the maximum and minimum points (s_i, z_i) that satisfy $i = 1$. This is

$$H_g = z_d - z_p, \tag{15}$$

where the sub-index d and p refers, respectively, to the maximum and minimum index i such that $\delta_i = 1$. Thus these index corresponds to the water dam and the powerhouse location, respectively.

Regarding the length of the penstock, L_P, it can be determined as the summation of the successive pipe lengths of between consecutive elbows, this is

$$L_P = \sum_{\forall (i,j)} \left[(s_j - s_i)^2 + (z_j - z_i)^2\right]^{\frac{1}{2}} \qquad \forall\,(i, j) \;\middle|\; \begin{array}{l} \delta_i = \delta_j = 1, \\ \delta_k = 0 \;\forall k \in \{i, j\}\,. \end{array} \tag{16}$$

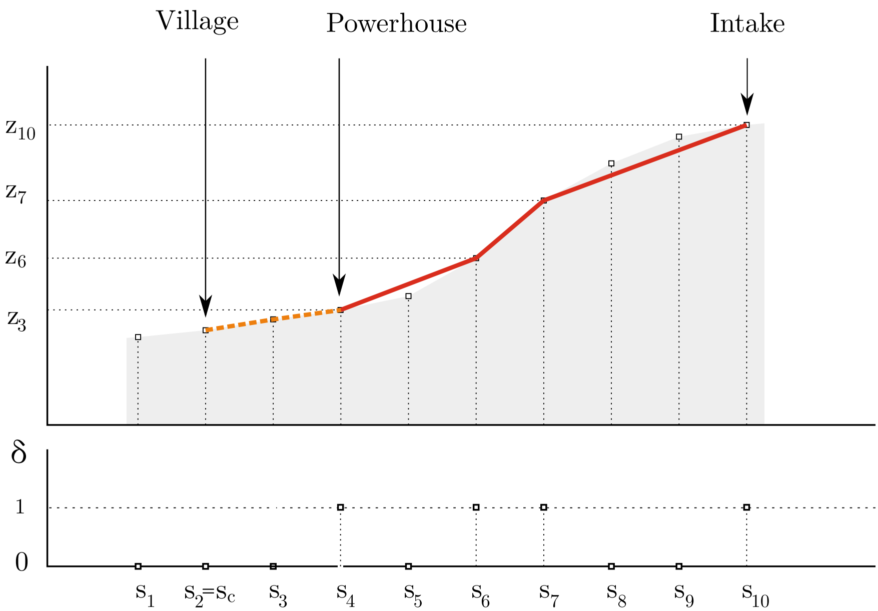

Fig. 4 Illustrative example of the layout modeling, considering an arbitrary terrain (blue dashed line) discretized by means of $N = 10$ points (squares). The arbitrary solution $\Delta = [0\,0\,0\,1\,0\,1\,1\,0\,0\,1]$ has been represented (penstock in red continuous line, distribution line in orange dashed line). Note that the connection point to the village is located in $i_c = 2$

A similar analysis can be made to determine the length of the distribution line, L_E, which can be calculated as the length of the river interval between the powerhouse location and the nearest point to the village, s_c. This is

$$L_E = \sum_{i=min(i_c,i_p)}^{max(i_c,i_p)} \left[(s_{i+1} - s_i)^2 + (z_{i+1} - z_i)^2\right]^{\frac{1}{2}} . \tag{17}$$

Please note that this expression covers the possibilities of the village connection point, s_c, being lower than the powerhouse and the opposite.

3.3 *Formulation of the Problem*

In this work, the problem consists of finding the best location of the powerhouse, and the water intake, together with the diameter and layout of the penstock. This problem is formulated in single (SO) and multi-objective (MO) modes. The SO problem is formulated as a cost minimization problem, while the MO additionally pursuits the maximization of the generated power.

The constraints applied to the problem cover the minimal energy supply required for the village, the maximum amount of water which is allowed to be extracted, and the feasibility of the penstock deployment on the terrain. These constraints are detailed below.

3.3.1 Power Constraint

The fundamental requirement of the MHPP relies in the need of a certain power level that satisfied the considered energy needs of the village. To this end, a value of the necessary power supply, P_{min}, is established on the basis of the initial evaluation of the community supplied, and usually covers illumination and shared household appliances. The constraint is then established as

$$P \geq P_{min}$$

This expression can be transformed by introducing Eqs. (15) and (16), resulting in

$$\frac{\eta\rho}{2C_D^2 S_{noz}^2}\left[\frac{z_d - z_p}{\frac{1}{2gc_D^2 S_{noz}^2} + \frac{k_{fric}}{D_p^5}\sum_{\forall(i,j)}\sqrt{(s_j - s_i)^2 + (z_j - z_i)^2}}\right]^{\frac{3}{2}} \geq P_{min}. \tag{18}$$

3.3.2 Flow Constraint

The water flow available in the stream constitutes a strong limitation to the size of the MHPP, and thus the turbine flow Q must be limited by an maximum extraction, which is defined as a fraction κ of the natural flow rate Q_{river}. This constraint is introduced in the form of

$$Q \leq \kappa Q_{river},$$

This equation can be formulated in terms of the variables of the decision variables by introducing (15) and (16), resulting in

$$\left[\frac{z_d - z_p}{\frac{1}{2gc_D^2 S_{noz}^2} + \frac{k_{fric}}{D_p^5}\sum_{\forall(i,j)}\sqrt{(s_j - s_i)^2 + (z_j - z_i)^2}}\right]^{\frac{1}{2}} \leq \kappa Q_{river}. \tag{19}$$

3.3.3 Feasibility Constraints

In order to guarantee that the obtained solutions are feasible, a set of constraints are proposed in such way that the height differences between the penstock and the terrain are small enough to be covered by using supports (see point 5 in Fig. 4) or excavations (see points 8 and 9 in Fig. 4), respectively. This is done by means of two different constraints:

- The pipe can be disposed at a certain height from the terrain profile only if this distance is smaller than the maximum available length of the supports, denoted by ϵ_{sup}.
- The pipe can be disposed under a certain depth from the terrain profile only if this distance is smaller than the maximum depth of excavations that is possible to be made, denoted by ϵ_{exc}.

Note that the both ϵ_{exc} and ϵ_{sup} must be estimated on the basis of the properties of the terrain. Using $z_{P,i}$ to denote the height of the penstock at coordinate s_i, the feasibility constraints are written as

$$z_{P,i} - z_i \leq \epsilon_{sup} \qquad \forall i = 1 \ldots N, \tag{20a}$$

$$z_j - z_{P,j} \leq \epsilon_{exc} \qquad \forall j = 1 \ldots N. \tag{20b}$$

4 Evolutionary Computational Approach

Evolutionary algorithms are meta-heuristic approaches capable of achieving significant results in complex optimization problems [48]. Although many evolutionary algorithms have been proposed in the literature [50], Genetic Algorithms (GAs) have been especially relevant in many engineering optimization problems [51–53]. GAs are population and nature-inspired approaches that are based on the process of natural selection. The main idea of GAs lies in the encoding of the solutions in a chromosome-like structure, in which each optimization variable is codified as a gen.

