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Optimization of biomass fuelled systems for distributed power generation using Particle Swarm Optimization

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Abstract

With sufficient territory and abundant biomass resources Spain appears to have suitable conditions to develop biomass utilization technologies. As an important decentralized power technology, biomass gasification and power generation has a potential market in making use of biomass wastes. This paper addresses biomass fuelled generation of electricity in the specific aspect of finding the best location and the supply area of the electric generation plant for three alternative technologies (gas motor, gas turbine and fuel cell-microturbine hybrid power cycle), taking into account the variables involved in the problem, such as the local distribution of biomass resources, transportation costs, distance to existing electric lines, etc. For each technology, not only optimal location and supply area of the biomass plant, but also net present value and generated electric power are determined by an own binary variant of Particle Swarm Optimization (PSO). According to the values derived from the optimization algorithm, the most profitable technology can be chosen. Computer simulations show the good performance of the proposed binary PSO algorithm to optimize biomass fuelled systems for distributed power generation.

Keywords: Biomass; Distributed power generation; Particle Swarm Optimization; Profitability index

1. Introduction

Renewable electricity generation has emerged as one of the favoured 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 [1].

Biomass is one of the most promising renewable energy sources, 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 refs. [2,3]. 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 being 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 some additional advantages, such as forest pests reduction and forest fire risk decrease. 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 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

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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.

Gas derived form 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. This article is mainly concerned with three biomass fuelled systems. These systems are gas motor, gas turbine and fuel cell-microturbine hybrid power cycle.

Biomass-based gas (biogas) as a fuel for diesel engines offers the advantage of reduced emissions while retaining the efficiency of the conventional diesel engine. The engine can operate at high compression ratio with a wide range of gas composition. A disadvantage of biogas use in diesels is the high auto-ignition temperature [4].

The work of Gumz [5] is the earliest reference found describing the concept of combining a pressurized gasifier with a gas turbine engine, although Gumz himself references an earlier work proposing this concept. He also states that the combination could certainly benefit from future development of pressurized hot gas cleaning to avoid excessive turbine blade wear. Gumz's work deal with coal-fuelled plants, but the concept is similar when using biomass as fuel. Gas turbines can offer solutions to today's energy situation as a supplement or support function to the conventional central generation and power system [6]. Complimentary answers are needed to meet projected growth in new load and peak demand while providing power system stability, security and end-user power quality solutions.

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 cells: proton exchange membrane fuel cell (PEMFC), phosphoric acid fuel cell (PAFC), molten carbonate fuel cell (MCFC), solid oxide fuel cell (SOFC) [7]. 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 °C 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 power output by a gas turbine. As result, higher overall efficiency is expected (approximately 60%) in comparison to that obtained from individual system [7–9].

Microturbines, which are typically fuelled with natural gas, generate between 25 kW and 200 kW of electricity. Their relatively low cost and small size low 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, a fuel cell is associated with a biogas microturbine to produce electric power [10,11].

In this paper, optimizing three biomass fuelled systems (gas motor, gas turbine and fuel cell-microturbine hybrid power cycle) for a region mainly covered by natural forest vegetation is intended. Comparing the performance of the three systems is also claimed. For a realistic problem formulation, 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 [12]. Meanwhile, some new AI-based methods are introduced and developed. Although these AI-based methods do not always guarantee the globally optimal solution, they provide suboptimal (near globally optimal) solutions in a short CPU time. This paper employs a modern AI-based method, Particle Swarm Optimization (PSO) [13–15], to solve the problem of deciding the most profitable technology (gas turbine, gas engine or fuel cell-microturbine hybrid power cycle). For each technology, optimal location and supply area of the biomass plant, net present value and generated electric power are determined. In this work, the fitness function for the PSO algorithm is the profitability index.

