Wind turbine selection for wind farm layout using multi-objective evolutionary algorithms

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ABSTRACT

Wind energy has become the world's fastest growing energy source. Although wind farm layout is a well known problem, its solution used to be heuristic, mainly based on the designer experience. A key in search trend is to increase power production capacity over time. Furthermore the production of wind energy often involves uncertainties due to the stochastic nature of wind speeds. The addressed problem contains a novel aspect with respect of other wind turbine selection problems in the context of wind farm design. The problem requires selecting two different wind turbine models (from a list of 26 items available) to minimize the standard deviation of the energy produced throughout the day while maximizing the total energy produced by the wind farm. The novelty of this new approach is based on the fact that wind farms are usually built using a single model of wind turbine. This paper describes the usage of multi-objective evolutionary algorithms (MOEAs) in the context of power energy production, selecting a combination of two different models of wind turbine along with wind speeds distributed over different time spans of the day. Several MOEAs variants belonging to the most renowned and widely used algorithms such as SPEA2 NSGAII, PESA and msPEA have been investigated, tested and compared based on the data gathered from Cancun (Mexico) throughout the year of 2008. We have demonstrated the powerful of MOEAs applied to wind turbine selection problem (WTS) and estimate the mean power and the associated standard deviation considering the wind speed and the dynamics of the power curve of the turbines. Among them, the performance of PESA algorithm looks a little bit superior than the other three algorithms. In conclusion, the use of MOEAs is technically feasible and opens new perspectives for assisting utility companies in developing wind farms.

1. Introduction

Energy is a vital input for social and economic development (Baños et al., 2011). Deployment of 100% renewable energy system is technically and economically feasible in the future (Mathiesen, Lund, & Karlsson, 2011). The wind energy is one of the most powerful and profitable way to satisfy the demands of sustainable development (Sebitosi, 2008), while the production of wind energy has grown 30% per year over the last 10 years (Pacala & Socolow, 2004). It is worth noting that wind power has the lowest relative greenhouse gas emissions, the least water consumption demands and the most favorable social impacts, but it requires more land and has relatively high costs (Hernández-Escobedo, Manzano-Agugliaro, & Zapata-Sierra, 2010). Some agencies (European Wind Energy Association and the German Aerospace Center) have drawn up scenarios where renewable energies, including wind farms, could supply 80% of Europe's entire electricity demand by 2050. The National Renewable Energy Laboratory in the US assessed how wind could supply 20% of the entire US electricity demand by 2030 Lindenberg (2009). Other study demonstrates that the wind electricity potential in Canada is many times the current total electricity demand (Harvey, 2013).

The results of wind energy resource studies depend on the quality of the available wind energy data as well as on the assumptions about technology and available space (Manzano-Agugliaro, Alcayde, Montoya, Zapata-Sierra, & Gil, 2013). Therefore, such studies can only provide an approximation of the overall wind

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energy potential. Furthermore, it is important to consider that the wind energy potential can vary significantly for different regions (Hernandez-Escobedo, Manzano-Agugliaro, Gazquez-Parra, & Zapata-Sierra, 2011). It is worth noting that wind power has the lowest relative greenhouse gas emissions, the least water consumption demands and the most favorable social impacts, but it requires more land and has relatively high costs (Hernández-Escobedo et al., 2010).

Meteorological stations save an enormous quantity of statistical data every 10 min. Among the information they record is the average wind speed over the 10-min interval as well as the maximum wind speed and wind direction. Processing the data of a whole year provides important information about the wind regime of a given area (Alemán-Nava et al., 2014; Cancino-Solórzano & Xiberta-Bernat, 2009). Using these statistical data it is possible to calculate the energy output that a certain type of wind turbine can produce in the region as well as uptime/downtime average times (Hernández-Escobedo et al., 2010). Different models of wind turbine produce different amounts of energy depending on the wind speed (m/s) (Slootweg, De Haan, Polinder, & Kling, 2003).