The working principle of a GA consists of creating a set of different individuals (population), that represents different potential solutions of the problem. These individuals evolve through a certain number of iterations named generations (see Fig. 5), successively creating new offspring that adapts better to the optimization landscape, in accordance with the survival principle of the Darwinian theory. The adaptation of an individual is measured through its quality or fitness, this is, the evaluation of the solution as an input of the objective function of the problem.

A set of genetic operators, such as selection, crossover and mutation, are used to create the offspring. The selection is an elitist operation that is based on selecting the parents that participate in the crossover and mutation operations. Therefore, individuals with higher quality have more probability of being selected as parents. The

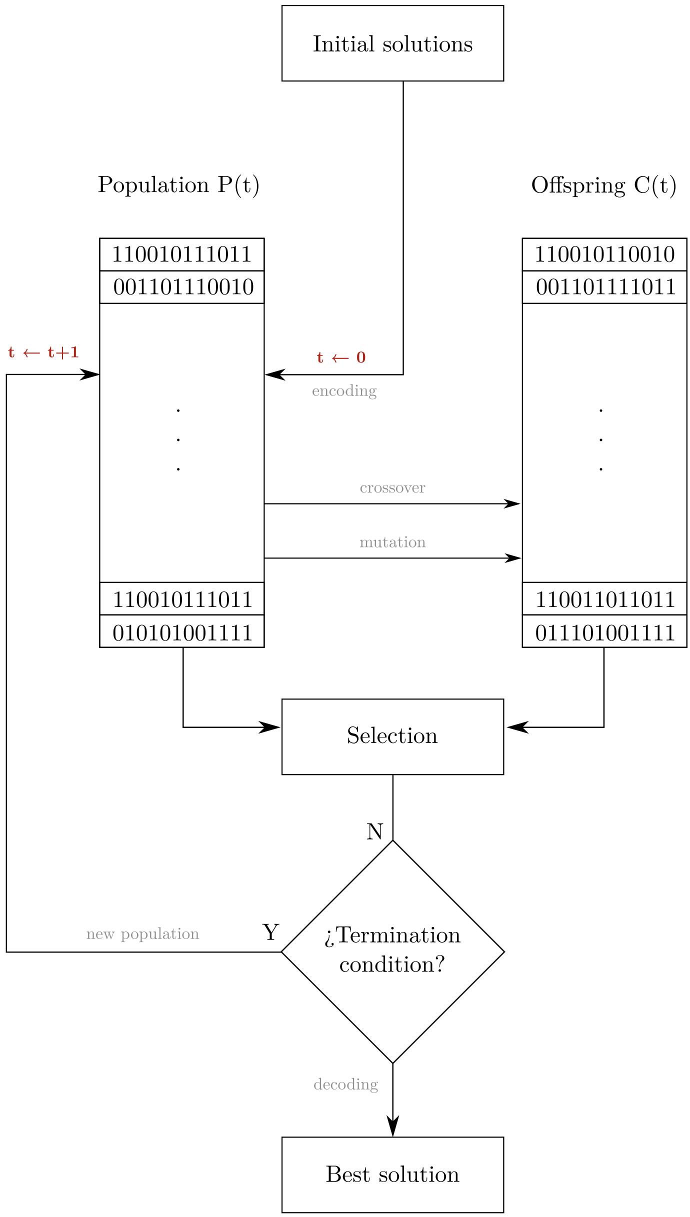

Fig. 5 Working principle of a genetic algorithm

crossover operation is based on combining the genetic information of two different individuals, creating other two new individuals. With respect to the mutation operator, it consists in changing the genetic information of an individual to generate a new one. Both crossover and mutation are probabilistic operations, and are capable of developing a good exploration and exploitation capabilities with a proper tuning.

The application of a GA to address the proposed optimization problem is based on codifying the possible layouts of the MHPP into individuals, containing the information related to the location of powerhouse and dam, the layout of the penstock and the diameter of the pipe. The fitness of the individuals is defined through the objective functions of the optimization problem. As was previously mentioned, two different configurations have been considered such as SO and MO approaches. In the single-objective case, the fitness function is the cost of the plant, and thus it is a minimization problem. On the contrary, in the MO case the GA simultaneously minimize the cost and maximizes the power. In this second case, the multi-objective case, the optimization is achieved by applying the Pareto dominance-based technique NSGA-II [54].

4.1 Single-Objective Optimization Problem

Among the many possible implementations of SO GAs, a mupluslambda scheme [55] (summarized in Algorithm 1) has been used in this work. This algorithm begins with a random initial population P_i, which is evaluated. Then, the offspring μ is created by means of crossover and mutation operations, whose probabilities are, respectively, p_{cx} and p_{mut}. Next, the offspring is evaluated, and the new population λ is selected from the offspring generated together with the previous population P_g. The benefits of this approach lie in the strong elitism, as the offspring and parents have to compete each other to be selected [55].

Algorithm 1: GA mupluslambda.

Create initial population P_i;
Evaluate P_i;
$P_g = P_i$;
while $stop == False$ **do**
    Parents' selection;
    Create offspring μ (crossover p_{cx} and mutation p_{mut});
    Evaluate μ ;
    Select new population λ (μ + P_g);
    $P_g = \lambda$;
end

The stop criteria of the GAs is generally based on a certain number of generations, after which the algorithm finishes. The final population contains the best solutions for the optimization problem.

4.1.1 Individual Representation

Each individual representing a possible design of the MHPP is a list containing the ones or zeros (binary variables) that constitute the solution Δ (according to (14)). Also, the diameter D_P of the penstock is also embedded in the chromosome in the form of a 5 bits codification, assuming that the penstock has the same diameter along its layout. The length S of the chromosome is either N or $N + 5$ depending on whether the diameter of the pipes is considered or not (see Sect. 5 for more details). The first N bits correspond to the discrete data obtained from the profile of the river (see the scheme in Fig. 6a). When the diameter D_P is considered as an optimization variable, it is embedded in the chromosome by the last five bits (see Fig. 6a). Using this codification for D_P, 32 decimal numbers can be represented. As the diameter cannot be equal to 0, the decimal numbers represented are within the interval $\{1 - 32\}$, determining the value in centimeters of the diameter D_p.

Although random generation is used to create the initial population of the GA, in order to provide feasible solutions in the initial step and avoiding discarding invalid ones, a tailored individual generator is proposed. This algorithm consists of selecting two random points (p_1 and p_2) within the interval $[1, S]$ (with $p_1 < p_2$), and filling up with ones the variables δ_i within the interval $[p_1, p_2]$ (see Fig. 6).

With this approach, the individuals of the initial population will not suffer from the demanding feasibility constraints described in Sect. 3.3, favouring an efficient exploration during the first generations of the GA.