PSO is a nature-inspired evolutionary stochastic algorithm developed by Kennedy and Eberhart [13]. This technique, motivated by social behaviour 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 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 neighbouring particles, making use of the best position encountered by itself and its neighbours. The main advantages of PSO are: it is very easy to implement and there are few parameters to adjust. In addition, PSO has been successfully applied in many different areas, such as artificial neural network training, fuzzy system control and mainly function optimization.

This paper is organized as follows. After introduction, a brief review about PSO is presented in Section 2. In Sections 3 and 4, the problem description and the objective function are presented, respectively. Experimental results are shown is Section 5. Finally, conclusions are presented in Section 6.

2. Particle Swarm Optimization

2.1. The 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:

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

where $x_i^t = [x_{i,1}^t, \ldots, x_{i,N}^t]$ 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:

$$v_{i,j}^t = \omega v_{i,j}^{t-1} + c1\mathrm{rand}1_i(\mathrm{pbest}_{i,j}^{t-1} - x_{i,j}^{t-1}) + c2\mathrm{rand}2_i(\mathrm{gbest}^{t-1} - x_{i,j}^{t-1}) \quad (2)$$

where $\mathrm{pbest}_i^{t-1} = [\mathrm{pbest}_{i,1}^{t-1}, \ldots, \mathrm{pbest}_{i,N}^{t-1}]$ is the best solution achieved for the ith particle at the $(t-1)$th iteration and $\mathrm{gbest}^{t-1} = \left[\mathrm{gbest}_1^{t-1}, \ldots, \mathrm{gbest}_N^{t-1}\right]$ is the best position found for all particles in the swarm at the $(t-1)$th iteration. $c1$ and $c2$ 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. $\mathrm{rand}1_i$ and $\mathrm{rand}2_i$ are real random numbers uniformly distributed between 0 and 1, that make stochastic changes in the particle trajectory. Finally, ω is the inertia weight factor and represents the weighting of a particle's previous velocity. Suitable selection of inertia weight in Eq. (2) provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution.

From Eq. (2), we can find that the current flying velocity of a particle comprises three terms. The first term is the particle's previous velocity revealing that a PSO system has memory. The second term and the third term represent a cognition-only model and a social-only model, respectively. The cognition-only model treats individuals as isolates and reflects private thinking, whereas the social-only model implies that individuals compare the effectiveness of neighbours' beliefs and change toward those that are relatively successful [14].

2.2. The proposed binary PSO algorithm

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 propose in ref. [16] 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].

$$S(v_{i,j}^t) = \frac{1}{1 + e^{-v_{i,j}^t}} \quad (3)$$

The position of the ith particle in ref. [16] is updated according to expression (4):

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

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

In ref. [17], Afshinmanesh et al. 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 ('·'), OR ('+') and XOR ('⊕') operators. The procedure for updating particle position and velocity can be summarized as follows:

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

$$v_{i,j}^t = c1_{i,j} d1_{i,j}^{t-1} + c2_{i,j} d2_{i,j}^{t-1} \quad (6)$$

where $\mathbf{c1}_i = [c1_{i,1}, \ldots, c1_{i,N}]$ and $\mathbf{c2}_i = [c2_{i,1}, \ldots, c2_{i,N}]$ are random N-length binary strings, whose components are '0' or '1' with the same probability. In Eq. (6), $\mathbf{d1}_i^{t-1} = [d1_{i,1}^{t-1}, \ldots, d1_{i,N}^{t-1}]$ 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 ($\mathrm{pbest}_i^{t-1} = [\mathrm{pbest}_{i,1}^{t-1}, \ldots, \mathrm{pbest}_{i,N}^{t-1}]$), and $\mathbf{d2}_i^{t-1} = [d2_{i,1}^{t-1}, \ldots, d2_{i,N}^{t-1}]$ is the Hamming distance vector between the position of the ith particle at the $(t-1)$th iteration and the previous global best position ($\mathrm{gbest}^{t-1} = [\mathrm{gbest}_1^{t-1}, \ldots, \mathrm{gbest}_N^{t-1}]$). The Hamming distance is computed by means of the XOR operator:

$$d1_{i,j}^{t-1} = \mathrm{pbest}_{i,j}^{t-1} \oplus x_{i,j}^{t-1} \quad (7)$$

$$d2_{i,j}^{t-1} = \mathrm{gbest}_j^{t-1} \oplus x_{i,j}^{t-1} \quad (8)$$

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.

