Profitability Comparison Between Gas Turbines and Gas Engine in Biomass-Based Power Plants Using Binary Particle Swarm Optimization

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Abstract. This paper employs a binary discrete version of the classical Particle Swarm Optimization to compare the maximum net present value achieved by a gas turbines biomass plant and a gas engine biomass plant. The proposed algorithm determines the optimal location for biomass turbines plant and biomass gas engine plant in order to choose the most profitable between them. Forest residues are converted into biogas . The fitness function for the binary optimization algorithm is the net present value. The problem constraints are: the generation system must be located inside the supply area, and its maximum electric power is 5 MW. Computer simulations have been performed using 20 particles in the swarm and 50 iterations for each kind of power plant. Simulation results indicate that Particle Swarm Optimization is a useful tool to choose successful among different types of biomass plant technologies. In addition, the comparison is made with reduced computation time (more than 800 times lower than that required for exhaustive search).

1 Introduction

Gumz (1950) 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 was speaking of coal-fueled plants but the concept is similar when using biomass as fuel. [1].

Stationary engines are rated by the amount of power that can be continuously delivered at the coupling. Speed ratings are based upon mechanical stresses and the ability of the piston and the piston rings to receive adequate lubrication and to seal combustion gases. Like-model engines operating at different installations may experience varying consumption rates due to variations in operations conditions, purification standards, product quality, and in-service-hours [2].

The gasifier heats with limited oxygen supply the forest residues, the final result is a very clean-burning gas fuel suitable for direct use in gas turbines or gas engine.

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Choosing between biomass gas turbines or biomass gas engine is a computationally heavy task, if the electric power generated by the plant is about 5 MW [3]. When a realistic problem formulation 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 [4]. 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) [5][6][7], to solve the problem of determining the most profitable technology (gas turbine o gas engine), after determining optimal location for biomass plant supplied with forest residues. In this work, the fitness function for the PSO algorithm is the net present value (eq. (10)) .

PSO is a nature-inspired evolutionary stochastic algorithm developed by James Kennedy and Russel Eberhart in 1995 [5]. 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 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: it is very easy to implement and there are few parameters to adjust.

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. In the $(t+1)$-th iteration, the position of i-th particle is update adding to its previous position the new velocity vector, according to the following equation:

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \boldsymbol{v}_i^{t+1}, \quad i = 1, ..., P \tag{1}$$

where $\boldsymbol{x}_i^t$ denotes the position vector of the i-th particle at the t-th iteration, $\boldsymbol{v}_i^t$ represents the velocity vector at the t-th iteration, both $\boldsymbol{x}_i^t$ and $\boldsymbol{v}_i^t$ are N-dimensional vectors, N being the number of variables of the function to be optimized. P is the number of particles in the swarm.

The velocity vector is updated according to the following equation:

$$\boldsymbol{v}_i^{t+1} = \omega \cdot \boldsymbol{v}_i^t + c_1 \cdot rand_1 \cdot (\boldsymbol{p}_{i,best}^t - \boldsymbol{x}_i^t) + c_2 \cdot rand_2 \cdot (\boldsymbol{g}_{best}^t - \boldsymbol{x}_i^t) \tag{2}$$

where $\boldsymbol{p}_{i,best}^t$ is the best solution achieved for the i-th particle at the t-th iteration and $\boldsymbol{g}_{best}^t$ is the best position found for all particles in the swarm at the

t-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. $rand_1$ and $rand_2$ 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 particles previous velocity.

From equation (2), we can find that the current flying velocity of a particle comprises three terms. The first term is the particles 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.

2.2 The Proposed Binary Approach

In spite of usual formulation for PSO uses real-number coding, we have applied in this work a discrete PSO algorithm which uses binary-number coding. In the proposed binary PSO algorithm, $\boldsymbol{x}_i^t$ and $\boldsymbol{v}_i^t$ are N-length binary vectors. Equation (1) is applied using the exclusive-or ('XOR') operator instead of real adding:

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t \oplus \boldsymbol{v}_i^{t+1}, \quad i = 1, ..., P \tag{3}$$

Here, the velocity vector can be interpreted as a change vector. Thus, if $v_i^t[j]$='1', then $x_i^{t+1}[j] = \bar{x}_i^t[j]$, $\bar{x}_i^t[j]$ being the logical negation of $x_i^t[j]$. However, if $v_i^t[j]$='0', then $x_i^{t+1}[j] = x_i^t[j]$ (no change happens).