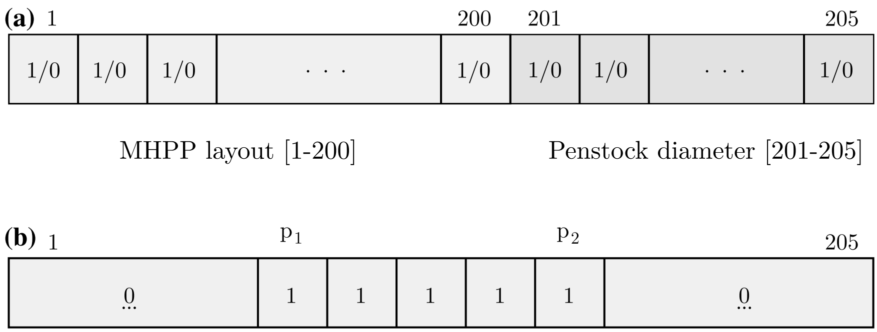

Fig. 6 Individual representation considering the diameter of the penstock D_p (**a**) and individual generation scheme (**b**)

4.1.2 Fitness Function

The cost function defined in expression (12) determines the fitness of each individual, in such way that the lower the cost, the better the solution is. In order to discard the invalid solutions and avoid their participation in the following generations, death-penalty is used. Following this, the fitness of each individual will be calculated as

$$\begin{cases} if \ \textbf{solution valid} & F = (8), \\ \quad\quad else & F = -\infty, \infty, \quad according\, to\, (18), (19), (20). \end{cases}$$

4.1.3 Genetic Operators

Given the good results that the tournament selection mechanism has demonstrated in the literature [56], it has been used in this work. This mechanism consists in selecting a number of individuals that compete each other to be chosen as a parent, being the best one selected as a parent to participate in the crossover and mutation operations [56]. The size of the tournament has been defined as three, as it has been proven suitable for a wide variety of problems.

Regarding the crossover operation, a two-points scheme is used. This consists of swapping the genetic information of the parents by mean of two points that act as indexes of the exchange. With respect to the mutation algorithm, a tailored method has been proposed. This consists in a modified flip-bit method, in which the probability of flipping a one to a zero is considerable higher than a zero to a one. The aim of this method is to reduce the cost of the layout by reducing the number of elbows of the penstock and thus its length. It is relevant to note that, given the proposed scheme for the initial generation, these individuals will have a high number of ones, and thus, a high number of elbows which translates into a high cost. With this mutation scheme, the cost is expected to be gradually reduced through the generations. For this scheme, the probability of converting a one to a zero, p_{hl}, and a zero to a one, p_{lh}, have to be established (see Sect. 5 for more details).

4.2 Multi-objective Optimization Problem

In this case, the objective is simultaneously the minimization of the cost (electrical and penstock) and the maximization of the power generation of the MHPP, in accordance with (10), (11), and (8), respectively. The MOGA used is the NSGA-II [54], based on the Pareto dominance and that has demonstrated to be capable of providing good results for a wide range of optimization problems in engineering [57]. The Pareto dominance establishes that a solution dominates another iff it is strictly superior in all considered objectives. Therefore, the aim of the NSGA-II is to find all non-dominated solutions, which form the so-called Pareto front. For the optimization problem addressed in this work, the Pareto front will consist of a curve in the 2D plane cost-power. The implementation of the MO-GA is summarized in Algorithm 2.

The main differences with respect to the single-objective case are the following:

i The evaluation of the individuals for the two objectives is required to be calculated
ii The selection mechanism is based on the Pareto dominance. For this reason, the Pareto front is updated after every generation, being this composed by all the non-dominated solution when the algorithm finishes.

Algorithm 2: GA based on NSGA-II.

Create initial population P_i;
Evaluate P_i;
$P_g = P_i$;
while $stop == False$ **do**
    Parents' selection;
    Create offspring μ (crossover p_{cx} and mutation p_{mut});
    Evaluate μ;
    Calculate dominance;
    Update Pareto front;
    Select new population based on dominance λ ($\mu + P_g$);
    $P_g = \lambda$;
end

Using the MO approach provides the decision maker with a big picture of the potential of the emplacement, allowing the consideration of different layouts if required (changes in the budget, power requirements, etc).

4.2.1 Individual Representation

The individual representation is the same as that considered in the SO case.

4.2.2 Fitness Function

In this case, the fitness of each individual is a tuple of three components (one for each objective). As was done in the SO mode, the death penalty is applied in order to penalize the invalid solutions. Note that the death penalty must be employed in each of the considered objectives, this is

$$\begin{cases} \text{if } \textbf{solution valid} & F = (8), (10), (11), \\ \qquad \text{else} & F = \infty, \quad \text{according to (18), (19), (20).} \end{cases} \tag{21}$$

4.2.3 Genetic Operators

The crossover and mutation schemes used are the same of the single-objective case.

5 Simulation Results

In this section, the proposed evolutionary approach is applied to a real location. The selected scenario consists of designing a MHPP to supply the small village of San Miguelito, in the Department of Santa Bárbara (Honduras). This rural remote community gathers ideal environmental characteristics, and given its location it lacks access to the national electrification grid. A topographic survey of the terrain is used in this Section. Also, a satellite image of the emplacement has been obtained, being i shown in Fig. 7.

5.1 Scenario Settings

The topographic survey provided a discretization of $N = 67$ points (represented in Fig. 8 for a better understanding), in the form of (13).

Fig. 7 Aerial view of the studied river profile (black) and a small tributary (white)

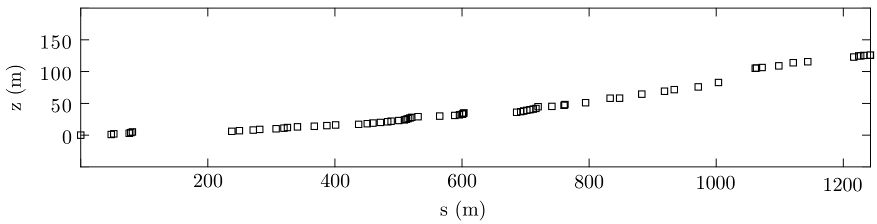

Fig. 8 Topographic data points (squares)

Table 1 Parameters of the case study

Parameter	Symbol	Value	Units
Minimal power requirement	P_{min}	8	kW
Flow of the natural course	Q_{river}	50	L/s
Maximum flow extraction allowance	κ	0.5	–
Equivalent cost of elbows	λ_c	50	m
Maximum depth of excavations	ϵ_{exc}	1.5	m
Maximum height of supports	ϵ_{sup}	1.5	m
Cost coefficient of the pipe	k_P	700	$\$/m^3$
Cost coefficient of the distribution line	k_E	22	$\$/m$

The objective of this problem is designing a MHPP to supply the community with a basic power need of 8 kW. The flow of the river is 50 l/s, and a 50% fraction is considered allowed to be extracted. The characteristics of the terrain permits the installation of supports and excavations up to 1.5 m. In addition, an equivalent cost of $\lambda_c = 50$ m is considered for the pipe elbows. The selected commercially available pipe is 600 kPa uPVC, which is suitable for pressures up to 87 m [29]. For this pipe, the coefficient has been estimated as $K_P = \$700/\text{m}^3$. With respect to the distribution line, a typical value of $k_E = \$20/\text{m}$ has been used. Note that these parameters consider the additional related costs (transport, deployment, etc). These parameters have been summarized in Table 1.