In this work, we have applied an improved version of the binary PSO algorithm proposed in ref. [17], which incorporates an inertia weight factor, as in the classical continuous approach [13]. In the proposed binary PSO algorithm, particle position and particle velocity are N-length binary vectors. Particle position is updated by using the XOR operator instead of real adding, as in [17]:

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

In our approach, the velocity vector can be interpreted as a change vector. Thus, if $v_{i,j}^t = \text{'1'}$, then $x_{i,j}^t = \overline{x_{i,j}^{t-1}}$, $\overline{x_{i,j}^{t-1}}$ being the logical negation of $x_{i,j}^{t-1}$. However, if $v_{i,j}^t = \text{'0'}$, 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:

$$v_{i,j}^t = \overline{\omega_{i,j}} + \omega_{i,j}(c1_{i,j}(\mathrm{pbest}_{i,j}^{t-1} \oplus x_{i,j}^{t-1}) + c2_{i,j}(\mathrm{gbest}_j^{t-1} \oplus x_{i,j}^{t-1})) \quad (10)$$

where vectors $\text{pbest}_i^{t-1} = [\text{pbest}_{i,1}^{t-1}, \ldots, \text{pbest}_{i,N}^{t-1}]$, $\text{gbest}^{t-1} = [\text{gbest}_1^{t-1}, \ldots, \text{gbest}_N^{t-1}]$, $\mathbf{c1}_i = [c1_{i,1}, \ldots, c1_{i,N}]$ and $\mathbf{c2}_i = [c2_{i,1}, \ldots, c2_{i,N}]$ have already been defined, and symbols '+' and '·' 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.
- $\overline{\boldsymbol{\omega}_i} = [\overline{\omega_{i,1}}, \ldots, \overline{\omega_{i,N}}]$ 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 *exploits* 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 pbest_i^{t-1} and gbest^{t-1} solutions, with a partially stochastic behaviour due to the random learning vectors $\mathbf{c1}_i$ and $\mathbf{c2}_i$.

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 pbest_i and gbest solutions. In this work, an exponentially decreasing function is used for probability P_ω.

3. Problem description and coding of the solution

3.1. Problem description

The problem to be solved consists on comparing three commonly used systems for biomass-based power generation. The systems to be compared are: gas motor, gas turbine and fuel cell-microturbine hybrid power cycle. We are interested in determining the optimal location and supply area of the electric generation plant for the three biomass fuelled systems. The net present value and the electric power generated from the three biomass fuelled systems will also be computed.

In this work, the size of the electric generation system depends on:

- Biomass quantity that can be collected from a given region mainly covered by natural forest vegetation.
- Technology to produce electricity from biomass. Three biomass fuelled systems are here regarded: gas motor, gas turbine and fuel cell-microturbine hybrid power cycle.

Location of the biomass-based power plant (parcel p) mainly depends on the characteristics of the considered region to collect biomass. In this work, K parcels of constant area have been regarded, most of them characterized by a predominant biomass type (forest residues in this work). These parcels also present other relevant characteristics, such as accessibility [18].

The values of the variables involved in the problem are obtained from databases or Geographic Information Systems (GIS). These 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 obtained from parcel i (ton/(km^2 yr)).
- LHV_i: lower heat value of biomass in parcel i (MWh/ton).
- L_p: length of the electric line that connects the power plant to the grid (km).
- $\text{dist}\,(p, i)$: 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 (Euro/ton).

