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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]

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

with

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

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]

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

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

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

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

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

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],

$$P_w(v) = \begin{cases} 0 & v < v_c, v > v_f \\ P_r\frac{v - v_c}{v_r - v_c} & v_c \leqslant v \leqslant v_r \\ P_r & v_r \leqslant v \leqslant v_f \end{cases} \tag{8}$$

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,

$$f_w(P_w) = \begin{cases} F_1 & P_w = 0 \\ \beta\left(\frac{k}{c}\right)\left(\frac{\alpha}{c}\right)^{k-1}\exp\left(-\left(\frac{\alpha}{c}\right)^k\right) & 0 \leqslant P_w \leqslant P_r \\ F_2 & P_w = P_r \end{cases} \tag{10}$$

with

$$\begin{cases} \beta = \frac{V_r - V_c}{P_r} \\ \alpha = V_c + \beta P_w \end{cases}$$

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

$$F_2 = \beta * \left(\exp\left(-\left(\frac{V_r}{c}\right)^k\right) - \exp\left(-\left(\frac{V_f}{c}\right)^k\right)\right)$$

Then, the cumulative distribution function (CDF) of wind generator is expressed by,

$$F_w(P_w) = 1 - \exp\left(-\left(\frac{V_c + \beta P_w}{c}\right)^k\right).$$

3. Probabilistic economic emission dispatch optimization

This paper considers the economic emission dispatch (EED) problem as the combination of two subproblems. The first one is a multiobjective optimization of fuel cost and greenhouse gases emission of thermal units (TU) which accounts the wind and PV generations by their expected values. While the second subproblem considers the CDF of either wind and PV power in order to compute the total necessary reserve. In fact, this work takes into account only the required reserve for compensating the disparity between actual renewable generated power and expected values and considers that reserve is guaranteed by the system TUs and the power contributing in reserve of each one is depending on the shape slope of the spinning reserve cost.

Using the expected values of renewable sources, the residual load power P_D^r can be defined as,

$$P_D^r = P_D - \sum_{i=1}^{N_W} E(P_{w_i}) - \sum_{i=1}^{N_{pv}} E(P_{pv_i}) \quad (11)$$

where P_D is the active power demand.

Then, this paper considers the EED problem solution as a multi-objective problem of cost and emission objective functions to satisfy the residual demand.

3.1. Objective functions

The EED problem is modeled as a multiobjective optimization problem of three functions. The first one is the operating cost while the second function is the amount of greenhouse emissions and finally the active power losses.

3.1.1. Minimization of consumed fuel cost

The classical economic dispatch problem of finding the optimal combination of power generation, that minimizes the total fuel cost, while satisfying required demand at each bus [4], is formulated as,

$$f_1 = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2), \quad (12)$$

where a_i, b_i and c_i are the fuel cost coefficients of generator i, P_{Gi} is the power produced per unit (p.u) by generator i and N_G is the number of generators.

3.1.2. Minimization of greenhouse gas emissions

Then, the second considered objective function in the amount of greenhouse gas emissions is given as the sum of a quadratic and exponential functions of each generator [4] and is given by,

$$f_2 = \sum_{i=1}^{m_g} \left(10^{-2}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \psi \exp(\lambda_i P_{Gi})\right), \quad (13)$$

where $\alpha_i, \beta_i, \gamma_i$ and λ_i are the emission coefficients of generator i.

3.1.3. Minimization of active power losses

The third objective function is the active power losses which present the real power losses in transmission lines [32,33]. It is expressed by,

$$f_3 = \sum_{i=1}^{N_b} \mathcal{V}_i \sum_{j=1}^{N_b} \mathcal{V}_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}), \quad (14)$$

where $\mathcal{V}_i$ and δ_i are the size and the argument of the voltage at ith bus, and Y_{ij} and θ_{ij} are the size and the argument of the nodal admittance matrix. The problem of the tree formulated functions f_1, f_2 and f_3 is constrained by several equality and inequality constraints.