The wind resource use fairly depends on the selected wind turbine. For every wind turbine model, the generated power (kW) can be calculated using the provided power curve from the manufacturer (Carrillo, Montaño, Cidrás, & Díaz-Dorado, 2013; Lydia, Kumar, Selvakumar, & Kumar, 2014). This way, different wind turbine models can be evaluated according to the characteristics of the wind for a specific region. Nowadays, the wind turbine selection problem based on the specific wind regimen has become an important task proved by the large number of examples found in the specialized academic literature. In 2009, for the Kingdom of Bahrain, Jowder (2009) uses a classical method to compare 5 wind turbines at 60 m height (Gamesa G58, Nordex N60, Nordex 70, Gamesa G80, and Nordex N80), determining that the most suitable turbine was Gamesa G58. Wind energy assessment of the São João do Cariri (SJC) in Paraiba (PB) state situated in Brazilian northeast was evaluated by de Araujo Lima and Filho (2012) using 3 different types of wind turbine (Bonus Mk III, Vestas V27 and Bonus Mk III). Alimi, Maatallah, Dahmouni, and Nasrallah (2012) assess eight commercial turbines at different hub heights for wind power generation on the central coast of the gulf of Tunis (Anbonus MK III-30, V39-35, V82-0.9, Dewind 1250 kW, GE 1500 kW, Vestas V80, Repower (2000 kW) MM 70-65 and Nordex (2300 kW) N90-100). For the Niger Delta region, Adaramola, Oyewola, Ohunakin, and Akinnawonu (2014) evaluated the performance of four wind turbine models ranging from 35 to 500 kW (G-3120, P19-100, WES-30 and ZEUS 500), obtaining that the energy output from wind turbine G-3120 was the highest. In Saudi Arabia on 2014, Al-Hadhrami (2014) evaluated the energy output of 16 wind turbines in the category of 1–3 kW, 5–10 kW, 15–20 kW and 50–80 kW rated powers, and the effect of hub height on energy output; the highest percentage change in annual energy yield (AEY) was obtained for an increase in hub height of 10 m from 20 to 30 m. Adaramola, Agelin-Chaab, and Paul (2014) assess the wind power generation along the coastal region of Ghana using 4 different wind turbines (WES30, CF-100, Polaris 15–50, and Garbi150/28). Based on the above mentioned references, a limited number of wind turbines has been evaluated on site in order to validate the energy possibilities of a region. Moreover, the combination of wind turbines for a wind farm has not been yet tested and there is no available studies that permits the optimization of the standard deviation for the average generated energy and the gross generated power.

This paper describes the usage of multi-objective optimization problems in the context of power energy production with the usage of 26 different wind turbines, selecting a combination of two of them respecting different wind speeds distributed over different time spans of the day. To solve the addressed problem we use different multi-objective evolutionary algorithms. The used algorithms are adaptations of four well-known MOEAs such as: NSGAII (Deb, Pratab, Agrawal, & Meyarivan, 2002), PESA (Corne, Knowles, & Oates, 2000), msPESA (Gil, Márquez, Baños, Montoya, & Gómez, 2007) and SPEA2 (Zitzler, Laumanns, & Thiele, 2001). Every implemented algorithm provides a solution set (called Pareto Set) for the addressed problem. These algorithms have already been successfully used in other kinds of planning problems, e.g. greenhouse planning (Márquez et al., 2011), cartographic problems (Manzano-Agugliaro, San-Antonio-Gómez, López, Montoya, & Gil, 2013), vehicle routing problems with time windows (Baños, Ortega, Gil, Fernández, & de Toro, 2013) or power systems optimization (Montoya et al., 2010; Zavoianu et al., 2013).

The paper is organized as follows. Section 2 presents the related works using EAs for wind farms layout. Section 3 presents the problem definition. Section 4 summarises the implemented multi-objective evolutionary algorithms. Section 5 shows the computational experiments with the proposed method and results. Finally, conclusions are given in Section 6.

2. Related works

Although wind park layout is a well known problem, its solution used to be heuristic, mainly based on the designer experience (Khan & Rehman, 2013). Due to the complexity of the wind farm layout design problem, traditional optimization approaches such as linear programming, branch-and-bound, dynamic programming, or backtracking cannot be applied (Khan & Rehman, 2013). Optimal wind farm designing is the result of a process, due to the non-differentiable nature of the problem; EAs are efficient techniques to work out this kind of optimization problem (Mora, Barón, Santos, & Payán, 2007).

Multimegawatt wind-turbine systems, often organized in a wind park, are the backbone of the power generation based on renewable-energy systems (Liserre, Cardenas, Molinas, & Rodriguez, 2011). Therefore, there are places where it is not suitable to place a certain model of wind turbine. One of the most important factors when considering the design of wind farms is the placement of the generators. As wind flows through the generator field, it loses part of its energy. This effect is known as "wake", and it means that the location of an wind turbine affects nearby wind turbines as well. Evolutionary Algorithms have been successfully used in the past (Kusiak & Zheng, 2010) to optimize the placement of wind turbines in order to minimize the effect of wake, in a 2D grid (Emami & Noghreh, 2010; Grady, Hussaini, & Abdullah, 2005). Minimizing wake is important in order to maximize the energy production, which is one of the most important objectives to attain (Kusiak & Song, 2010). For the sake of simplicity, as well as for practical reasons, this study will consider that the wind turbines are placed in a straight line perpendicular to the direction of the strongest wind regime.

Mosetti, Poloni, and Diviacco (1994) proposed one of the first optimization approaches to wind turbine distribution at a given site in order to extract the maximum energy for the minimum installation costs. This problem has been widely studied by means of genetic algorithms, GA (Emami & Noghreh, 2010; Grady et al., 2005). A comprehensive survey covering the use of GA which specifically looks at the research on different wind farm layout design problems (Wind turbine height, rotor diameter, or wake decay model) is done by Khan and Rehman (2013). A combinatorial optimization model for wind turbines type and number choice and placement considering the given wind park area shape and size is developed by Mustakerov and Borissova (2010) studding 24 turbine models. They state that the several wind park area conditions