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

$$E_\text{g} = \eta \sum_{i=1}^{K} S_i U_i D_i \text{LHV}_i \qquad (11)$$

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

$$P_\text{e} = \frac{E_\text{g}}{T} \qquad (12)$$

3.2. Coding of the solution

Before using the proposed binary PSO to determine location of biomass power plant, the representation of a feasible solution (particle position) must be defined. A solution consists of three parts: (1) X component of location plant; (2) Y component of location plant; (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_X being sizes in X-dimension 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 sitting of the plant but also the sizing of 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 $(2S+1) \times (2S+1)$ region. Thus, the total number of bits used to code the solution is:

$$N = \log_2 L_X + \log_2 L_Y + \log_2 S \qquad (13)$$

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) are defined and adapted to the particularities of this work.

4.1. Initial investment

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

$$\mathrm{INV} = \mathrm{INV_f} + I_s P_e + C_L L_p \tag{14}$$

where $\mathrm{INV_f}$ is the fixed investment (Euro), I_s the specific investment (Euro/MW), and C_L the electric line cost (Euro/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 (yr). It can be written as:

$$\mathrm{PV_{IN}} = p_g E_g \frac{K_g(1 - K_g^{V_u})}{1 - K_g} \tag{15}$$

where p_g is the selling price of the electric energy injected to the network (Euro/MWh), E_g the sold and produced electric energy (MWh/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 $C_c = \sum_{i=1}^{K}(C_{cu_i} U_i S_i D_i)$.

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

The annual maintenance and operation costs are $C_{mo} = C_{mof} + mE_g$, where C_{mof} is the fixed annual cost of maintenance and operation and m the average maintenance cost (Euro/MWh).

Finally, the present value of cash outflows is:

$$\mathrm{PV_{OUT}} = C_c \frac{K_c(1 - K_c^{V_u})}{1 - K_c} + C_t \frac{K_t(1 - K_t^{V_u})}{1 - K_t} + C_{mo} \frac{K_{mo}(1 - K_{mo}^{V_u})}{1 - K_{mo}} \tag{16}$$

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 net present value (NPV) of an investment is defined as follows:

$$\mathrm{NPV} = \mathrm{PV} - \mathrm{INV} \tag{17}$$

$\mathrm{PV} = \mathrm{PV_{IN}} - \mathrm{PV_{OUT}}$ being the present value. An investment is profitable when $\mathrm{NPV} > 0$.

4.5. Profitability index

The profitability index (PI) is chosen in this work as objective fitness function. It is defined as follows:

$$\mathrm{PI} = \frac{\mathrm{NPV}}{\mathrm{INV}} = \frac{\mathrm{PV}}{\mathrm{INV}} - 1 \tag{18}$$

We can also say that an investment is profitable when $\mathrm{PI} > 0$.

5. Experimental results

The region considered to apply the proposed method consists of $128 \times 128 = 16384$ parcels of constant surface, $S_i = 2\,\mathrm{km}^2$. The region is covered by natural forest vegetation. Therefore, forest residues constitute the biomass type. 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 1.

Parameters which are characteristics of the type of generation unit are listed in Table 2. The fuel cell-microturbine hybrid power cycle generation unit requires the highest specific investment, but gas engine average maintenance costs are twice higher than gas turbine or fuel cell maintenance costs and less useful lifetime. Also, the total mean efficiency of the electric generation is depended on the type of generation unit.

Fig. 1 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. Location of the electrical lines inside the considered region is also shown in Fig. 1.

