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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:

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

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