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Wind power modeling using harmony search with a novel parameter setting approach

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ABSTRACT

A significant portion of the world's renewable energy is being provided by wind farms. The produced power of a wind farm in not always a constant value because it is highly dependent on the environmental conditions. As the amount of wind power rapidly increases, wind power estimation will be an important issue in electricity markets. A number of wind power estimation methodologies have been developed that are competing to provide the best estimation to the electric power industry. In this paper, a harmony search (HS) algorithm is proposed for modeling the power of a wind farm by finding the optimal weighting factors of a mathematical model. HS with a novel parameter setting approach, named HS-NPSA, is also developed to eliminate the tedious parameter assigning efforts of HS algorithm. In order to evaluate the usefulness of the proposed methodologies, the performance of HS-based algorithms is compared with those of the other heuristic techniques in terms of mean absolute percentage error (MAPE). Simulation results confirm the superiority of HS-NPSA algorithm for wind power modeling.

1. Introduction

Nowadays, renewable energy sources are more preferable since they are environment friendly with zero emissions in comparison with the conventional energy sources. Wind energy is one of the renewable energy sources that has received a lot of attention since 19th century (Islam et al., 2013). A connected to grid wind farm cannot be regarded as a fossil fuel power plant from the dispatching centre point of view because the wind farm's output power is dependent on the environmental conditions and is not always a constant value. Since wind power has a significant impact on the operation of electricity markets and power systems in areas with the highest penetration of wind power, the problems caused by the uncertain nature of wind speed and its occurrence in the system operations have drawn attention of system operators, utilities and researchers towards the state-of-the-art wind power estimation methods. For the scheduling purpose, it seems necessary to estimate the output power of any wind park. Moreover, the obtained information is useful from the perspective of resource planning, decision making, and integration of wind energy into the power system (Bilgili and Sahin, 2013). As a result, an accurate methodology is needed to accurately model the wind farm output power.

There are a variety of approaches for estimation of wind energy (Tascikaraoglu, 2014; Foley et al., 2012) which can be classified into two main categories: (1) approaches based on analysis of wind energy historical data which provide good results for monthly or even higher modeling scales and (2) approaches based on numerical weather prediction model which provide more accurate estimation data for short-term and very short-term estimation scales (Rahmani et al., 2013). In the latter, the selected model not only should be able to provide a good compromise between simplicity and accuracy but also can be used in a wide range of applications. Study of literature shows that wind power prediction tool (WPPT) (Madsen et al., 2005), generalized wind power prediction tool (GWPPT) (Croonenbroeck and Dahl, 2014), autoregressive moving average (ARMA), autoregressive integration moving average (ARIMA) (Liu et al., 2012; Erdem and Shi, 2011), artificial neural network (ANN) (Cao et al., 2012; Zhang et al., 2012; Amjady et al., 2011), fuzzy system (FS) (Zhang et al., 2012; Hong et al., 2010), support vector machine (SVM) (Mohandes et al., 2004), and grey predictor rolling model (El-Fouly et al., 2007) have been proposed for wind energy estimation. In order to obtain more accurate results, some researchers have also combined the methodologies such as particle swarm optimization (PSO) and neuro-fuzzy adaptive model (Pousinho et al., 2011), genetic algorithm (GA) and FS (Damousis and Dokopoulos, 2001), ANN and nearest

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neighbour approach (Jursa and Rohrig, 2008), and PSO with ant colony optimization (ACO) (Rahmani et al., 2013).

In this paper, a polynomial mathematical model considering wind speed and environment temperature is used to estimate the wind power. The model consists of a number of weighting factors whose values should be determined by an optimization technique. For this aim, harmony search (HS) heuristic method is proposed which tries to simulate the musicians' improvisation process to find optimal solution of an optimization problem.

Heuristic methods have shown a notable success rate in solving complex optimization problems. They are usually classified in two ways: population-based search methods and local-based search methods. The methods based on the former consider many solutions at the same time. Iteratively, they recombine the characteristics of the current solutions to produce new ones. The methods based on the latter consider one solution at a time. The current solution is modified during the search process using neighbourhood structures by considering a given acceptance rule, until a promising point near the initial solution is obtained. HS has the advantage of population-based methods whereby it recombines the characteristics of many solutions at the same time to produce a new solution named 'new harmony'. This is conducted by use of two operators: memory consideration and randomness. On the other hand, HS also has the advantage of local search-based method whereby it finely tunes the solution using a pitch adjustment operator.