Table 1
Standard values for parameters

Parameter	Value
C_{tu_i} (Euro/ton km)	0.3
C_L (Euro/km)	3×10^4
T (h/yr)	7500
$\mathrm{INV_f}$ (Euro)	1.5×10^6
p_g (Euro/MWh)	100
d	0.08
r_g	0.04
r_c	0.06
r_t	0.08
r_{mo}	0.04
C_{mof} (Euro)	240000

Table 2
Specific values for unit generation

Gas engine		Fuel cell		Gas turbine	
Parameter	Value	Parameter	Value	Parameter	Value
m (Euro/MWh)	8.0	m (Euro/MWh)	4.0	m (Euro/MWh)	4.0
η	0.2	η	0.6	η	0.3
I_s (Euro/MW)	0.2×10^6	I_s (Euro/MW)	2.0×10^6	I_s (Euro/MW)	1.2×10^6
V_u (yr)	10	V_u (yr)	15	V_u (yr)	15

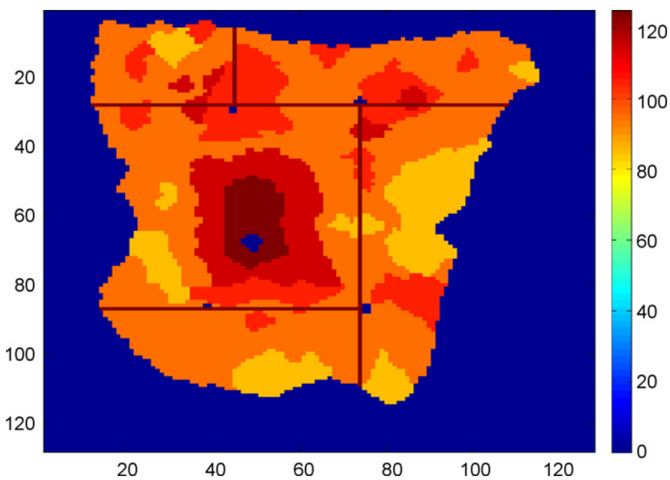

Fig. 1. Theoretical biomass potential (ton/(km^2 yr)).

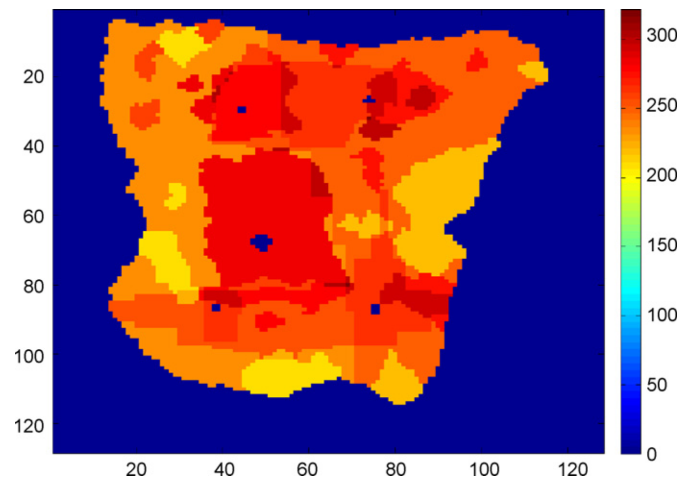

Fig. 2. Available biomass potential (MWh/yr)).

Fig. 2 shows the available biomass potential. It has been created taking the following parameters into account: U_i, S_i (km^2), D_i (ton/(km^2 yr)) and LHV$_i$ (MWh/ton). By multiplying the four variables for all the parcels that comprise the entire region, it results the available biomass potential, expressed in (MWh/yr), as depicted in Fig. 2.

Commonly, PSO calculation process ceases at a maximum number of iterations [19,20]. Experience is needed in this parameter choosing. It will consume a lot of calculation time if the parameter is set too big, while no optimized result could be got if it is set too small.

Population size is associated to the search space. If this parameter is too small, the algorithm is probable to converge to a local optimum; however, if the population size is too large, it will engage large computer memory and demand high calculation time. After tests, authors have evidenced that good performance of PSO is achieved when the population size is about 30. This value is close to the 30–50 population size pointed out in ref. [13]. Therefore, simulation data are: $P = 30$, $N = 20$ and 60 iterations. The constraints for simulation are: (1) The electric power generated by the plant is limited to 5 MW and (2) the generation system must be located inside the supply area.

