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Particle swarm optimization for biomass-fuelled systems with technical constraints

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ABSTRACT

This paper introduces a binary particle swarm optimization-based method to accomplish optimal location of biomass-fuelled systems for distributed power generation. The approach also provides the supply area for the biomass plant and takes technical constraints into account. This issue can be formulated as a nonlinear optimization problem. In rural or radial distribution networks the main technical constraint is the impact on the voltage profile. Biomass is one of the most promising renewable energy sources in Europe, but more research is required to prove that power generation from biomass is both technically and economically viable. Forest residues are here considered as biomass source, and the fitness function to be optimized is the profitability index. A fair comparison between the proposed algorithm and genetic algorithms (GAs) is performed. For such goal, convergence curves of the average profitability index versus number of iterations are computed. The proposed algorithm reaches a better solution than GAs when considering similar computational cost (similar number of evaluations).

1. Introduction

Renewable electricity generation has emerged as one of the favored options for dealing with fossil fuel depletion, green house gas emissions and subsequent adverse effects like global warming. As an outcome of the Kyoto protocol, one of the European Union's objectives is to increase the contribution of renewable energy sources up to 12% of the total energy supplied by 2010.

Biomass is one of the most promising renewable energy sources in Europe, but more research is required to prove that power generation from biomass is both technically and economically viable. In such sense, some interesting results can be found in Kumar et al. (2003) and Jurado and Cano (2006). The main advantage of biomass-based power generation is that the cycle of growth and combustion of biomass has a net zero level of CO_2 production. Also, the use of biomass generates employment and rural economic progress where it takes place, contributing to sustainable development.

There are many forms of biomass, the forest residues constitute one of the most important biomass sources. In this paper, we are concerned with forest residues as biomass source. They are not habitually convertible in by-products. However, they can be used as organic fuel, providing the following additional advantages: reducing forest pests, decreasing the forest fire risk, reducing environmental impacts, etc. The principle factors to assess the possibilities of forest residues to generate electrical energy are: forest vegetation density, type of trees, accessibility and orography of the terrain, age of the forest vegetation, size of tops, needles, branches, etc.

There are several options to produce electricity from biomass: combustion, gasification and pyrolysis, gasification being the most efficient one. Gasification of biomass is a thermal treatment, which ensues in a high production of gaseous products and small amounts of char and ash. Steam reforming of hydrocarbons, partial oxidation of heavy oil residues, selected steam reforming of aromatic compounds, and gasification of coals and solid wastes to yield a mixture of H_2 and CO, accompanied by water–gas shift conversion to produce H_2 and CO_2, are well-proved processes (Jurado et al., 2001).

Gas derived from biomass gasification is a renewable fuel, which can be used for electricity production. The gasifier heats with limited oxygen supply the forest residues, the final result being a very clean-burning gas fuel suitable for direct use in gas turbines or gas engine. In this article, the chosen biomass-fuelled system is a fuel cell-microturbine hybrid power cycle.

A fuel cell is an electrochemical device that converts chemical energy directly into electrical energy. It is based on the inverse reaction of the electrolysis. Different types of fuel cells exist with different performances and components. The classification is based on the electrolyte, resulting in the following types of fuel

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cells: proton exchange membrane fuel cell (PEMFC), phosphoric acid fuel cell (PAFC), molten carbonate fuel cell (MCFC), solid oxide fuel cell (SOFC) (Ellis et al., 2001). Among them, the most promising one is the SOFC. It is composed of an electrolyte metallic oxide, no porous and good conductive, it can be manufactured in different geometric setups (planar, tubular, monolithic, etc.) and it is characterized fundamentally by their high operating temperature (between 800 and 1000 °C). These high temperatures simplify system configuration by permitting internal reforming and accepting their components determined gases that are very polluting for another type of fuel cells. The high operating temperatures facilitate the development of cogeneration systems as well as hybrid power systems formed by the own fuel cell and a gas turbine. The thermal energy generated by electrochemical reactions in the fuel cell is utilized to produce more output power by a gas turbine. As result, higher overall efficiency is expected (approximately 60%) in comparison to that obtained from individual systems (Ellis et al., 2001; Williams et al., 2004; Kuchonthara et al., 2003).

Microturbines (MT) generate between 25 and 200 kW of electricity. Their relatively low cost and small size allow them to be located near where they are needed. They can operate at very low emission levels and reduce the efficiency losses and environmental impact of large transmission and distribution systems. In this paper, SOFC is associated with a biogas microturbine (SOFC-MT system) to produce electric power (Jurado and Saenz, 2003; Jurado, 2003).