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

$$\boldsymbol{v}_i^{t+1} = \bar{\boldsymbol{\omega}}_i^t + \boldsymbol{\omega}_i^t \cdot \left(\boldsymbol{c}_{i,1} \cdot (\boldsymbol{p}_{i,best}^t \oplus \boldsymbol{x}_i^t) + \boldsymbol{c}_{i,2} \cdot (\boldsymbol{g}_{best}^t \oplus \boldsymbol{x}_i^t)\right) \tag{4}$$

where the inertia vector $\boldsymbol{\omega}_i^t$ is a random N-length binary vector and $\bar{\omega}_i^t$ its logical negation. $\boldsymbol{c}_{i,1}$ and $\boldsymbol{c}_{i,2}$ are also random N-length binary vectors. In equation 4, symbol + represents the logical OR operator and symbol $\cdot$ represents the logical AND operator.

In our approach, parameter p_i has been defined. It represents a probability which decreases with the number of iterations. Here, parameter p_i is applied to generate inertia vector $\boldsymbol{\omega}_i^t$ as follows: $\omega_i^t[j]$='0' with p_i probability, in such a way that at the initial iterations (high p_i values) the algorithm explores the search space and at the last iterations (low p_i values) the algorithm exploit the search space. The idea is to allow particle swarm to perform a random exploration over the space search at the initial iterations. Later, when the particle swarm has acquired enough knowledge about the problem, its movement is conducted by the best solution $\boldsymbol{p}_{i,best}^t$ and the best position $\boldsymbol{g}_{best}^t$ at the t-th iteration, in order to reach a suboptimal solution with reduced computational cost.

3 Problem Description

The problem to be solved consists on comparing the use of a gas turbines or a gas engine in biomass-based power generation systems. The size of the generation system depends on: 1) biomass quantity that can be collected, 2) selection of parcels where to collect the biomass. Location of power plant (parcel p) mainly depends on the characteristics of the 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 [8].

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 yield 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).
- $dist(p, i)$: 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, eff, the electricity produced, E_g (MWh/yr), is equal to:

$$E_g = eff \cdot \sum_{i=1}^{K} (S_i \cdot U_i \cdot D_i \cdot LHV_i) \tag{5}$$

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

$$Pe = \frac{E_g}{T} \tag{6}$$

4 Objective Function: Net Present Value

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 net present value is chosen as the objective function.

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

$$INV = INV_f + I_s \cdot P_e + C_L \cdot L_p \tag{7}$$

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

4.2 Cash Inflows

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

$$PV_{IN} = p_g \cdot E_g \cdot \frac{K_g \cdot (1 - K_g^{V_u})}{1 - K_g} \tag{8}$$

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 $K_g = \frac{1+r_g}{1+d}$, 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 (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 $C_c = \sum_{i=1}^{K}(C_{cu_i} \cdot U_i \cdot S_i \cdot D_i)$.

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

The annual maintenance and operation costs are $C_{mo} = m \cdot E_g$, m being average maintenance costs (Euro/MWh) and E_g the produced electric energy (MWh/yr).

Finally, the present value of cash outflows is:

$$PV_{OUT} = C_c \cdot \frac{K_c \cdot (1 - K_c^{V_u})}{1 - K_c} + C_t \cdot \frac{K_t \cdot (1 - K_t^{V_u})}{1 - K_t} + C_{mo} \cdot \frac{K_{mo} \cdot (1 - K_{mo}^{V_u})}{1 - K_{mo}} \tag{9}$$

where $K_c = \frac{1+r_c}{1+d}$, $K_t = \frac{1+r_t}{1+d}$ and $K_{mo} = \frac{1+r_{mo}}{1+d}$, 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) is defined as follows:

$$NPV = PV_{IN} - PV_{OUT} - INV \tag{10}$$

An investment is profitable when $NPV > 0$.

5 Experimental Results

The region considered to apply the proposed method consists of $128 \times 128 = 16384$ parcels of constant surface, $S_i = 2$ 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:

Table 1. Standard values for parameters

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

Parameters which are characteristics of the type of unit generation are listed in table 2. The gas turbine unit generation requires a higher specific investment than gas engine, but gas engine maintenance costs are twice higher than gas turbine maintenance costs and less useful lifetime:

Table 2. Specific values for unit generation

Gas turbine	Value	Gas engine	Value
$m(Euro/MWh)$	0.05	$m(Euro/MWh)$	0.6
eff	0.3	eff	0.2
$I_s(Euro/MW)$	$1.2 \cdot 10^6$	$I_s(Euro/MW)$	$0.2 \cdot 10^6$
$V_u(yr)$	15	$V_u(yr)$	10

Figure 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 $\cdot$ yr)), and provides a measure of the primary biomass resource. Location of the electric line inside the considered region is also shown in figure 1.