In a typical realization the proposed PSO algorithm provides the output values presented in Table 3. Gas motor has been shown the most profitable (highest profitability index). In spite of gas motor reaches the highest profitability index, project based on fuel cell gets the highest net present value.

Figs. 3–5 show the optimal location and supply area for the biomass plant in the same realization that has been considered previously. Note that the optimal location is different in each case.

A fair comparison between the proposed binary PSO algorithm and Genetic Algorithms is performed for the three alternative biomass fuelled technologies (gas motor, gas turbine, fuel cell). For such goal, convergence curves of the average profitability index versus number of iterations are computed using the same population size ($P = 30$). Results are shown in Figs. 6–8. As shown in these figures, PSO reaches a better solution than GA with a lower number of iterations. Table 4 depicts mean profitability index and its standard deviation for each technol-

Table 3
Output values

Gas motor		Fuel cell		Gas turbine	
Parameter	Value	Parameter	Value	Parameter	Value
PI	2.82	PI	1.59	PI	1.93
NPV (kEuro)	7278	NPV (kEuro)	17767	NPV (kEuro)	13885
P_e (MW)	4.98	P_e (MW)	4.84	P_e (MW)	4.73
Supply area (km^2)	1458.0	Supply area (km^2)	450.0	Supply area (km^2)	876.0

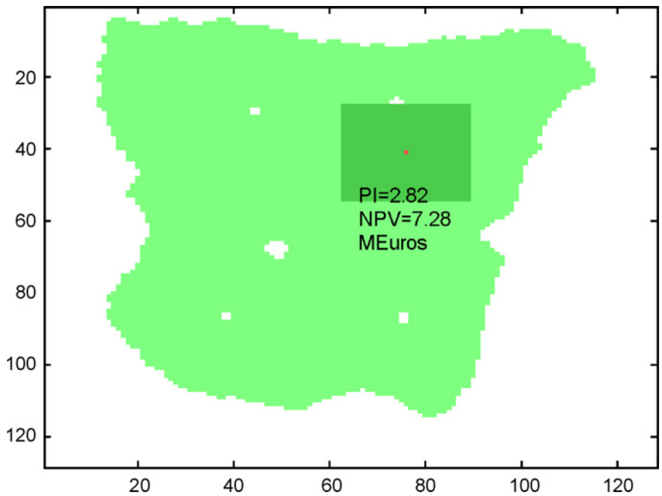

Fig. 3. Gas motor. Optimal location and supply area for the biomass plant.

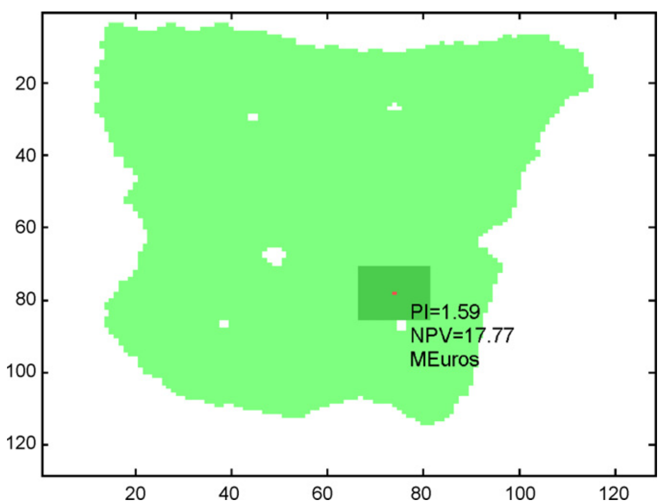

Fig. 4. Fuel cell. Optimal location and supply area for the biomass plant.