A biomass-based power system presents the problem of determining the optimal placement and the supply area for the biomass plant in order to provide a given electric power. It is probably that distributed generation (DG) will consider some distributed source connected to remote areas, where electric networks are weak and the demand is small. Given the more resistive feature of the distribution networks, it is awaited that generators will have a significant impact, positive or negative in unlike circumstances, on the voltage profile. As a result, a planning technique for DG must study the effect that generation will have on the network voltage. In rural or radial distribution networks the main constraint for the power flow is the impact on the voltage profile (Jurado and Cano, 2006). As a result, the DG planning technique must include an appropriate power flow technique. When a realistic problem formulation with all above-mentioned considerations is to be solved, most analytical, numerical programming or heuristic methods are unable to work well. In recent years, artificial intelligence (AI)-based methods, such as genetic algorithms (GAs), have been applied to similar problems with promising results (Boone and Chiang, 1993). Meanwhile, some new AI-based methods have been introduced and developed. Although these AI-based methods do not always guarantee the globally optimal solution, they provide suboptimal (near-globally optimal) solutions in short CPU times. This paper employs a modern AI-based method, particle swarm optimization (PSO) (Kennedy and Eberhart, 1995; Eberhart and Kennedy, 1995; Kennedy, 1997), to solve the problem of determining the optimal placement and the supply area for a biomass-fuelled system. In this work, the fitness function for the PSO algorithm is the profitability index (Eq. (21)).

PSO is a nature-inspired evolutionary stochastic algorithm developed by Kennedy and Eberhart (1995). This technique, motivated by social behavior of organisms such as bird flocking and fish schooling, has been shown to be effective in optimizing multidimensional problems. PSO, as an optimization tool, provides a population-based search procedure, in which individuals, called particles, change their positions (states) with the time. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The main advantages of PSO are: (1) it is very easy to be implemented and (2) there are few parameters to adjust.

2. Particle swarm optimization

2.1. Classical approach

The classical PSO algorithm is initialized with a swarm of particles randomly placed on the search space. At the tth iteration, position of the ith particle is updated by adding to its previous position the new velocity vector, according to the following equation:

$$x_{i,j}^t = x_{i,j}^{t-1} + v_{i,j}^t, \quad i = 1, \ldots, P, \; j = 1, \ldots, N \tag{1}$$

where $\mathbf{x}_i^t = [x_{i,1}^t, \ldots, x_{i,N}^t]$ denotes the position vector of the ith particle at the tth iteration, and $\mathbf{v}_i^t = [v_{i,1}^t, \ldots, v_{i,N}^t]$ represents the velocity vector of the ith particle at the tth iteration, N being the number of variables of the function to be optimized and P the number of particles in the swarm.

The velocity vector $\mathbf{v}_i^t$ is updated according to the following equation:

$$v_{i,j}^t = \omega \cdot v_{i,j}^{t-1} + c_1 \cdot \mathrm{rand}_{1_i} \cdot (\mathrm{pbest}_{i,j}^{t-1} - x_{i,j}^{t-1}) + c_2 \cdot \mathrm{rand}_{2_i} \cdot (\mathrm{gbest}^{t-1} - x_{i,j}^{t-1}) \tag{2}$$

where $\mathbf{pbest}_i^{t-1} = [\mathrm{pbest}_{i,1}^{t-1}, \ldots, \mathrm{pbest}_{i,N}^{t-1}]$ is the best solution achieved for the ith particle at the $(t-1)$th iteration, and $\mathbf{gbest}^{t-1} = [\mathrm{gbest}_1^{t-1}, \ldots, \mathrm{gbest}_N^{t-1}]$ is the best position found for all particles in the swarm at the $(t-1)$th iteration. c_1 and c_2 are positive real numbers, called learning factors or acceleration constants, that are used to weight the particle individual knowledge and the swarm social knowledge, respectively. rand_{1_i} and rand_{2_i} are real random numbers uniformly distributed between 0 and 1, that make stochastic changes in the ith particle trajectory. Finally, ω is the inertia weight factor, which represents the weighting of a particle's previous velocity; a suitable selection of inertia weight in (2) provides a balance between global and local explorations, thus requiring less iterations on average to achieve a suboptimal solution.

From Eq. (2), we can find that the current flying velocity of a particle comprises three terms. The first term is related to the particle's previous velocity, revealing that a PSO system has memory. The second and third terms represent the cognitive-model part and the social-model part, respectively.

2.2. Binary PSO

The classical version of the PSO algorithm operates in a continuous search space. In order to solve optimization problems in discrete search spaces, several binary discrete PSO algorithms have been proposed. In this section some of these algorithms are briefly reviewed.

In a binary discrete space the position of a particle is represented by a N-length bit string and the movement of the particle consists of flipping some of these bits.

Kennedy and Eberhart (1997) propose the first binary version of PSO. This algorithm updates the velocity vector $\mathbf{v}_i^t$ according to Eq. (2), but variable $v_{i,j}^t$ is interpreted as the probability of the bit at position j of particle i at the tth iteration to become '1'. Since the computed velocity can be greater than 1.0 or even less than 0.0, a sigmoid function (Eq. (3)) is applied to variable $v_{i,j}^t$ in order to transform velocity values into the range [0.0, 1.0].

$$S(v_{i,j}^t) = \frac{1.0}{1.0 + e^{-v_{i,j}^t}} \tag{3}$$

The position of the ith particle in Kennedy and Eberhart (1997) is updated according to expression

$$x_{i,j}^t = \begin{cases} `1' & \text{if } (\text{rand} < S(v_{i,j}^t)) \\ `0' & \text{otherwise} \end{cases} \tag{4}$$

where rand is a real random number uniformly distributed between 0 and 1.