3.2. Problem constraints

The problem constraints are classified on equality constraint presenting the power balance and inequality constraints which are the variables bounds.

3.2.1. Equality constraint

Such constraint presents the active power balance of the whole electrical network. The power losses are neglected in this work the this constraint is formulated by,

$$\sum_{i=1}^{N_G} P_{Gi} - P_{loss} - P_D^r = 0, \quad (15)$$

where P_D and P_{loss} are, respectively, the active power demand and the active power losses with $P_{loss} = f_3$.

3.2.2. Inequality constraint

Each voltage and active power generation P_{Gi} is restricted by an upper and a lower limits, and expressed by,

$$\mathcal{V}_i^{min} \leqslant \mathcal{V}_i \leqslant \mathcal{V}_i^{max}, \quad (16)$$

$$P_{gi}^{min} \leqslant P_{gi} \leqslant P_{gi}^{max}. \quad (17)$$

3.3. Required reserve

Since the generated power of TUs are obtained, the total required reserve can be given as

$$TR = \sum_{i=1}^{N_G} P_{Gi} + \sum_{i=1}^{N_W} P_{w_i} + \sum_{i=1}^{N_{PV}} P_{pv_i} - P_D$$

We note that the expected value of the total required reserve is a null value and its PDF is equal to the convolving product of all RES PDFs. In the case of two generators wind and photovoltaic, the TR CDF is given by

$$CDF(TR) = \int_{-\infty}^{+\infty} F_w(TR - P_{pv}) f_{pv}(P_{pv}) dP_{pv} \quad (18)$$

Finally, the reserve cost is added to the solutions values of f_1. The cost contributing reserve power P_{SRi} can be expressed by [34],

$$C_{SRi}(P_{SRi}) = x_i + y_i P_{SRi} \quad (19)$$

where x_i and y_i are the spinning reserve cost of the ith thermal generator. Since this function is linear, and in order to obtain minimum total cost, the function with the minimum slope is primarily used in terms of the required reserve. the probabilistic operating cost $f\prime_1$ is the updated value of the cost presented by f_1 taking into consideration the power reserve cost. It is expressed as follows:

$$f_1' = f_1 + \sum_{i=1}^{N_G} C_{SRi}(P_{SRi}) \quad (20)$$

4. Resolution method

A general multiobjective optimization problem can be mathematically expressed as follows [35]:

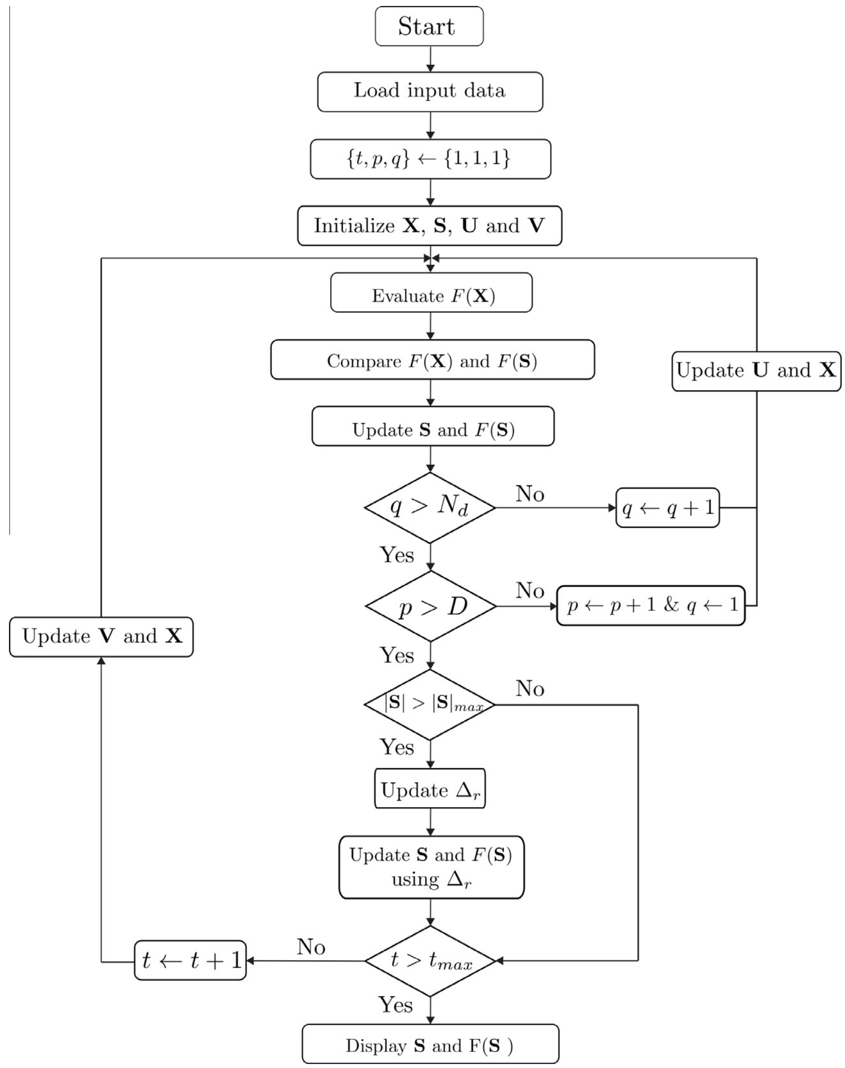

Fig. 1. Flow chart of FMOPSO.

$$\text{Minimize} \quad \mathbf{F}(\mathbf{x}) = \left[f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_{N_{obj}}(\mathbf{x})\right] \tag{21}$$
$$\text{Subject to} \quad g_k(\mathbf{x}) \leqslant 0, k = 1, \ldots, N_c,$$

where $\mathbf{x} = [x_1, x_2, \ldots, x_D]^T$ with x_j can be either real, integer or boolean values, and D is the research space dimension. $f_r(\cdot)$ are the N_{obj} objective functions and $g_k(\cdot)$ are the N_c constraint functions of the problem.

The family of optimal solutions of this MOP is composed of all those potential solutions such that the components of the corresponding objective vectors whose elements cannot be simultaneously improved. This is known as the concept of Pareto optimality. In a minimization problem, Pareto dominance and Pareto optimality are defined as follows [36]:

Definition 1 (*Pareto dominance*). A given vector $\mathbf{x} = [x_1, x_2, \ldots, x_D]$ is said to dominate $\mathbf{y} = [y_1, y_2, \ldots, y_D]$ if and only if $\forall j \in \{1, 2, \ldots, D\}, x_j \leqslant y_j$ and $\exists j_0 \in \{1, 2, \ldots, D\}, x_{j_0} < y_{j_0}$.

Definition 2 (*Pareto optimality*). For a general MOP, a given solution $\mathbf{x}^{\star} \in \mathcal{F}$, where $\mathcal{F}$ is the feasible solution space, is Pareto optimal if and only if there is no $\mathbf{x} \in \mathcal{F}$ that dominates $\mathbf{x}^{\star}$.

4.1. Particle swarm optimization (PSO)

PSO is inspired by the flocking behavior of the birds. The PSO process is based on population search where each particle i has a position $\mathbf{x}_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,D}]^T$ and a velocity $\mathbf{v}_i = [v_{i,1}, v_{i,2}, \ldots, v_{i,D}]^T$ in a D-dimension research space. In iteration t, the velocity and the position are updated using the following expressions