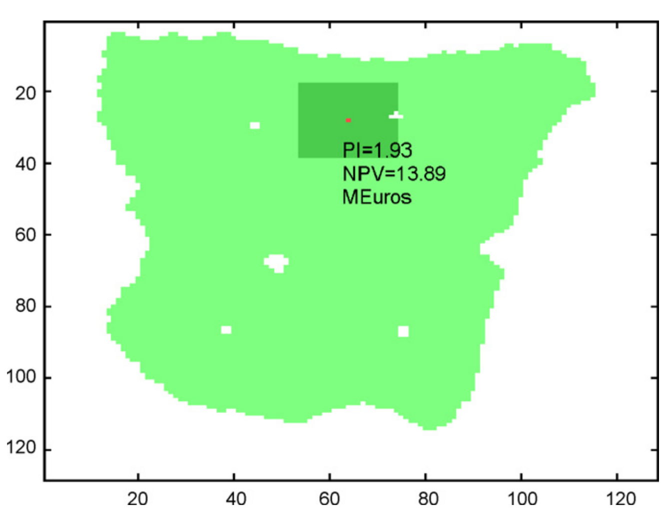

Fig. 5. Gas turbine. Optimal location and supply area for the biomass plant.

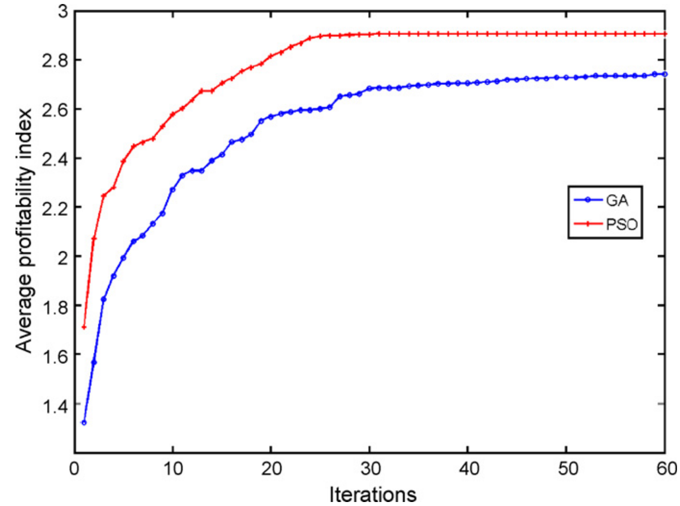

Fig. 6. Gas motor. Average profitability index vs. number of iterations.

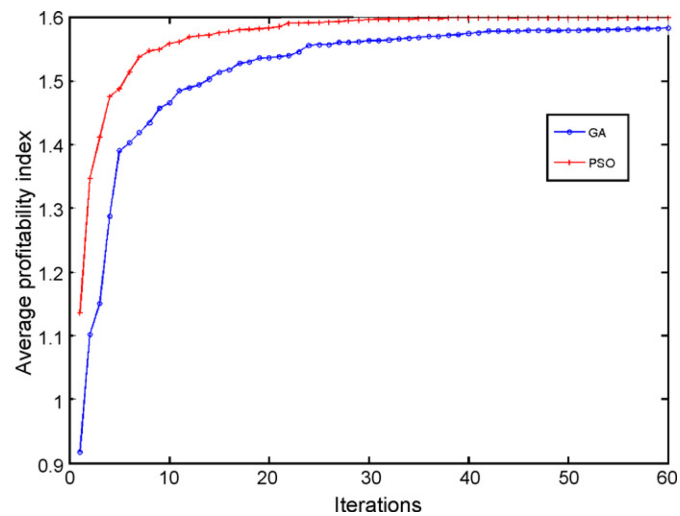

Fig. 7. Fuel cell. Average profitability index vs. number of iterations.