Afshinmanesh et al. (2005), propose a different binary PSO algorithm. In this algorithm distance and velocity are defined as the changes in bits of a binary string. The algorithm uses the Hamming distance, and the logical AND ('$\cdot$'), OR ('+') and XOR ('$\oplus$') operators. The procedure for updating particle position and velocity can be summarized as follows:

$$x_{i,j}^t = x_{i,j}^{t-1} \oplus v_{i,j}^t, \quad i = 1, \ldots, P, \; j = 1, \ldots, N \tag{5}$$

$$v_{i,j}^t = c_{1_{i,j}} \cdot d_{1_{i,j}}^{t-1} + c_{2_{i,j}} \cdot d_{2_{i,j}}^{t-1} \tag{6}$$

where $\mathbf{c_1}_i = [c_{1_{i,1}}, \ldots, c_{1_{i,N}}]$ and $\mathbf{c_2}_i = [c_{2_{i,1}}, \ldots, c_{2_{i,N}}]$ are random N-length binary strings, whose components are '0' or '1' with the same probability. In Eq. (6), $\mathbf{d_1}_i^{t-1} = [d_{1_{i,1}}^{t-1}, \ldots, d_{1_{i,N}}^{t-1}]$ is the distance vector (in the Hamming sense) between the position of the ith particle at the $(t-1)$th iteration and its previous best position ($\mathbf{pbest}_i^{t-1} = [\text{pbest}_{i,1}^{t-1}, \ldots, \text{pbest}_{i,N}^{t-1}]$, and $\mathbf{d_2}_i^{t-1} = [d_{2_{i,1}}^{t-1}, \ldots, d_{2_{i,N}}^{t-1}]$ is the Hamming distance vector between the position of the ith particle at the $(t-1)$th iteration and the previous global best position ($\mathbf{gbest}^{t-1} = [\text{gbest}_1^{t-1}, \ldots, \text{gbest}_N^{t-1}]$. The Hamming distance is computed by means of the XOR operator:

$$d_{1_{i,j}}^{t-1} = \text{pbest}_{i,j}^{t-1} \oplus x_{i,j}^{t-1} \tag{7}$$

$$d_{2_{i,j}}^{t-1} = \text{gbest}_j^{t-1} \oplus x_{i,j}^{t-1} \tag{8}$$

This algorithm is completed with a mechanism based on an artificial immune system in order to limit the maximum number of bits with value '1' in the velocity vector.

Amonchanchahigul and Kreesuradej (2006) propose other different approach to the Binary PSO. The learning process of each particle considers three methods: learning from the global best value, learning from the best value found for each particle and learning without any reference value. In Rastegar et al. (2004), a binary PSO algorithm based on learning automata can be found. Finally, in Sadri and Suen (2006) concepts as birth and mortality rates are incorporated into the Kennedy and Eberhart's (1997) binary PSO, in order to combine GA ideas with PSO.

In this work, we have applied a improved version of the binary PSO algorithm proposed in Afshinmanesh et al. (2005), which incorporates a inertia weight factor, as in the classical continuous approach (Kennedy and Eberhart, 1995). In the proposed binary PSO algorithm, particle position ($\mathbf{x}_i$) and particle velocity ($\mathbf{v}_i$) are N-length binary vectors. Particle position is updated by using the XOR operator instead of real adding, as in Afshinmanesh et al. (2005):

$$x_{i,j}^t = x_{i,j}^{t-1} \oplus v_{i,j}^t, \quad i = 1, \ldots, P, \; j = 1, \ldots, N \tag{9}$$

In our approach, the velocity vector can be interpreted as a change vector. Thus, if $v_{i,j}^t = `1'$, then $x_{i,j}^t = \bar{x}_{i,j}^{t-1}$, $\bar{x}_{i,j}^{t-1}$ being the logical negation of $x_{i,j}^{t-1}$. However, if $v_{i,j} = `0'$, then $x_{i,j}^t = x_{i,j}^{t-1}$ (no change happens).

The velocity vector (change vector) is updated by applying the following equation:

$$v_{i,j}^t = \bar{\omega}_{i,j} + \omega_{i,j} \cdot (c_{1_{i,j}} \cdot (\text{pbest}_{i,j}^{t-1} \oplus x_{i,j}^{t-1}) \\ + c_{2_{i,j}} \cdot (\text{gbest}_j^{t-1} \oplus x_{i,j}^{t-1})) \tag{10}$$

where vectors $\mathbf{pbest}_i^{t-1} = [\text{pbest}_{i,1}^{t-1}, \ldots, \text{pbest}_{i,N}^{t-1}]$, $\mathbf{gbest}^{t-1} = [\text{gbest}_1^{t-1}, \ldots, \text{gbest}_N^{t-1}]$, $\mathbf{c_1}_i = [c_{1_{i,1}}, \ldots, c_{1_{i,N}}]$ and $\mathbf{c_2}_i = [c_{2_{i,1}}, \ldots, c_{2_{i,N}}]$ have already defined, and symbols '+' and '$\cdot$' represent the logical OR and AND operators, respectively.