$$\begin{cases} \mathbf{v}_i(t) = \omega\mathbf{v}_i(t-1) + r_1c_1(\mathbf{p}_i(t-1) - \mathbf{x}_i(t-1))\ldots \\ \qquad\qquad + r_2c_2\left(\mathbf{p}_g(t-1) - \mathbf{x}_i(t-1)\right), \\ \mathbf{x}_i(t) = \mathbf{x}_i(t-1) + \mathbf{v}_i(t), \end{cases} \tag{22}$$

where $i = 1, \ldots, N$ and N is the population size, ω is the inertia weight, c_1 and c_2 are two positive constants, r_1 and r_2 are random values in the range $[0, 1]$, $\mathbf{p}_i$ is the personal best of the particle i, and $\mathbf{p}_g$ is the global best of population. The performance of each particle is evaluated according to a predefined fitness function which is related to the considered problem.

4.2. Fast multiobjective particle swarm optimization

In the design of optimization algorithms, there is generally a trade-off between performance and computational complexity. FMOPSO aims to extends the conventional PSO, which was initially designed to deal with mono-objective problems, to multiobjective problems without using variable functions aggregation weights. It is proposed to combine sequentially two kinds of population motion. First, a uniform motion is used to guarantee a great exploration of the whole research space which helps the population to find quickly the optimal solutions in the relative motion toward