5.2 Genetic Algorithm Settings

The problem proposed is addressed by means of a GA, which employs the crossover and mutation operators proposed in Sect. 4.[1] Table 2 contains the main configuration parameters of the GA implementations.

5.3 Results

5.3.1 Single-Objective Mode

This case study represents the basic problem of optimizing a MHPP, regarding the location of the powerhouse and the dam, the layout of the penstock and its elbows, and the diameter of the pipe used. To determine the most suitable parameters of the GA, the influence of the crossover and mutation probabilities, this is p_{cx} and p_{mut},

[1]The code is available in [58]. The simulator has been developed using Python and DEAP [59].

Table 2 Parameters of the GA

Parameter	Value
λ	2000
μ	2000
Individuals (MO)	2000
Generations	100
Selection	Tournament size = 3 (SO) NSGA-II (MO)
Crossover	Two-point scheme $p_{cx} = [0.6, 0.7, 0.8]$
Mutation	Modified bit-flip $p_m = [0.4, 0.3.0.2]$, $p_{hl} = 0.8$, $p_{lh} = 0.2$
Number of trials	30

Table 3 Results of the SO problem

GA parameters				
p_{cx}	0.5	0.6	0.7	0.8
p_{mut}	0.5	0.4	0.3	0.2
Final population				
Mean fitness	10572	11403	12714	13593
Std. dev. fitness	1665.4	2243.6	2800.2	2788.1
Best individuals				
Gross height (m)	94.76	94.76	94.76	94.76
Flow rate (L/s)	13.716	13.716	13.716	13.716
Power (kW)	8.035	8.035	8.035	8.035
Penstock length (m)	753.15	753.15	753.15	753.15
Distribution line length (m)	21.39	21.39	21.39	21.39
Number of nodes	12	12	12	12
Pipe diameter (cm)	10	10	10	10
Penstock cost ($)	9471.9	9471.9	9471.9	9471.9
Distribution line cost ($)	470.58	470.58	470.58	470.58
Total cost (Fitness) ($)	9942.5	9942.5	9942.5	9942.5

has been evaluated by using the values listed in Table 2. The results obtained are summarized in Table 3. In addition, the layout corresponding to the best individual has been represented in Fig. 9.

In sight of the results listed in Table 3, some comments can be made. First, it can be seen that the four combinations of crossover and mutation probabilities led to the same optimal solution. With respect to the optimal solution, the dominance of the distribution line over the cost of the penstock in the overall cost is evidenced, as the powerhouse is located next to the connection point. This can be understood by means of the versatility of the penstock layout with respect to the distribution line. Displacing the penstock layout along the domain result in small fluctuations of the penstock

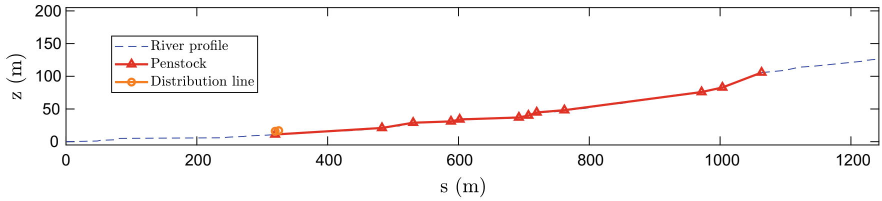

Fig. 9 Best solution obtained for SO problem. The penstock (black line), the elbows (black triangles) and the distribution line (orange line) are represented. In addition, the raw data points are also plotted (blue circles), together with a linear interpolation of these (blue dashed line)

cost (indeed two different penstocks that cover different areas of the terrain have the same cost). This does not happens with the distribution grid, as its costs is strongly conditioned by the location of the powerhouse. Nevertheless, the combination of $p_{cx} = 0.5,\ \ p_{mut} = 0.5$ has demonstrated a better overall performance, with a mean fitness of \$10572.

5.3.2 Comparison with Other Algorithm

In this section, the optimization problem proposed is addressed by means of the ILP proposed in [30], where the authors develop a linear formulation of the problem, to be solver by a Branch and Bound Algorithm (BBA). Although the linear formulation permits noticeably shorter solving times, the non-linear nature of the distribution grid definition (see expression 17) and the effects of the penstock (see expression 6) cannot be modeled, and thus, these are not able to be considered in the ILP problem. Nevertheless, the optimal diameter, $D_p = 10\,\text{cm}$, obtained by the GA is proposed for the ILP problem. The optimal layout obtained by this approach is represented in Fig. 10. Observing this last, it can be seen as the consideration of the cost of the distribution line, C_e, can constitute a conditioning for the problem. For the sake of comparison, the main variables of this solution are compared with the best solution obtained by the GA in Table 4.

It can be seen that the ILP approach provides a better (cheaper) penstock. This is due to the non consideration of the distribution grid, which strongly conditions

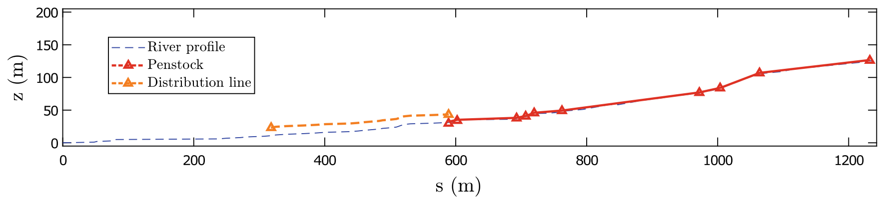

Fig. 10 Best solution obtained for SO problem obtained by using BBA [30]

Table 4 Comparison of the results of the GA and the BBA

	GA	BBA
Gross height (m)	94.76	94.45
Flow rate (l/s)	13.716	13.974
Power (kW)	8.035	10.994
Penstock length (m)	753.15	653.01
Distribution line length (m)	21.39	282.34
Number of nodes	12	10
Pipe diameter (cm)	10	10
Penstock cost ($)	9471.9	8071
Distribution line cost($)	598.96	6211.5
Total cost ($)	9942.5	14282

the location of the powerhouse. As was expected, in spite of the more economic penstock, the solution obtained by the ILP provides a much more expensive layout, as the cost of the distribution grid is noticeably higher than in the GA solution.

In conclusion, the results demonstrate the capability of the proposed GA to address the complex problem of finding the optimal layout of the MHPP with good results.