The remaining terms are now defined:

- $\boldsymbol{\omega}_i = [\omega_{i,1}, \ldots, \omega_{i,N}]$ is the inertial vector of the ith particle. It is a random N-length binary vector, whose components are '0' with probability P_ω.
- $\bar{\boldsymbol{\omega}}_i = [\bar{\omega}_{i,1}, \ldots, \bar{\omega}_{i,N}]$ is the one's complement of inertial vector $\boldsymbol{\omega}_i$.

In our improved binary PSO approach, a very important parameter is probability P_ω, here called *inertial probability*. As just stated, bits in $\boldsymbol{\omega}_i$ are '0' with probability P_ω. Inertial probability decreases with the number of iterations, in such a way that at the initial iterations (high P_ω values) the algorithm *explores* the search space and at the last iterations (low P_ω values) the algorithm *exploit* the search space.

It must be noted that if $\omega_{i,j} = `0'$, then $v_{i,j}^t = `1'$, and so position of the ith particle is changed. However, if $\omega_{i,j} = `1'$, the movement of the ith particle at the tth iteration is conducted by $\mathbf{pbest}_i^{t-1}$ and $\mathbf{gbest}^{t-1}$ solutions, with a partially stochastic behavior due to the random learning vectors $\mathbf{c_1}_i$ and $\mathbf{c_2}_i$.

The idea is to allow particle swarm to perform a random exploration over the space search at the initial iterations. Later, when the swarm has acquired enough knowledge about the problem, the movement of each particle is mainly conducted by $\mathbf{pbest}_i$ and $\mathbf{gbest}$ solutions. In this work, an exponentially decreasing function is used for probability P_ω:

$$P_\omega^t = P_\omega^1 \exp(-\lambda \cdot (t-1)), \quad t = 1, 2, \ldots, t_{\max} \tag{11}$$

where P_ω^t is the inertial probability at the tth iteration, P_ω^1 the initial inertial probability and $t_{\max}$ the maximum number of iterations. Parameter λ is computed as follows:

$$\lambda = \frac{\ln\left(\frac{P_\omega^1}{P_\omega^{t_{\max}}}\right)}{t_{\max} - 1} \tag{12}$$

where $P_\omega^{t_{\max}}$ is the final inertial probability.

3. Problem description and coding of the solution

3.1. Problem description

The problem to be solved consists on determining the optimal location of a forest residues-based biomass power plant. The size of the generation system depends on: (1) biomass quantity that can be collected and (2) selection of parcels where to collect the biomass. Location of power plant (parcel p) mainly depends on the characteristics of considered parcels. In this work, K parcels of constant area have been regarded, all of them characterized by a predominant biomass type (forest residues in this work). These parcels also present other relevant characteristics, such as accessibility (Freppaz et al., 2004).

The values of the variables involved in the problem are obtained from databases or geographic information systems (GIS). In this work, a raster-based GIS has been considered. A raster model represents the region under study as a tessellation, with grid cells having a certain length and width and covering the entire rectangular area of interest. The values in a given cell (sometimes called pixel) represent the geographic feature set corresponding to the entire cell area. The real world is modelled as a complete covering of square cells. For the problem here considered, raster data model is better suited than vector data model, because it is required to deal with the overlaying of different geographic features (or variables) (Harmon and Anderson, 2003). The geographic variables considered in this work are the following:

- S_i: Area of parcel i (km^2).
- U_i: Usability coefficient of parcel i. It is applied to take into account only the usable surface.
- D_i: Net density of dry biomass yield from parcel i (ton/(km^2 yr)).
- LHV_i: Lower heat value of biomass in parcel i (MW h/ton).
- L_p: Length of the electric line that connects the power plant to the grid (km).
- $\mathrm{dist}(p,i)$: Distance between parcel i and the power plant, which is located in parcel p (km).
- C_{cu_i}: Biomass collection unit cost in parcel i (€/ton).

Therefore, given the total mean efficiency of the electric generation system, η, the electricity produced, E_g (MW h/yr), is equal to

$$E_g = \eta \cdot \sum_{i=1}^{K} (S_i \cdot U_i \cdot D_i \cdot \mathrm{LHV}_i) \tag{13}$$

Assuming a plant running time of T(h/yr), the electric power, P_e(MW) is

$$P_e = \frac{E_g}{T} \tag{14}$$

Compliance with limits associated to technical constraints (voltage and generated power) is an underlying objective for DG systems, which requires particular attention. The best solution can be found in terms of other objectives (in this work, the profitability index), but if this solution violates the technical constraints of the DG system, it might not be feasible. Voltage regulation is one of the principal problems related to DG and distribution networks, and in many cases it represents a barrier to the large diffusion of DG on the distribution system. Therefore, for a solution to be acceptable, voltage must be between a lower and an upper bound. On the other hand, generated power must be smaller than a fixed limit, but close to it.

3.2. Coding of the solution

The optimization problem to be addressed in this work could be considered a real coded problem (decision variables and fitness function are real valued). However, the way in which geographic data are represented in a raster-based GIS approach limits the accuracy of the obtained solutions by real coded algorithms, such as classical PSO or real coded GAs. Therefore, a discrete optimization (binary PSO) has been considered more suitable than a continuous one.

Before using the proposed Binary PSO to determine location of the biomass power plant, the representation of a feasible solution (particle position) must be defined. A solution consists of three parts: (1) X component of plant location; (2) Y component of plant location; and (3) size of supply area for the power plant. These components are binary Gray coded in order to exploit some useful properties of Gray code related with the Hamming distance.