Figure 2 shows the available biomass potential. It has been created taking the following parameters into account: D_i(ton/(Km^2 $\cdot$ yr)), U_i, S_i(Km^2) 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 figure 2.

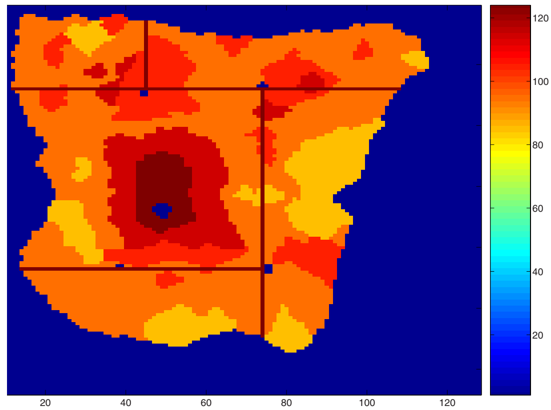

Fig. 1. Theoretical biomass potential (ton/(Km^2 · yr))

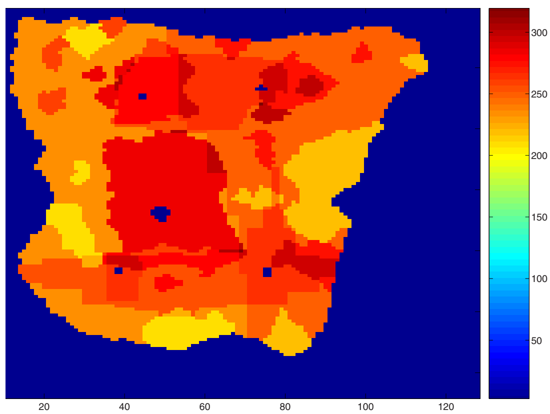

Fig. 2. Available biomass potential (MWh/yr))

Table 3. Output values

Gas turbine	Value	Gas Engine	Value
$NPV(KEuro)$	16586.23	$NPV(KEuro)$	9117.04
$P_e(MW)$	4.75	$P_e(MW)$	4.98
Supply area	880.0	Supply area	1584.0

Simulation data are: $P = 20$, $N = 20$ and 65 iterations. The constraints for simulation are: 1) The electric power generated by the plant is limited to 5 MW; 2) The generation system must be located inside the supply area.

The proposed PSO algorithm provides the output values in table 3. Gas turbine has been shown more profitable (higher net present value) than gas engine.

Figure 3 shows the optimal location and supply area for the gas turbine plant and for the gas motor plant in a typical realization. Note that the optimal location is different in each case.

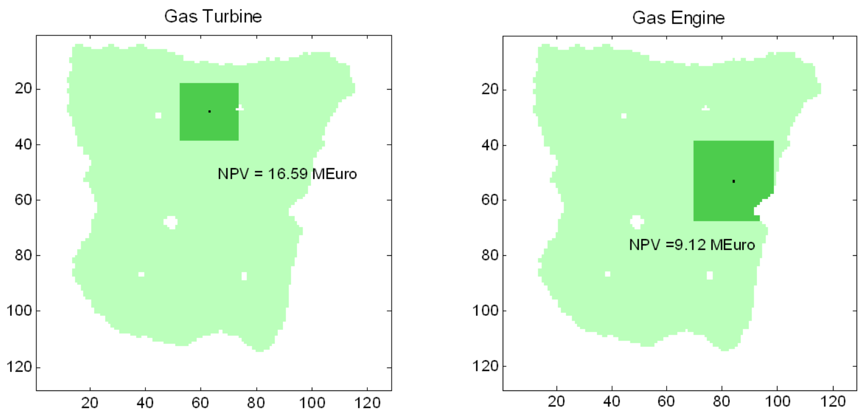

Fig. 3. Optimal location and supply area for the biomass plant

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 discrete binary version of the PSO algorithm, which makes use of the profitability index as objective function. The proposed approach have 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 turbine has been shown more profitable than gas motor, and the net present value of the gas turbine-based project has achieved 16.58 MEuro. Computer simulations have shown the good performance of the proposed method. Convergence is reached in few iterations (about 25) and computational cost more than 800 times lower than that required for exhaustive comparison.

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