5.3.3 Multi-objective Mode

In this Section, the results of the MO problem are presented. This approach constitutes a deep analysis on the influence of the different parameters of the optimization problem, and thus the potential of the proposed emplacement for the MHPP can be evaluated. The results of the MO approach consist in the Pareto front [60], which is formed by a set of non-dominated solutions, that correspond to optimal combinations of the objective values. In this case, the economic objective of minimizing the cost of the MHPP and the maximization of the power generated are combined. The Pareto front is represented in Fig. 11.

Given the difficulty of interpreting its morphology, due to its three-dimensional nature, an interpolation surface is proposed in Fig. 12, which is developed by means of a tessellation for a better understanding.

In sight of the morphology of the Pareto front shown in Fig. 12, some comments can be made. For this, a simple scheme of the Pareto front is drawn in Fig. 13. Using this scheme, the result of fixing each of the three objectives (cost of the penstock, cost of the distribution line, and power) can be evaluated.

First, fixing the cost of the distribution line, C_e, (see Fig. 14 top) implies a maximum reachable power, which can be increased if the cost of the distribution line is also increased. This is reasonable, as fixing the cost of the distribution grid translates into fixing the location of the dam. The higher this cost is, the further the dam is placed from the community, and the larger range of domain is thus available.

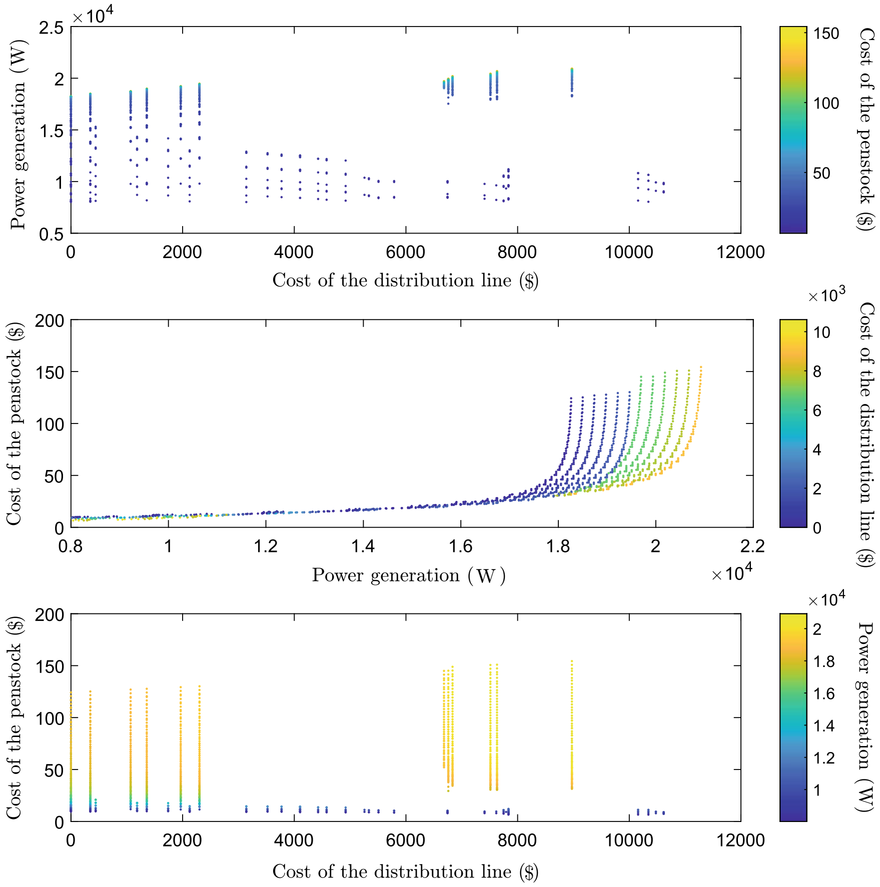

Fig. 11 Representation of the Pareto Front

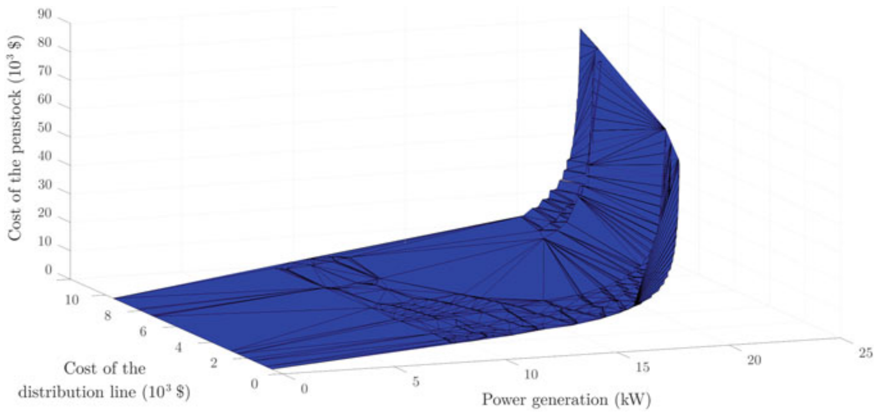

Fig. 12 Interpolation of the Pareto Front

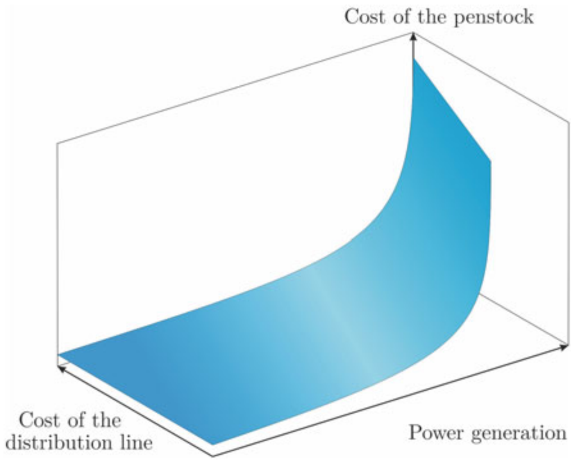

Fig. 13 Qualitative representation of the Pareto front

Secondly, the competitive nature of minimizing both the cost of the penstock and the cost of the distribution grid can be verified through the fixation of the generated power P (see Fig. 14 middle). As was expected, higher values of the power imply higher costs. A relevant aspect to note is the appearance of a minimum cost of the distribution grid, C_e for power generation values above a certain limit. This is understandable, as solutions with zero cost of the distribution grid can be obtained for low values of power P, but not for high ones, as fixing the location of the dam strongly conditions the range of possible combinations.

Finally, the fixation of the cost of the penstock, C_p, imply a extremely high sensibility of the solutions with respect to the cost of the distribution grid (see Fig. 14 bottom), as only small variations in power can be reached by displacing the penstock along the terrain, with the consequent high variances of the distribution grid due to moving the location of the dam.