We have considered a rectangular search space with $x \in [1, L_X]$ and $y \in [1, L_Y]$, L_X and L_Y being sizes in X- and Y-dimension, respectively. Supply area is a square shaped region which has the plant at the centroid. In order to obtain not only the location of the power plant but also the supply area, a prefixed number of supply region sizes have been assumed (i.e. size number 0 corresponds to a 1×1 region, size number 1 corresponds to a 3×3 region and maximum size number S corresponds to a $(2 \cdot S + 1) \times (2 \cdot S + 1)$ region). Thus, the total number of bits used to code the solution is

$$N = \log_2 L_X + \log_2 L_Y + \log_2 S \tag{15}$$

4. Objective function: profitability index

The objective function takes into consideration costs and benefits. Specifically, initial investment and collection, transportation, maintenance and operation costs are considered, together with benefits from the sale of electrical energy. Therefore, the profitability index is chosen as the objective function.

In this section some interesting parameters to evaluate the profitability index of the project are reviewed. The initial investment, the present value of cash inflows (benefits) and cash outflows (costs) and the net present value are studied and adapted to the particularities of this work.

4.1. Initial investment

The initial investment (INV) for the design, construction of the generation plant and required equipment is expressed as

$$\mathrm{INV} = \mathrm{INV}_f + I_s \cdot P_e + C_L \cdot L_p \tag{16}$$

where INV_f is the fixed investment (€), I_s is the specific investment (€/MW) and C_L the electric line cost (€/km).

4.2. Cash inflows

The present value of cash inflows ($\mathrm{PV_{IN}}$) is obtained from the sold electric energy during the useful lifetime, V_u. It can be written as

$$\mathrm{PV_{IN}} = p_g \cdot E_g \cdot \frac{K_g \cdot (1 - K_g^{V_u})}{1 - K_g} \tag{17}$$

where p_g is the selling price of the electric energy injected to the network (€/MW h), E_g the sold and produced electric energy (MW h/yr) and $K_g = (1 + r_g)/(1 + d)$, r_g being the annual increase rate of the sold energy price and d the nominal discount rate.

4.3. Cash outflows

The present value of cash outflows ($\mathrm{PV_{OUT}}$) is the sum of the following costs during the useful lifetime of the plant: annual collection cost, C_c, annual transport cost, C_t and annual maintenance and operation costs, C_{mo}.

The annual cost of biomass collection is $C_c = \sum_{i=1}^{K} (C_{\mathrm{cu}_i} \cdot U_i \cdot S_i \cdot D_i)$.

The annual cost of biomass transport is $C_t = \sum_{i=1}^{K} (C_{\mathrm{tu}_i} \cdot U_i \cdot S_i \cdot D_i \mathrm{dist}(p,i))$, where C_{tu_i} is the biomass transport unit cost in parcel i (€/(tonkm)).

The annual maintenance and operation costs are $C_{mo} = C_{mof} + m \cdot E_g$, where C_{mof} is the fixed annual cost of maintenance and operation, which mainly consists of the minimum labor cost of the plant (€/yr), and m is the average maintenance cost (€/MW h).

Finally, the present value of cash outflows is

$$\mathrm{PV_{OUT}} = C_c \cdot \frac{K_c \cdot (1 - K_c^{V_u})}{1 - K_c} + C_t \cdot \frac{K_t \cdot (1 - K_t^{V_u})}{1 - K_t} + C_{mo} \cdot \frac{K_{mo} \cdot (1 - K_{mo}^{V_u})}{1 - K_{mo}} \tag{18}$$

where $K_c = (1 + r_c)/(1 + d)$, $K_t = (1 + r_t)/(1 + d)$ and $K_{mo} = (1 + r_{mo})/(1 + d)$, r_c being the annual increase rate of C_c, r_t the annual increase rate of C_t and r_{mo} the annual increase rate of C_{mo}.

4.4. Net present value

The present value (PV) of an investment is the present value of cash inflows (PV_{IN}) minus the present value of cash outflows (PV_{OUT}) during the useful lifetime of the plant. Therefore, it can be written as

$$PV = PV_{IN} - PV_{OUT} \tag{19}$$

The net present value (NPV) is defined as the present value (PV) minus the initial investment (INV):

$$NPV = PV - INV \tag{20}$$

4.5. Profitability index

The fitness function that has been used in this work is the profitability index (PI) which is defined as follows:

$$PI = \frac{NPV}{INV} = \frac{PV_{IN} - PV_{OUT} - INV}{INV} = \frac{PV_{IN} - PV_{OUT}}{INV} - 1 \tag{21}$$

An investment is profitable when $PI > 0$.

5. Experimental results

The region considered to apply the proposed method consists of $128 \times 128 = 16\,384$ parcels of constant surface, $S_i = 0.0625\,\mathrm{km}^2$. The size of the supply area for the power plant is coded by 6 bits ($2^6 = 64$ different sizes are possible). The region is covered by natural forest vegetation, the forest residues being the biomass source. In the region under study, there are parcels where neither extraction of forest residues nor placement of the generation plant is possible. The region under study and the single line diagram illustrating the topology of the test distribution network are shown in Fig. 1.

