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Original Research Article

Probabilistic economic/environmental power dispatch of power system integrating renewable energy sources

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ABSTRACT

The study of different integration aspects of renewable energy sources (RES) becomes very important to overcome problems caused by their variability or uncertainty. This paper treats the economic environmental power dispatch as a probabilistic multiobjective problem. The operation cost is considered as the sum of deterministic part and probabilistic one. First, the problem is solved based on expected values of generated RES power. Then, using the cumulative distribution function (CDF) of each RES, the CDF of the required reserve to compensate RES power variability is developed. After that, respecting to the reserve contribution of each thermal generator, the probabilistic part of the global generation cost as well as its CDF are developed. In order to solve the proposed multiobjective problem, a new computation approach based on particle swarm is investigated. Finally, the proposed approach is applied to solve the active power dispatch problem of IEEE 30-bus test system in two cases with and without RESs. The simulation results show that the proposed approach allows to get the complete information about the cumulative distribution function of the actual global cost of the system operation.

1. Introduction

The economic environmental dispatch (EED) is a multiobjective optimization problem aiming to minimize simultaneously the operating cost and the amount of greenhouse gases emitted by generation units. This problem is generally constrained by the generated power limits besides active and reactive power balance. The optimization is reached by scheduling produced power of generation units [1,2]. Many studies have been developed in order to present resolution approaches of this problem. An opposite numbers have been utilized to improve the convergence rate of the Harmony search in [3], a multi-objective chaotic particle swarm optimization has been developed in [4] and an advanced parallelized particle swarm optimization algorithm has been proposed in [5] for solving EED problem. Another study has been carried out in [6] in order to present a quality measure procedure for evaluating different resolution techniques.

Nowadays, with the growing use of renewable energy sources (RESs) for economic and/or environmental reasons, systems power operators have to start changing their power management policies because of the changing conducted by the intermittent RESs generation. Many studies have been done to reach a great power management in microgrids such as the approach developed in [7] which proposes a dynamic assignment of renewable energy tokens algorithm for collaborative microgrids based on the load management side and allowing to keep the power balance. Besides, the paper [8] proposes non-uniform hierarchical 16-QAM to provide a reliable data transmission over wireless links to achieve an efficient information exchange between the participants in such collaborative system. Particularly, integrating RESs into power system requires a new vision of the EDD problem. In [9], a probabilistic approach based on the convolution technique to assess the long-term performance of a hybrid solar wind power system is developed in order to deal with the RES variability in the economic dispatch.

Due to their ability and their implementation easiness, evolutionary algorithms (EAs) are more and more used to deal with complex multiobjective problems (MOPs) in power system field [10]. In [11], a multi-agent approach based on EAs is developed for solving the reactive power dispatch while others propose resolution approach based on interior point methods together with goal programming [12] or based on particle swarm optimizer [1,2,13]. Since Schaffer's vector evaluated genetic algorithm (VEGA) [14], a considerable amount of research has been proposed based on the genetic algorithm (GA) process. Horn et al. proposed a niched Pareto genetic algorithm (NPGA) which is based on a tournament selection scheme [15], while Srinivas and Deb presented a non-dominated sorting genetic algorithm (NSGA)

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[16] then Deb et al. improved this algorithm to overcome the computation complexity and the nonelitist solutions and presented a fast and elitist multiobjective genetic algorithm (NSGA-II) [17]. In addition, Zitzler and Thiele strength Pareto evolutionary algorithm (SPEA) [18] which was improved to SPEA2 [19]. In recent years, particle swarm optimization (PSO) has received a great attention for solving MOPs. This method is well-known as an efficient optimization algorithm. In fact, there are many versions of PSO and a lot of work for adapting PSO to problems with multiple objectives. For example, Coello et al. present in [20] an approach in which Pareto dominance is incorporated into PSO in order to allow it to handle problems with several objective functions. Further, authors propose in [21] a multiobjective PSO with time variant inertia and acceleration coefficients where inertia weight and PSO algorithm parameters expressions depend to iteration number. Another study developed in [22] proposes multiobjective PSO with dynamic population size. A competitive and cooperative co-evolutionary multiobjective PSO is proposed in [23] where subswarms compete then cooperate between them for having the best of the swarms bests, while in [24], correspond to each slave swarm one objective function of the MOP to find out non-dominated optima of this objective function. Other studies, presented in [25,26], use hybridization techniques.

This paper proposes a resolution approach for the probabilistic economic dispatch problem (EED) of a power system integrating RESs. Both the cost and the greenhouse gas emission of the system operation are minimized as a multiobjective optimization problem. Besides, a probabilistic study of the required reserve is done in order to give the cumulative distribution function (CDF) of the global operation cost. In order to resolve this problem, we investigate a metaheuristic method based PSO with enhancing the population velocity, proposing a matrix representation of its characteristics and employing a Pareto dominance for selecting and updating the solutions set. In order to simulate the approach results, the IEEE 30 bus test network is used and two cases are treated. First, the simultaneous optimization of the consumed fuel cost, the amount of pollutant emissions and the active power losses in transmission lines using the proposed approach compared to benchmark methods. Then, two thermal generators of the considered test network are replaced by wind and solar parks. The reminder of this paper is structured as follows. Section 2 presents a probabilistic modeling of RESs, Section 3 develops the probabilistic environmental economic dispatch problem formulation while Section 4 details the proposed optimization approach. Then, Section 5 presents results discussion and finally, Section 6 concludes this work.