An interesting analysis can be made by combining the costs related to the distribution grid and the penstock, being the Pareto front in Fig. 15 obtained as a result. In sight of the morphology of this Pareto front, some comments can be made. First, it can be seen that an improvement in one of the objectives necessarily implies worsening the other (counterbalanced objectives), what evidences the competitive nature of the cost of the plant and the power generation. Regarding the morphology, it is relevant to note that, for low values of power, a linear tendency can be observed (represented by a red dashed line in Fig. 15 for a better understanding).

This can be interpreted as a constant marginal cost of increasing the generated power. Indeed, the slope of this tendency, $r = \$656/\text{kW}$, represents the increment marginal cost of increasing the generated power in 1 kW. It can be easily understood the capacity of the solutions of reaching higher power levels by covering a higher range of the domain. For this reason, this slope is proposed as a reliable indicator of potential of the emplacement.

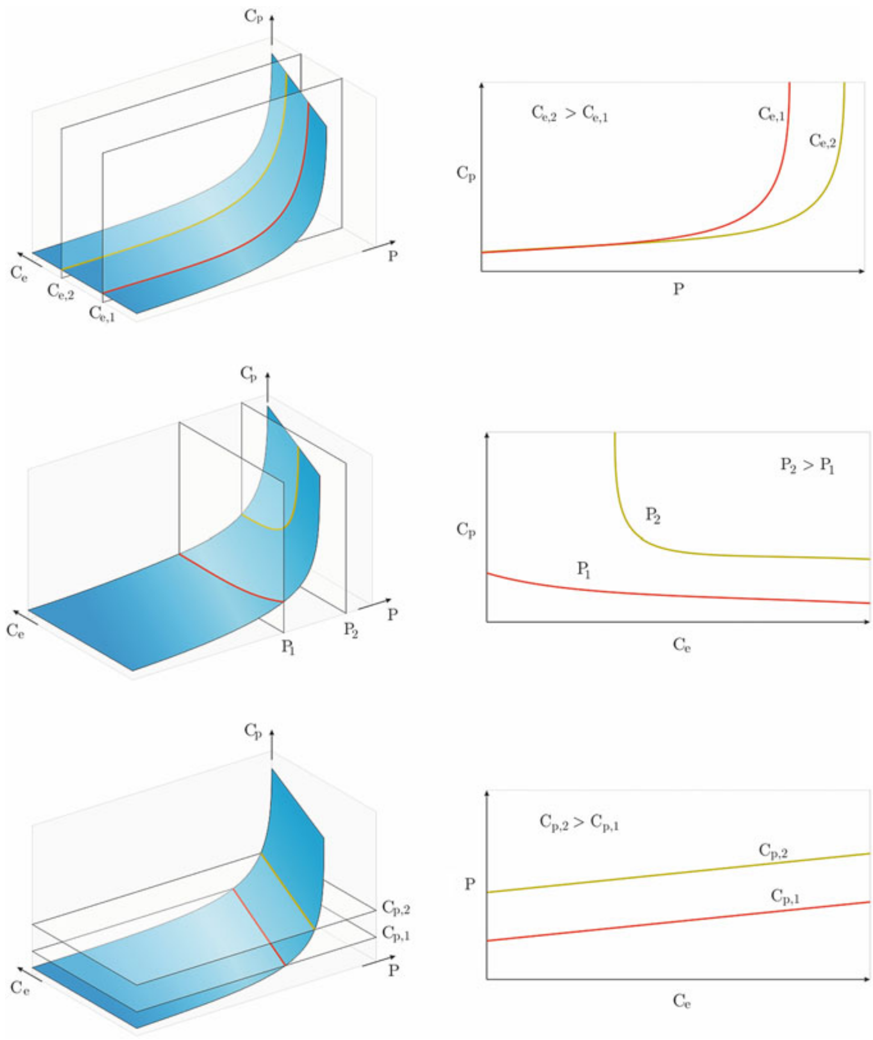

Fig. 14 Qualitative analysis of the morphology of the Pareto front

In addition, the abrupt change of this linear tendency which is observed for high values of power can also be understood by considering that the solutions can saturate the domain. For these solutions, the penstock covers the entire domain, and thus only small improvements in power can be reached by either modifying the nodes distribution and increasing the pipe diameter, which strongly affects the cost.

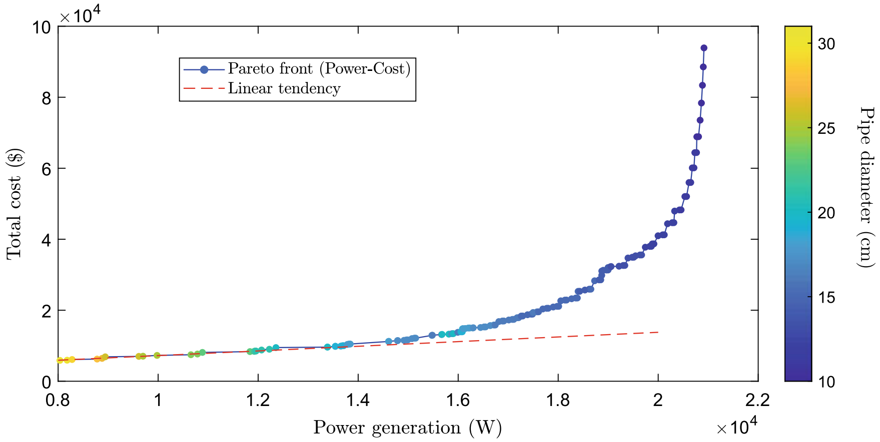

Fig. 15 Pareto front Power-Cost, electrical and penstock costs are added (coloured points and continuous blue line). The diameter of the pipe has been represented by color (see color bar). Note that the linear tendency has been also represented (red dashed)

6 Limitations of the Approach and Further Work

Despite the good results obtained in the previous section, some comments can be made regarding the limitations of the proposed approach.

First, it is relevant to note that the 2D simplification of the river profile constitutes the main limitation for the application of this approach. Thus, the reliability of the results is strongly conditioned by its application to low curvature river profiles.

Secondly, it has been assumed that the village and the river are near enough to consider that the distribution line is desirable to be deployed along the river profile. For this reason, this approach is not adequate if there is a substantial distance between these two elements, as in these cases the distribution line is generally desired to be deployed through rough terrain, for the sake of costs savings.

Considering these two issues related to the application of the proposed approach, the extension of this study to a 3D domain is proposed as a further work, with the aim of improving the modeling of the distribution line and providing a reliable model of the deployment of the penstock for rivers with non-negligible curvature.

7 Conclusions

The main conclusions of the work presented in this chapter can be summarized as follows:

- A model of a MHPP has been developed, allowing the study of the influence of the different design parameters on the performance and the costs.