A radial feeder with 10-nodes, as shown in Fig. 1, is considered to assess the performance of the proposed optimization approach. The radial feeder is connected through a substation (the so-called slack node, which corresponds to node no. 1) to a sub-transmission system. The electrical characteristics of the considered radial feeder are presented in Table 1. More detailed information about the considered radial feeder can be found in Wang and Nehrir (2004).

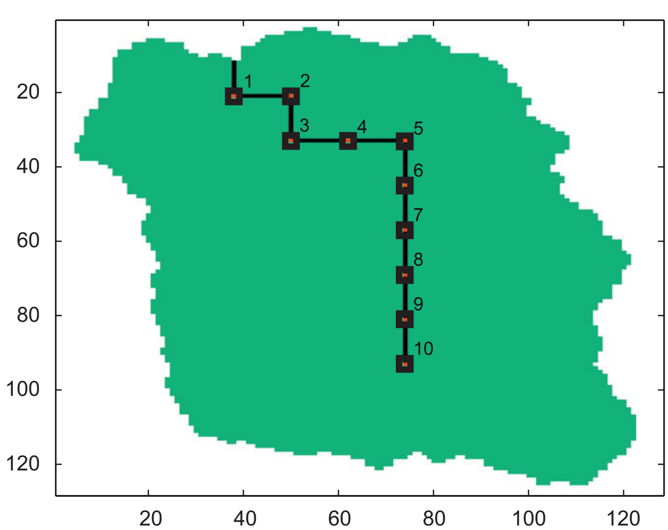

Fig. 1. Region under study, showing possible injection nodes to the distribution electrical network.

Table 1
Electrical characteristics of the radial feeder

Resistance per unit	0.1793
Reactance per unit	0.1542
Load at each node (nodes from 1 to 10) (MW)	0.5

Table 2
Standard values for parameters (SOFC-MT system)

Parameter	Value
η	0.6
INV_f (€)	1.5×10^6
C_L (€/km)	3×10^4
p_g (€/MW h)	100
C_{mof} (€/yr)	2.4×10^5
d	0.08
r_c	0.06
r_{mo}	0.04
T (h/yr)	7500
I_s (€/MW)	2×10^6
V_u (yr)	15
C_{tu_i} (€/(Ton km))	0.3
m (€/MW h)	4.0
r_g	0.04
r_t	0.08

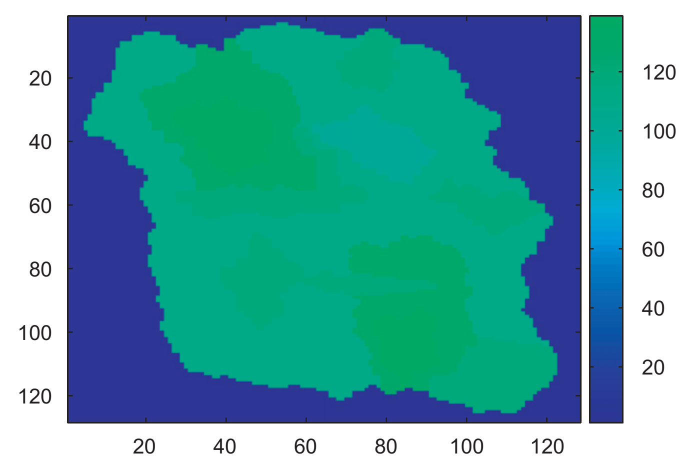

Fig. 2. Theoretical biomass potential (ton/(km^2 yr)).

As shown in Table 1, the electrical distribution system is composed of uniformly distributed loads. The biomass power plant is added to the distribution system as a new node (node no. 11).

The available information for each parcel comprises S_i, U_i, D_i, LHV_i, L_p, dist(p,i) and C_{cu_i}. Other parameter values are shown in Table 2.

Fig. 2 presents the theoretical biomass potential, which is defined from the net density of dry biomass that can be obtained at any parcel, D_i (ton/(km^2 yr)), and provides a measure of the primary biomass resource.

Fig. 3 shows the available biomass potential. It has been created taking the following parameters into account: D_i (ton/(km^2 yr)), U_i, S_i(km^2) and LHV_i (MW h/ton). Multiplying

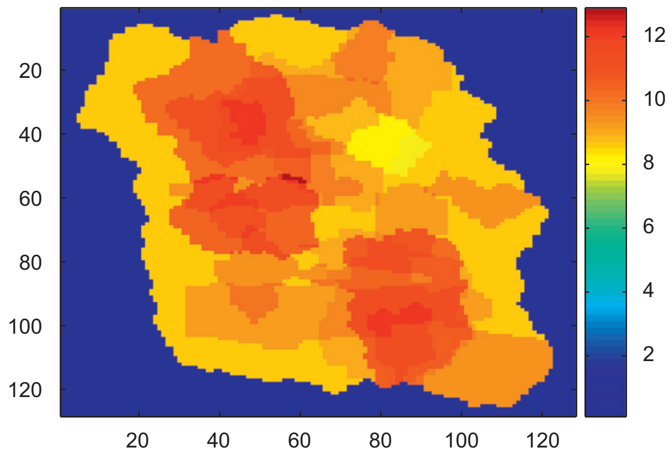

Fig. 3. Available biomass potential (MW h/yr)).