In order to enhance the potential of HS, different improvements have been developed in the literature (Ingram and Zhang, 2009). Most of these improvements seek to find new improvisation schemes or combine HS with different techniques. This paper tries to introduce a novel parameter setting approach for HS algorithm to eliminate tedious and experience-requiring parameter assigning efforts.

The rest of this paper is organized as follows: Section 2 describes the mathematical model and optimization problem. Harmony search and a modified version which makes use of a novel parameter setting approach are explained in Section 3. Simulation results are shown in Section 4 and the conclusion is given in Section 5.

2. Wind power modeling using optimization algorithm

The model used in this study for estimation of the wind power is a mathematical model developed in (Kothari and Nagrath, 2003). This model which includes *S*-curve and parabola for two input variables (wind speed and environment temperature) is defined by Eq. (1).

$$P_m(v,T) = z_1 v^3 + z_2 v^2 + z_3 v + z_4 T^2 + z_5 T + z_6 \quad \text{(kW)} \tag{1}$$

where P_m is the model's output power of wind farm, v denotes the wind speed (m/s), T is the environment temperature (°C) and the constant values of z_i ($i=1,2,\ldots,6$) indicate the weighting factors.

As Eq. (1) shows, at each operating condition (wind speed and environment temperature), a corresponding output power is returned by the model. However, the main problem is the optimization of the values of the weighting factors. This work can be done by the help of an efficient optimization algorithm. The optimization algorithm tries to find the optimal values of the weighting factors in a six dimensional search space. As a result, the optimized model should be able to return the power of wind farm with high degree of accuracy.

In order to implement an optimization algorithm, an objective function should be defined. We make use of Eq. (2) as the objective function to minimize the difference between the model and actual wind powers.

$$F(\bar{z}) = \frac{1}{Q}\sum_{q=1}^{Q} \left|P_m^q - P_{actual}^q\right| \tag{2}$$

where F is the objective function value, $\bar{z} = [z_1\ z_2\ z_3\ z_4\ z_5\ z_6\ ]$ is a vector which contains the weighting factors, P_{actual} denotes the actual value of the output power and Q is the number of training data.

3. Harmony search

3.1. Overview of harmony search

Inspired by music phenomenon, harmony search (HS) was originally proposed by Geem et al. (2001) for solving optimization problems. In music phenomenon, musical instruments are played by certain musical notes according to musicians' experiences or randomness in an improvisation process and musicians improve their experiences based on an aesthetic standard. By the same way, decision variables can be given certain values according to computational intelligence or randomness in the optimization process and can be improved based on objective function.

Search process of HS is started by memorizing a number of feasible solutions, so called harmonies, in harmony memory (HM). The number of notes in a harmony is equal to the number of decision variables of the problem (n). At each iteration, a new harmony is played and compared with the harmonies stored in HM.

In order to select the value of each decision variable in the new harmony, there are three choices:

(1) The value can be randomly selected from all the candidate values. The probability of this choice is controlled by a parameter named harmony memory considering rate (*HMCR*) which is a constant value near 1. Therefore, the probability of generating a value randomly from the possible range of values is 1-*HMCR*.
(2) The value can be exactly same as the value of a random harmony from HM.
(3) The value can be something similar to the value of a random harmony from HM. The probability of this choice is defined by a parameter named pitch adjusting rate (*PAR*). The degree of similarity is controlled by a parameter named bandwidth (*bw*). Most often, the way to adjust *PAR* and *bw* at each iteration (t) is as follows (Mahdavi et al., 2007):

$$PAR(t) = PAR_{\min} + \frac{PAR_{\max} - PAR_{\min}}{t_{\max}} \times t \tag{3}$$

$$bw(t) = bw_{\max}\exp\left[Ln\left(\frac{bw_{\min}}{bw_{\max}}\right) \times \frac{t}{t_{\max}}\right] \tag{4}$$

```
Determine the number of harmonies (HM size), HMCR, PAR_max, PAR_min, bw_max, bw_min,
and t_max.
Generate a number of feasible harmonies for storing in HM.
Compute the objective function value for each harmony.
for    t = 1,2,…,t_max
    Update the time varying parameters.
    for    i= 1,2,…,n
        if rand(0,1) > HMCR
            x_new(i) = a random value from the possible range.
        else
        x_new(i) = corresponding value from a random harmony of HM.
            if rand (0,1) < PAR(t)
                x_new(i) = x_new(i) + bw(t) × [rand (0,1) − rand (0,1)].
            end
        end
    end
    Compute the objective function value of the new harmony.
    if F_new < F_worst
        Store the new harmony in HM.
        remove the worst harmony from HM.
    end
end
```

Fig. 1. Pseudocode of HS algorithm.