- A GA has been developed to address the optimization problem of finding the most suitable layout of the MHPP.
- The proposed approach has been successfully applied to a real case in a remote village in Honduras, where a set of topographic data has been used as input.
- A single-objective mode (total cost minimization) has been first used to address the optimization problem. An optimal solution with cost \$9942.5 has been obtained, demonstrating the capability of the algorithm to address complex non-linear problem formulations with good convergence rates.
- The configuration $p_{cx} = 0.5$, $p_{mut} = 0.5$ has demonstrated the best performance, providing the lowest mean fitness (\$10572) and standard deviation (\$1665.4) in the final population.
- A multi-objective mode (power maximization, penstock cost minimization and distribution line minimization) has additionally been applied to the optimization problem, being the Pareto front determined. This has provided a deep study of the potential of the emplacement. The marginal cost of increasing the generated power of the MHPP has been determined in \$656 per additional kWatt installed.

Acknowledgements This research has been partially funded by the University of Seville under the contract "Contratos de acceso al Sistema Español de Ciencia, Tecnología e Innovación para el desarrollo del programa propio de I+D+i de la Universidad de Sevilla" of D. G. Reina.

References

1. Nejat, Payam, Fatemeh Jomehzadeh, Mohammad Mahdi Taheri, Mohammad Gohari, and Muhd Zaimi Abd Majid. 2015. A global review of energy consumption, co2 emissions and policy in the residential sector (with an overview of the top ten co2 emitting countries). *Renewable and Sustainable Energy Reviews* 43: 843–862.
2. International Energy Agency. 2017. WEO-2017 Special Report: Energy Access Outlook.
3. Pereira, Marcio Giannini, José Antonio Sena, Marcos Aurélio Vasconcelos Freitas, and Neilton Fidelis Da Silva. 2011. Evaluation of the impact of access to electricity: A comparative analysis of South Africa, China, India and Brazil. *Renewable and Sustainable Energy Reviews* 15 (3): 1427–1441.
4. OECD. 2016. *Linking renewable energy to rural development, OECD green growth studies*. OECD Publishing.
5. Krewitt, Wolfram, Sonja Simon, Wina Graus, Sven Teskec, Arthouros Zervos, and Oliver Schafer. 2008. The 2 degrees c scenario-a sustainable world energy perspective (vol 35, pg 4969, 2007). *Energy Policy* 36 (1): 494–494.
6. Luderer, Gunnar, Volker Krey, Katherine Calvin, James Merrick, Silvana Mima, Robert Pietzcker, Jasper Van Vliet, and Kenichi Wada. 2014. The role of renewable energy in climate stabilization: Results from the EMF27 scenarios. *Climatic Change* 123 (3–4): 427–441.
7. United Nations Environment Programme. 2009. Renewables global status report: 2009 update. *Internet*. http://www.unep.fr/shared/docs/publications/RE_GSR_2009_Update.pdf.
8. Kanase-Patil, A.B., R.P. Saini, and M.P. Sharma. 2010. Integrated renewable energy systems for off grid rural electrification of remote area. *Renewable Energy* 35 (6): 1342–1349.
9. Bugaje, I.M. 2006. Renewable energy for sustainable development in Africa: A review. *Renewable and Sustainable Energy Reviews* 10 (6): 603–612.
10. Sahoo, Sarat Kumar. 2016. Renewable and sustainable energy reviews solar photovoltaic energy progress in India: A review. *Renewable and Sustainable Energy Reviews* 59: 927–939.

11. Saheb-Koussa, D., Mourad Haddadi, and Maiouf Belhamel. 2009. Economic and technical study of a hybrid system (wind–photovoltaic–diesel) for rural electrification in Algeria. *Applied Energy* 86 (7–8): 1024–1030.
12. Mohammed, Y.S., A.S. Mokhtar, Naomi Bashir, and R. Saidur. 2013. An overview of agricultural biomass for decentralized rural energy in Ghana. *Renewable and Sustainable Energy Reviews* 20:15–25.
13. Sachdev, Hira Singh, Ashok Kumar Akella, and Niranjan Kumar. 2015. Analysis and evaluation of small hydropower plants: A bibliographical survey. *Renewable and Sustainable Energy Reviews* 51: 1013–1022.
14. Kaldellis, J., and K. Kavadias. 2000. *Laboratory applications of renewable energy sources*. Athens: Stamoulis.
15. ESMAP. 2017. Technical and economic assessment of off-grid. Technical report, 12.
16. Muhammad Indra, al Irsyad, Anthony Halog, and Rabindra Nepal. 2019. Renewable energy projections for climate change mitigation: An analysis of uncertainty and errors. *Renewable Energy* 130: 536–546.
17. Jawahar, C.P., and Prawin Angel Michael. 2017. A review on turbines for micro hydro power plant. *Renewable and Sustainable Energy Reviews* 72: 882–887.
18. Khurana, S., and Anoop Kumar. 2011. Small hydro power, a review. *International Journal of Thermal Technologies* 1(1): 107–110.
19. Mandelli, Stefano, Jacopo Barbieri, Riccardo Mereu, and Emanuela Colombo. 2016. Off-grid systems for rural electrification in developing countries: Definitions, classification and a comprehensive literature review. *Renewable and Sustainable Energy Reviews* 58: 1621–1646.
20. Carravetta A., Derakhshan Houreh S., and Ramos H.M. 2018. *Pumps as turbines. Springer tracts in mechanical engineering*. Springer.
21. Cobb, Bryan R., and Kendra V. Sharp. 2013. Impulse (turgo and pelton) turbine performance characteristics and their impact on pico-hydro installations. *Renewable Energy* 50: 959–964.
22. Sangal, Saurabh, Arpit Garg, and Dinesh Kumar. 2013. Review of optimal selection of turbines for hydroelectric projects. *International Journal of Emerging Technology and Advance Engineering* 3: 424–430.
23. Herschy, Reginald W. 2014. *Streamflow Measurement*, vol. 3.
24. Thake, J. 2000. *Micro-hydro Pelton Turbine Manual: Design, manufacture and installation for small-scale hydropower*.
25. Mishra, Sachin, S.K. Singal, and D.K. Khatod. 2011. Optimal installation of small hydropower plant. A review. *Renewable and Sustainable Energy Reviews* 15 (8): 3862–3869.
26. Elbatran, A.H., O.B. Yaakob, Yasser M. Ahmed, and H.M. Shabara. 2015. Operation, performance and economic analysis of low head micro-hydropower turbines for rural and remote areas: A review. *Renewable and Sustainable Energy Reviews* 43: 40–50.
27. Haddad, Omid Bozorg, Mahdi Moradi-Jalal, and Miguel A. Marino. 2011. Design–operation optimisation of run-of-river power plants. In *Proceedings of the institution of civil engineers-water management*, vol. 164, 463–475. Thomas Telford Ltd.
28. Anagnostopoulos, John S., and Dimitris E. Papantonis. 2007. Optimal sizing of a run-of-river small hydropower plant. *Energy Conversion and Management* 48 (10): 2663–2670.
29. Alexander, K.V., and E.P. Giddens. 2008. Optimum penstocks for low head microhydro schemes. *Renewable Energy* 33 (3): 507–519.
30. Tapia, A., P. Millán, and F. Gómez-Estern. 2018. Integer programming to optimize micro-hydro power plants for generic river profiles. *Renewable Energy* 126: 905–914.
31. Gingold, P.R. 1981. The optimum size of small run-of-river plants. *International Water Power and Dam Construction* 33 (11).
32. Marliansyah, Romy, Dwini Normayulisa Putri, Andy Khootama, and Heri Hermansyah. 2018. Optimization potential analysis of micro-hydro power plant (MHPP) from river with low head. *Energy Procedia* 153: 74–79.
33. Iqbal, M., M. Azam, M. Naeem, A.S. Khwaja, and A. Anpalagan. 2014. Optimization classification, algorithms and tools for renewable energy: A review. *Renewable and Sustainable Energy Reviews* 39: 640–654.