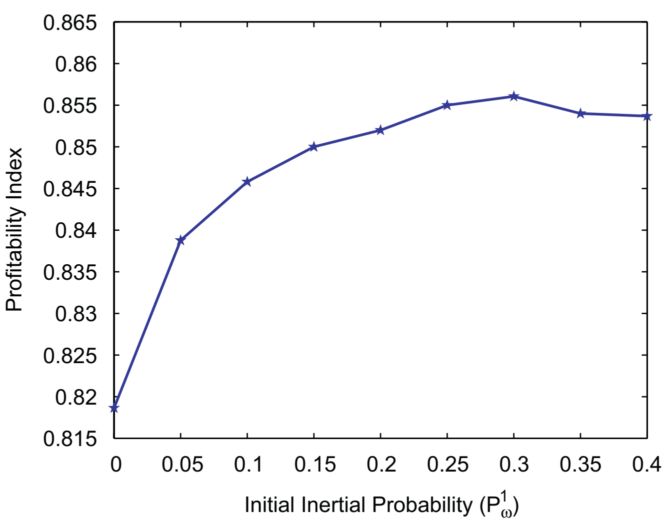

Fig. 4. Mean value of the profitability index vs. P^1_ω.

the four variables for all the parcels that comprise the entire region, it results the available biomass potential, expressed in (MW h/yr), as depicted in Fig. 3.

Simulation data are: $P = 15$, $N = 20$ and $t_{max} = 50$. A trade-off solution between profitability index and computational cost has been searched when choosing the population size P. The technical constraints to be considered in simulations are: (1) the electric power generated by the plant is limited to $P_{e_{max}} = 2\,MW$; (2) the voltage cannot be above 1.05 per unit or below 0.95 per unit; and (3) the generation system must be located inside the supply area.

The performance of our binary PSO algorithm has been assessed by computing the influence of probability P^1_ω on the profitability index for the chosen value of the population size ($P = 15$). Experimental results illustrating that influence are shown in Fig. 4, which are based on 30 replicate simulation runs.

As can be seen in Fig. 4, the quality of the solution provided by PSO increases with parameter P^1_ω until a maximum is reached at $P^1_\omega = 0.3$. In our experiments, this behavior has been observed for all considered values of parameter P (i.e. the profitability index increases with the initial inertia probability until $P^1_\omega = 0.3$, regardless of the population size). These experiments have also evidenced that a good election for the final inertial probability is $P^{t_{max}}_\omega = 0.001$.

Table 3
Results about the profitability index

Results	Profitability index
Mean	0.8561
Standard deviation	0.0123
Highest value	0.8723

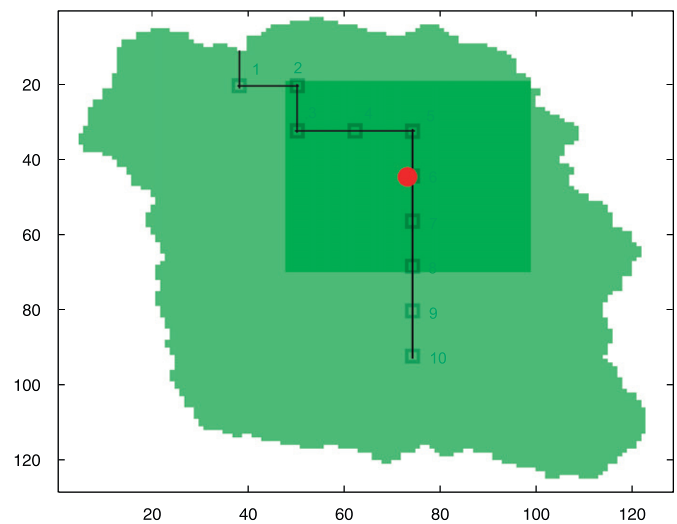

Fig. 5. Optimal location and supply area of the biomass power plant for the best found solution.

Once parameters for the proposed binary PSO approach have been properly chosen, we ran the optimization algorithm 30 times, the results about the profitability index being shown in Table 3.

As shown in Table 3, it has been achieved a value above zero for the profitability index. Therefore, the investment is profitable. However, energy from biomass, like all other forms of renewable energy, requires the support of market instruments, such as the renewable energy national programmes in order to make more profitable investments. Under these programmes, renewable energy suppliers can obtain grants. Nowadays, the grants in Spain are worth approximately 0.12€/kW h (Ministerio de Industria and Comercio y Turismo, 2007).

Fig. 5 shows the optimal location and the supply area of the biomass power plant for the best found solution. For this solution, the proposed PSO algorithm provides the following output values: profitability index, PI = 0.8723; net present value, NPV = 4.7937 M€; generated electric power, $P_e = 1.9941\,MW$; supply area: $162.5625\,km^2$.

As shown in Fig. 5, the biomass power plant is connected through node 6 to the distribution system. Note that node 6 is the closest one to the biomass power plant.

Further, Fig. 6 shows the voltage profile for the best found solution (highest value of the profitability index).