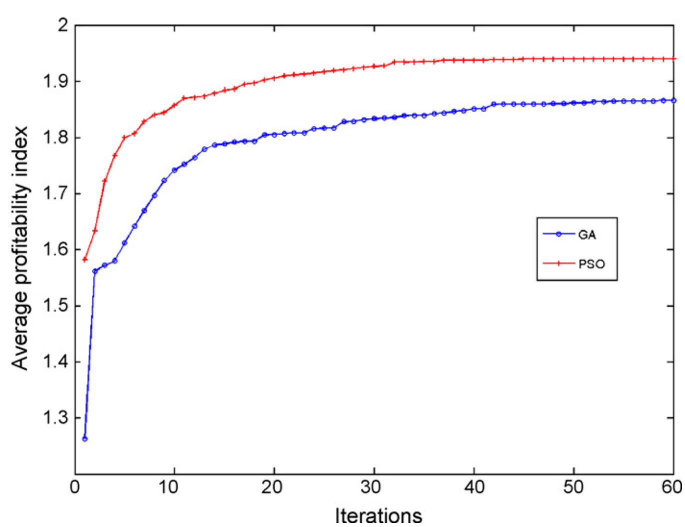

Fig. 8. Gas turbine. Average profitability index vs. number of iterations.

Table 4
Profitability index

	Gas motor		Fuel cell		Gas turbine	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
PSO	2.9054	0.0969	1.5987	0.0158	1.9388	0.0191
GA	2.7433	0.1441	1.5826	0.0302	1.8662	0.0501

Mean and standard deviation values.

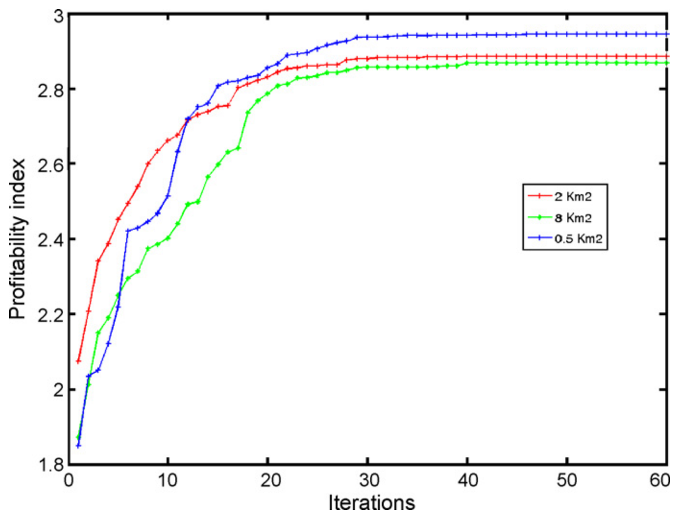

Fig. 9. Gas motor. Influence of parcel dimension.

ogy and algorithm. All of values have been obtained from 30 experiments.

Furthermore, influence of parcel dimension in the execution time (number of iterations) and in the solution accuracy has been reported. For such goal, experiments with parcels of different dimension ($0.5\,km^2$, $2\,km^2$ and $8\,km^2$) have been performed. As an example, the results of the experiments for gas motor are shown in Fig. 9. As shown in this figure, the best solution is accomplished for the parcel size of $0.5\,km^2$, but the execution time to reach this solution is the highest one, as expected.

6. Conclusions

This paper has presented a new approach to determine the optimal supply area and location for an electric generation system based on biomass. The proposed new approach is a discrete binary version of the PSO algorithm, which makes use of the profitability index as objective function. The proposed approach has been assessed using a region composed of 16384 parcels, all of them with the same area ($S_i = 2\,km^2$). In the region under study, gas motor has been shown the most profitable, however the net present value of the fuel cell-based project has achieved the highest net present value. Computer simulations have shown the good performance of the proposed method. Convergence is reached in few iterations, typically, a maximum of 25 iterations, which is equivalent to a computational cost, given by the number of fitness function evaluations, more than 1390 times lower than that required for exhaustive comparison.

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