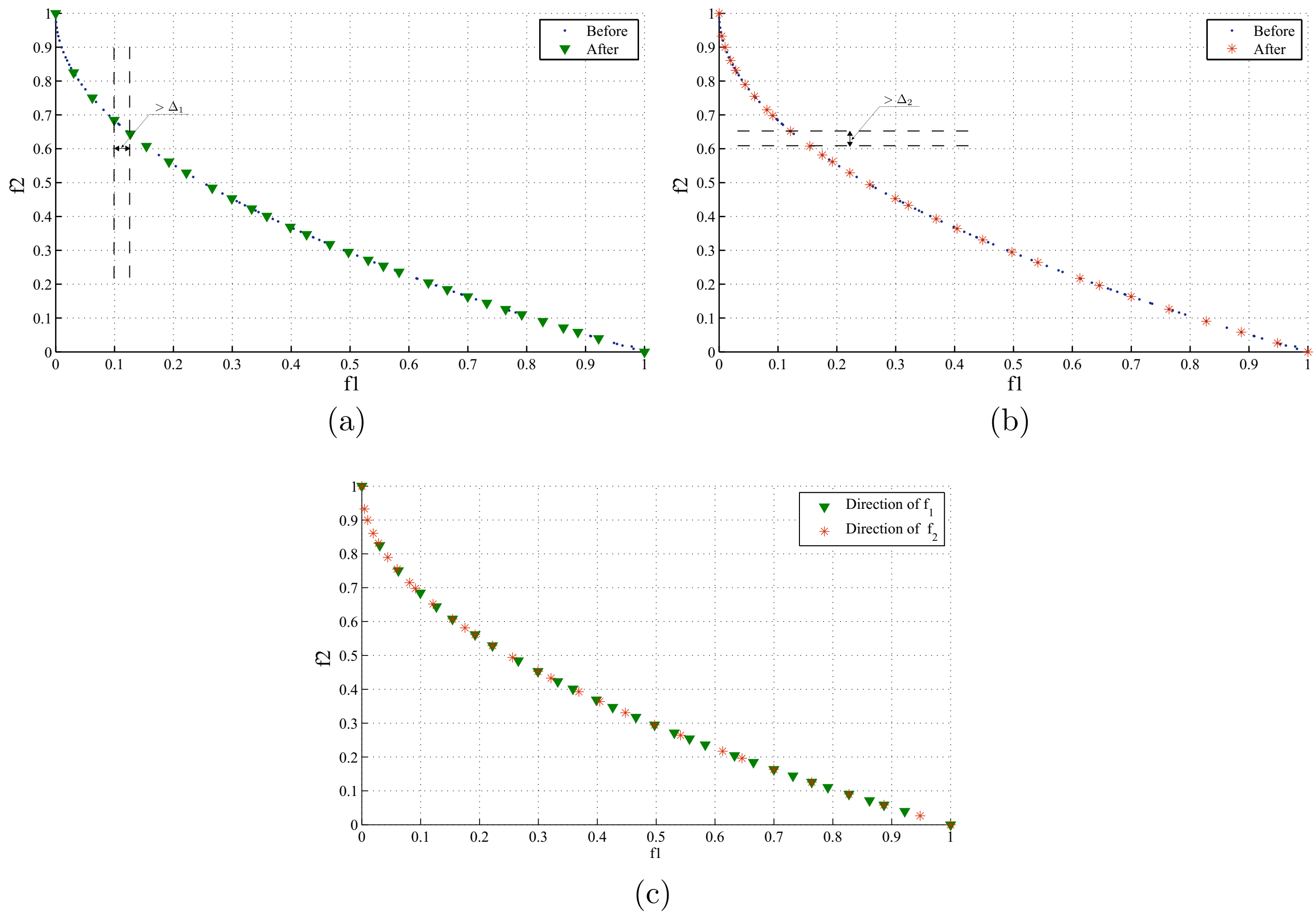

Fig. 2. Spacing selection in the direction of (a) function f_1, (b) function f_2 and (c) the obtained solutions curve in the case of bi-objective problem.

best particles as a second step of population motion. A parallel computing is used to evaluate the whole population fitness which allows us a fast computing. Then, this fitness is compared with fitness values of the particles in the solutions set **S**. The comparison is based on Pareto dominance allowing the updating of the set **S** and the adding of other solutions which are incomparable to the existing ones. Then, in order to continue exploring effectively the search space, the velocity and the position of the population are updated. Fig. 1 shows the flow chart of the proposed approach.

The sets **X**, **U** and **V** representing the position, the uniform and the relative population motion velocities, respectively, and **S** is the non-dominated solutions set. They can be expressed in a matrix form as,

$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N], \tag{23}$$

$$\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_N], \tag{24}$$

$$\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_N], \tag{25}$$

$$\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_m] \tag{26}$$

where m is the set size which varies in each iteration until reaching $|\mathbf{S}|_{\max}$, the defined maximum size of **S**. The proposed algorithm includes two major concepts:

The motion velocity: a uniform motion is proposed as a first exploration of research space followed by a relative motion in the direction of the best particles area. each research interval is divided to N_d smaller ones then an initial population is generated in the first segment of each variable research interval. We note $[a_j, b_j]$ the research space of the variable j and $\alpha_j = \frac{(b_j - a_j)}{N_d}$ the motion step following the direction j. Thus, the velocity of the uniform motion of the population particles is defined as,

$$\mathbf{u}_i(p + (q-1)D) = q\mathbf{w}(p), \tag{27}$$

with

$$\mathbf{w}(p) = [w_1(p), w_2(p), \ldots, w_D(p)]^T$$

and

$$w_j(p) = \begin{cases} \alpha_j & \text{for } j = p, \\ 0 & \text{for } j \neq p \end{cases}$$

where $p = 1, \ldots, D$ and $q = 1, \ldots, N_d$.

In the second step, particles follow the solutions in the set **S**. Thus, the proposed velocity of a particle i, at the iteration, t is given by

$$\mathbf{v}_i(t) = \omega(t)\mathbf{v}_i(t-1) + \rho(t)\sum_{l=1}^{m}(\mathbf{s}_l(t-1) - \mathbf{x}_i(t-1)), \tag{28}$$

The inertia weight $\omega(t)$ and acceleration coefficients $\rho(t)$ are dynamically updated, decreasing with iterations, in order to have a large velocity in the beginning, and to refine the research slower in the last iterations. Hence, we set $\omega(t) = \beta\frac{N_t - t}{N_t}$ and $\rho(t) = \gamma\frac{N_t - t}{N_t}$ with $\{\beta, \gamma\} \in (0, 1)$, and N_t is the iteration number.