34. Banos, Raul, Francisco Manzano-Agugliaro, F.G. Montoya, Consolacion Gil, Alfredo Alcayde, and Julio Gómez. 2011. Optimization methods applied to renewable and sustainable energy: A review. *Renewable and Sustainable Energy Reviews* 15 (4): 1753–1766.
35. Singal, S.K., R.P. Saini, and C.S. Raghuvanshi. 2010. Analysis for cost estimation of low head run-of-river small hydropower schemes. *Energy for Sustainable Development* 14 (2): 117–126.
36. Mohamad, Hasmaini, Hazlie Mokhlis, Hew Wooi Ping, et al. 2011. A review on islanding operation and control for distribution network connected with small hydro power plant. *Renewable and Sustainable Energy Reviews* 15 (8): 3952–3962.
37. Nand Kishor, R.P. Saini, and S.P. Singh. 2007. A review on hydropower plant models and control. *Renewable and Sustainable Energy Reviews* 11 (5): 776–796.
38. Leon, Arturo S., and Ling Zhu. 2014. A dimensional analysis for determining optimal discharge and penstock diameter in impulse and reaction water turbines. *Renewable Energy* 71: 609–615.
39. Basso, S., and G. Botter. 2012. Streamflow variability and optimal capacity of run-of-river hydropower plants. *Water Resources Research* 48 (10).
40. Yildiz, Veysel, and Jasper A. Vrugt. 2019. A toolbox for the optimal design of run-of-river hydropower plants. *Environmental Modelling & Software* 111: 134–152.
41. Yoo, Ju-Hwan. 2009. Maximization of hydropower generation through the application of a linear programming model. *Journal of Hydrology* 376 (1–2): 182–187.
42. Das, Himansu, Ajay Kumar Jena, Janmenjoy Nayak, Bighnaraj Naik, and H.S. Behera. 2015. A novel PSO based back propagation learning-MLP (PSO-BP-MLP) for classification. In *Computational intelligence in data mining*, vol. 2, 461–471. Springer.
43. Nayak, Janmenjoy, Bighnaraj Naik, A.K. Jena, Rabindra K. Barik, and Himansu Das. 2018. Nature inspired optimizations in cloud computing: Applications and challenges. In *Cloud computing for optimization: Foundations, applications, and challenges*, 1–26. Springer.
44. Alvarado-Barrios, Lázaro, A. Rodríguez del Nozal, A. Tapia, José Luis Martínez-Ramos, and D.G. Reina. 2019. An evolutionary computational approach for the problem of unit commitment and economic dispatch in microgrids under several operation modes. *Energies* 12 (11): 2143.
45. Anagnostopoulos, John S., and Dimitrios E. Papantonis. 2007. Flow modeling and runner design optimization in turgo water turbines. *International Journal of Mechanical, Aerospace, Industrial and Mechatronics Engineering*, 1 (4): 204–209.
46. Ehteram, Mohammad, Hojat Karami, Sayed-Farhad Mousavi, Saeed Farzin, and Ozgur Kisi. 2018. Evaluation of contemporary evolutionary algorithms for optimization in reservoir operation and water supply. *Journal of Water Supply: Research and Technology-Aqua* 67 (1): 54–67.
47. Tapia, A., D.G. Reina, and P. Millán. 2019. An evolutionary computational approach for designing micro hydro power plants. *Energies* 12 (5): 878.
48. Holland, John H. 1984. *Genetic algorithms and adaptation*. USA: Springer.
49. Itō, H., and K. Imai. 1973. Energy losses at 90 pipe junctions. *Journal of the Hydraulics Division* 99 (9): 1353–1368.
50. Dasgupta, Dipankar, and Zbigniew Michalewicz. 2013. *Evolutionary algorithms in engineering applications*. Springer Science & Business Media.
51. Reina, D.G., T. Camp, A. Munjal, and S.L. Toral. 2018. Evolutionary deployment and local search-based movements of 0th responders in disaster scenarios. *Future Generation Computer Systems* 88: 61–78.
52. Arzamendia, Mario, Derlis Gregor, Daniel Gutierrez Reina, and Sergio Luis Toral. 2017. An evolutionary approach to constrained path planning of an autonomous surface vehicle for maximizing the covered area of Ypacarai lake. *Soft Computing* 1–12.
53. Gutiérrez-Reina, Daniel, Vishal Sharma, Ilsun You, and Sergio Toral. 2018. Dissimilarity metric based on local neighboring information and genetic programming for data dissemination in vehicular ad hoc networks (vanets). *Sensors* 18 (7): 2320.
54. Deb, Kalyanmoy, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan. 2002. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE transactions on evolutionary computation* 6 (2): 182–197.
55. Ter-Sarkisov, Aram, and Stephen Marsland. 2011. Convergence properties of two $(\mu + \lambda)$ evolutionary algorithms on onemax and royal roads test functions. arXiv:1108.4080.

56. Luke, Sean. 2009. *Essentials of metaheuristics*, vol. 113. Lulu Raleigh.
57. Reina, D.G., J.M. León-Coca, S.L. Toral, E. Asimakopoulou, F. Barrero, P. Norrington, and N. Bessis. 2014. Multi-objective performance optimization of a probabilistic similarity/dissimilarity-based broadcasting scheme for mobile ad hoc networks in disaster response scenarios. *Soft Computing* 18 (9): 1745–1756.
58. Gutiérrez, D. 2018. Evolutionary MHPP. https://github.com/Dany503/Evolutionary-MHPP.
59. Fortin, Félix-Antoine, François-Michel De Rainville, Marc-André Gardner, Marc Parizeau, and Christian Gagné. 2012. Deap: Evolutionary algorithms made easy. *Journal of Machine Learning Research* 13 (Jul): 2171–2175.
60. Reina, D.G., R.I. Ciobanu, S.L. Toral, and C. Dobre. 2016. A multi-objective optimization of data dissemination in delay tolerant networks. *Expert Systems with Applications* 57 (C): 178–191.