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Maximization of generated power from wind energy conversion system using a new evolutionary algorithm

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A B S T R A C T

In this paper, a grid-connected Doubly Fed Induction Generator controlled by a Sliding Mode Controller (SMC) is used to maximize the Wind Energy Conversion System (WECS) output power. A SMC is implemented using a PID controller that is tuned using a new algorithm based on hybrid Differential Evolution with a Linearized Biogeography-Based Optimization (LBBO-DE). Biogeography-Based Optimization (BBO) is an evolutionary optimization algorithm based on a mathematical model of organism distribution. BBO permits a recombination of the solutions features by migration. A new migration model based on the sigmoid function is proposed. An analysis of the LBBO-DE is conducted using six different models, including the sigmoid model. Their performance were tested with 23 benchmark functions. The comparison reveals that the sigmoid model has the best performance. Therefore, the LBBO-DE with a sigmoid model is used to optimize the controller parameters to maximize the WECS output power. The LBBO-DE with the sigmoid model is compared with the Tyreus-Luyben tuning method, Genetic Algorithm (GA) and Linearized BBO (LBBO). The results showed that the LBBO-DE has the best performance. The proposed algorithm is verified using an experimental setup for the maximization of the generated power from the WECS and reducing power loss.

1. Introduction

Focus on developing the productivity of wind power has increased in the past decade. By using an electrical controller, many goals can be achieved especially in the variable speed processes [1–3]. Classical controllers can be replaced by modern controllers, such as a fuzzy controller [4], robust controller [5], or adaptive controller [6] due to the development and cost reduction of microprocessor based controllers. The Sliding Mode Controller (SMC) is one of the modern controllers that is suitable when dealing with variable speed processes. The SMC has advantages of reduced order and robustness against system parameter variations and disturbances, although it has an undesirable oscillations, as known "chattering" [7–9]. The SMC is implemented in this article by using two Proportional Integral Derivative (PID) controllers. Tuning the PID controller parameters cannot be achieved optimally by conventional techniques, such as the frequency response. Ziegler-Nichols rules, based on open and closed loop testing, were frequently used in the past [10,11]. On the other hand, many papers have recently focused on intelligent controllers, such as the Artificial Neural Network (ANN) controller, fuzzy control, and evolutionary algorithms-based controller [12].

In the last few decades, Evolutionary Algorithms (EAs) have proved their effectiveness as an optimization tool. EAs are often based on mathematics of a natural process in which the EA attempts to emulate the nature of some organisms in its method of selection, such as GA [13], Ant Colony Optimization (ACO) [14], Differential Evolution (DE) [15] and Particle Swarm Optimization (PSO) [16]. An EA usually consists of a set of random solutions for some optimization problems. These solutions interact with each other and they are subject to random changes. The random changes, to which the solutions are subjected, are called *mutations* while the interaction between the solutions, such as the crossover process in GA, is called *recombination*. Both mutation and recombination processes produce a new generation of solutions and thus the EA is transferred from one generation to another in its way to obtain the best-ever solution.

Biogeography-Based Optimization (BBO) depends on the mathematics of biogeography. Biogeography is a science that deals with the migration of plants and animals between their habitats (islands). BBO had been applied to various applications such as

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robot control tuning [17], antenna design [18], power system optimization [19], mechanical gear train design [20], biomedical applications [21] and satellite image classification [22]. Since BBO introduced by Ma and Simon [23], many of modifications have been applied to BBO.

Biogeography-Based Optimization has two mandatory drawbacks. First, it transacts with one independent variable at a time, so it is convenient with separable optimization problems, while most of our real-world problems are non-separable. Second, it has a weakness in its local search ability. As a result, another version of BBO was introduced by Simon [24], is called LBBO and uses some modifications applied to the standard version of BBO as gradient descent, boundary search, global grid search, re-initialization, and restart which will be later discussed.

In this paper, the motivation is to present a newer and better algorithm for some engineering applications, such as maximization of extractable power from the WECS. The presented results have been confirmed when compared to the relevant algorithms. To achieve these objectives, the performance of LBBO is improved by introducing a modified version. The modified version is a hybrid Differential Evolution with LBBO (LBBO-DE). A new migration model in LBBO, called sigmoid migration model, is also introduced in this paper, and a comparison among different migration models is carried out to examine their performance using the non-noisy 23 benchmarks that were accepted for the 2005 Congress of Evolutionary Computation (CEC).