2. Probabilistic power modeling of renewable energy sources

There are various models that express mathematically the electrical power produced by renewable technologies using deterministic or probabilistic approaches [27,28].

2.1. Probabilistic modeling of PV cell power

The energy produced by a photovoltaic (PV) generator is estimated based on manufacturer data as well as climate data (radiation and temperature). The output power of the PV generator can be calculated by [29]

$$P_{\mathrm{pv}} = rA\eta \tag{1}$$

with

$$\eta = \eta_{\mathrm{ref}}(1 - \gamma(T - T_{\mathrm{ref}})) \tag{2}$$

where r is the solar irradiance; A is the total area of the PV module; η is the PV generation efficiency. On the other hand, η varies with the cell temperature T, where η_{ref} is the reference efficiency of the photovoltaic generator, γ is the temperature coefficient of short-current [K] and T_{ref} is the reference cell temperature [K]. The solar irradiance r can be described reasonably by a beta distribution [30]

$$f_{\mathrm{r}}(r) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\left(\frac{r}{r_{\max}}\right)^{a-1}\left(1 - \frac{r}{r_{\max}}\right)^{b-1} \tag{3}$$

with

$$a = \mu\left[\frac{\mu(1-\mu)}{\sigma^2 - 1}\right] \tag{4}$$

$$b = (1-\mu)\left[\frac{\mu(1-\mu)}{\sigma^2 - 1}\right] \tag{5}$$

where $r_{\max}$, μ and σ are, respectively, the maximum, mean and standard deviation values of solar radiance. In this paper, it is assumed that the PV cell temperature forecasts are without errors. Then the probability density function (PDF) of PV cell power P_{pv} is given by

$$f_{\mathrm{pv}}(P_{\mathrm{pv}}) = \frac{1}{P_{\mathrm{pv}}^{\max}}\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\left(\frac{P_{\mathrm{pv}}}{P_{\mathrm{pv}}^{\max}}\right)^{a-1}\left(1 - \frac{P_{\mathrm{pv}}}{P_{\mathrm{pv}}^{\max}}\right)^{b-1} \tag{6}$$

where $P_{\mathrm{pv}}^{\max}$ is the maximum generated power. Then, the CDF of PV generation is expressed in Eq. (7).

$$F_{\mathrm{pv}}(P_{\mathrm{pv}}) = \int_0^{P_{\mathrm{pv}}} f_{\mathrm{pv}}(x)dx \tag{7}$$

2.2. Probabilistic modeling of wind power

The output power of a wind turbine varies at different wind speeds and accordingly to the power curve given by the manufacturer. Indeed, the power output of wind turbine can be approximated by [29,31],

$$P_{\mathrm{w}}(v) = \begin{cases} 0 & v < v_{\mathrm{c}}, v > v_{\mathrm{f}} \\ P_{\mathrm{r}}\frac{v - v_{\mathrm{c}}}{v_{\mathrm{r}} - v_{\mathrm{c}}} & v_{\mathrm{c}} \leqslant v \leqslant v_{\mathrm{r}} \\ P_{\mathrm{r}} & v_{\mathrm{r}} \leqslant v \leqslant v_{\mathrm{f}} \end{cases} \tag{8}$$

where P_{r} is the rated electrical power, v_{c} is the cut-in wind speed at which the turbine first starts to rotate and generate power, v_{f} the cut-off wind speed which is the breaking system employed to avoid damage to the rotor and v_{r} the rated wind speed [m/s] at which the power output reaches the best operating at P_{r}.

The wind speed is a random variable which mostly approximated by Weibull distribution [9].

$$f_v(V) = \left(\frac{k}{c}\right)\left(\frac{V}{c}\right)^{k-1}\exp\left(-\left(\frac{V}{c}\right)^k\right) \tag{9}$$

where c is a scale parameter and k is a shape parameter.

The wind power PDF is deduced from Eqs. (8) and (9) and since the function of wind power in terms of wind speed variable is strictly increasing, the PDF of P_{w} can be expressed by,

$$f_{\mathrm{w}}(P_{\mathrm{w}}) = \begin{cases} F_1 & P_{\mathrm{w}} = 0 \\ \beta\left(\frac{k}{c}\right)\left(\frac{\alpha}{c}\right)^{k-1}\exp\left(-\left(\frac{\alpha}{c}\right)^k\right) & 0 \leqslant P_{\mathrm{w}} \leqslant P_{\mathrm{r}} \\ F_2 & P_{\mathrm{w}} = P_{\mathrm{r}} \end{cases} \tag{10}$$

with

$$\begin{cases} \beta = \frac{V_{\mathrm{r}} - V_{\mathrm{c}}}{P_{\mathrm{r}}} \\ \alpha = V_c + \beta P_{\mathrm{w}} \end{cases}$$

$$F_1 = \beta * \left(1 - \exp\left(-\left(\frac{V_c}{c}\right)^k\right) + \exp\left(-\left(\frac{V_{\mathrm{f}}}{c}\right)^k\right)\right)$$

$$F_2 = \beta * \left(\exp\left(-\left(\frac{V_{\mathrm{r}}}{c}\right)^k\right) - \exp\left(-\left(\frac{V_{\mathrm{f}}}{c}\right)^k\right)\right)$$