As shown in Fig. 6, the voltage profile is kept within the allowed limits. As expected, node 1 (slack node) and node 11 (biomass power plant) present a voltage magnitude equals to 1 per unit, the later one being PV type (active power and voltage magnitude are constant values). In addition, since the biomass power plant is linked through node 6 to the distribution system, this node exhibits a voltage magnitude higher than that of neighbor nodes. Note that the voltage magnitude decreases as nodes go away from node 6 due to the voltage drop across the distribution system.

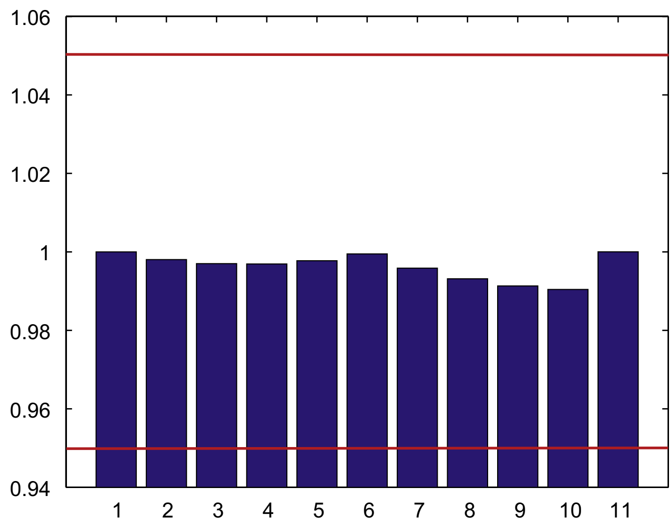

Fig. 6. Voltage profile of the test distribution network.

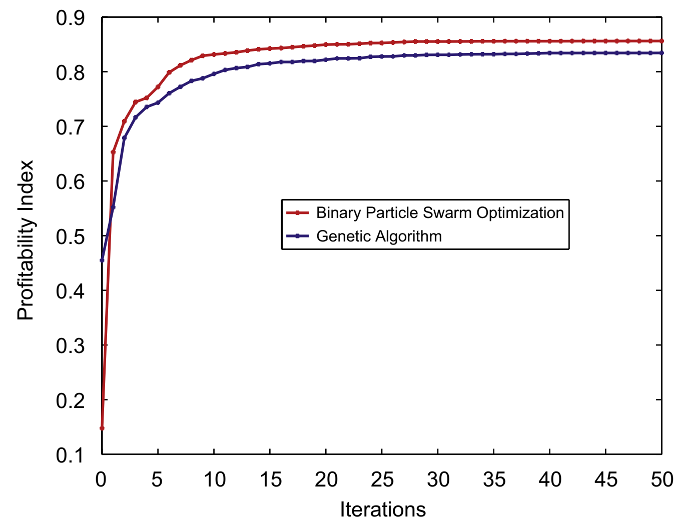

Fig. 7. Convergence curves for both algorithms (binary PSO and GAs).

Table 4
Number of evaluations of the fitness function for both PSO and GAs

Metaheuristic	Number of evaluations
Binary PSO	$P+P\cdot t_{\max}=15+15\times 50=765$
GA	$P+\lceil \frac{P\cdot SR}{2}\rceil\cdot 2\cdot t_{\max}=18+\lceil \frac{18\cdot 0.8}{2}\rceil\cdot 2\times 50=818$

Finally, comparative results between the proposed binary PSO algorithm and GAs for the problem we deal with are reported. The main characteristics of the GA used in this work are:

- Selection mechanism. Here, the so-called *elitist strategy* has been used in order to include into the gene pool the best found solutions.
- Crossover operator. In this work, single-point crossover is performed.
- Mutation operator. The exponentially decreasing function in Eq. (12) has been used for the mutation probability.

The mutation probability at the beginning of the algorithm (P_m^1) and the selection rate (SR) have been fixed to be 0.1 and 0.8, respectively, which are typical values found in the literature. With the aim to perform a fair comparison between both metaheuristics, the number of evaluations of the fitness function must be similar in both approaches. In such sense, the population size for GAs has been chosen to be $P=18$, the number of evaluations being compared in Table 4.

Note that the number of evaluations per iteration is 15 and 16 for PSO and GAs, respectively.

Fig. 7 compares the mean value of the profitability index as a function of the number of iterations when 30 replicate simulation runs are performed.

As shown in Fig. 7, the proposed binary PSO algorithm converges to better solutions than GAs. The results also show that the proposed binary PSO algorithm converges to good solutions in few iterations.

6. Conclusions

This paper has presented an AI-based method to determine the optimal supply area and location for an electric generation system based on biomass. The proposed AI-based method is a binary version of the PSO algorithm, which makes use of the profitability index as objective function. The solutions are coded using 20 bits. The paper has evidenced that a good planning technique must consider the technical constraints of the network, the voltage regulation being one of the principal problems to be addressed for DG systems. Computer simulations have shown the good performance of the proposed method in comparison to GAs. Further, acceptable solutions (PI $=0.8561$, on average) has been reached in few iterations. Therefore, convergence is quickly reached and computational cost is $2^{20}/(51\times 15)\approx 1370$ times lower than that required for exhaustive search.

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