This paper is organized as follows: Section 2 reviews the Biogeography-Based Optimization algorithm and presents the Linearized Biogeography-Based Optimization and its proposed modification. Section 3 introduces Differential Evolutionary algorithms. Section 4 explores six different migration models and the comparison between them. Section 5 presents the sliding mode control and Section 6 presents the dynamic model of the wind energy conversion system. In Section 7, a discussion and comparison of GA, BBO, LBBO, and LBBO-DE is investigated. Verification of the proposed algorithms is performed using an experimental setup for maximization of the wind energy conversion system, and is presented in Section 8. Finally, the conclusions are stated in Section 9.

2. Biogeography-Based Optimization

Biogeography-Based Optimization (BBO) is based on biogeography science. Its goal is to clarify the reason for the change in the geographical distribution of individuals in different environments over time. As early as the 19th century, biogeography was studied by Alfred Wallace and Charles Darwin [25,26], at which, researchers began to focus on this area. In BBO, every possible solution of the optimized problem is presented by a habitat (island). Each habitat has a fitness measurement which is called the Habitat Suitability Index (HSI). A good solution that has high HSI has a good performance in the optimization problem, while a habitat with a low HSI has a bad performance on the optimization problem. Each solution y_k has a number of features called a Suitability Index Variable (SIV), such as rainfall, topography, diversity of vegetation, or temperature. The number of SIVs in each solution y_k corresponds to the problem dimension.

The generation process of the next generation in BBO is performed by emigrating solution features to other islands, and receiving solution features by immigration from other islands [27]. The high species' count encourages species to leave the island, sharing their good SIVs with another island. Hence, islands with good HSI have high emigration rate μ_k and low immigration rate λ_k. Bad solutions have small species count, low emigration rate μ_k and high immigration rate λ_k.

BBO has basically two limitations. It changes with only one variable at a time in each solution. In addition, it has a weakness in its local search ability. Therefore, another version of BBO which is called Linearized Biogeography-Based Optimization (LBBO) with a gradient descent is being used. The gradient descent is one of the modifications applied here to standard BBO. Some of the modifications, such as boundary search, global grid search strategy, re-initialization and restart, will be discussed below.

2.1. LBBO migration

The immigration rate λ_k is probabilistically to decide whether or not a solution z_k tends to immigrate or not, where $\psi\in[1, N]$ is a randomly-selected parameter. The solution z_k is linearly combined with the k emigrating solutions such that z_k moves towards each emigrating solution y_j with an amount that is proportional to its emigration rate μ_j [24]:

$$z_k \leftarrow z_k + \mu j\left(y_j - z_k\right) \tag{1}$$

2.2. Gradient descent

To improve the LBBO's performance, it is provided with many local search operators. Gradient descent is implemented as shown in the following algorithm.

If $FE > \alpha\ FE_{max}$ or $(f_{min}(g) - f_{min}(g+1))/f_{min}(g) < \varepsilon_1$ then
Perform gradient descent on the N_g best individuals
End if

where FE is the current number of the function evaluations by the LBBO that has been performed and FE_{max} is the maximum function evaluation limit. The gradient descent is activated according to α value where $\alpha\in[0, 1]$; it is common to use $\alpha = 0.5$. $f_{min}(g)$ is the lowest value obtained for a generation. The quantity $(f_{min}(g+1) - f_{min}(g))/f_{min}(g)$ indicates the relative improvement in the best function value found by the LBBO from the g generation to the (g+1) generation. ε_1 is a threshold that is determined when the gradient descent is activated. The value $\varepsilon_1 = 0.1$ is typically chosen in this article.

2.3. Boundary search

As many optimization functions have their solutions on the boundary of the search domain, a boundary search is applied. If the best individual in the population is near with a small threshold of the search space boundary, it is then moved to the search space boundary. The boundary search is implemented with a similar rule as the gradient descent previously described.