The non-dominated set: In each iteration, fitness vectors of the whole population is evaluated and compared to fitness vectors of the whole solutions set. This comparison is based on Pareto dominance. The updating of the solutions set **S** is done by improving the existing results or adding incomparable ones.

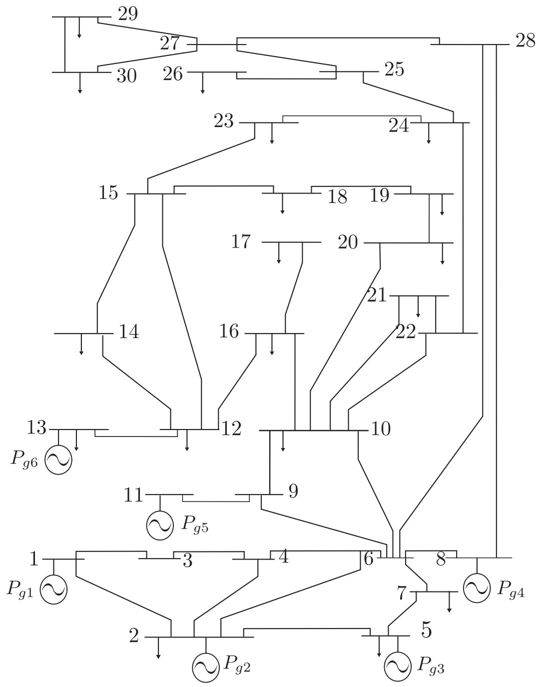

Fig. 3. Single-line diagram of modified IEEE 30 bus.

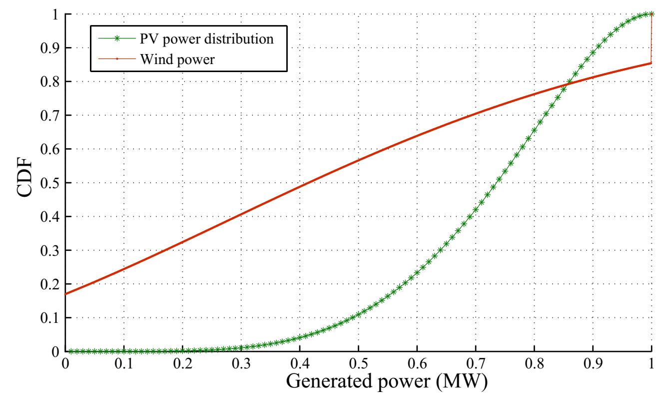

Fig. 4. Cumulative distribution of PV cell and wind power generations.

In order to reduce the complexity of the algorithm, while obtaining a well distributed Pareto set, only a subset of the solutions on all direction of the objective functions space is saved. Indeed, starting with $r = 1$ until $r = N_{obj}$, the obtained solutions are sorted in the direction of the function f_r, and then the solutions that are distant by at least $\Delta_r = \overline{\Delta}_r \frac{|\mathbf{S}|_{max}}{|\mathbf{S}|}$ are selected with $\overline{\Delta}_r$ is the average distance between two consecutive solutions on the direction of function f_r. The remaining solutions from step r are considered on step $r + 1$, in order to select in the same way a new subset of solutions on direction of function f_{r+1}. For instance, Fig. 2 shows the subset selection in the case of a bi-objective problem. The black bulls represent the solutions set while red and green ones represent the saved solutions by a successive selection in the direction of the function f_1 and f_2, respectively.

5. Simulation and results

Hereafter, the proposed optimization algorithm is used to solve the power dispatch problem in the case of a IEEE 30-bus test network. Fig. 3 presents this network which includes 30 buses, 6 thermal generators and 41 transmission lines. The grid data and the buses loads on a 100 MVA base of the test system are given in [37,38]. Table 1 presents the fuel cost of both operating and reserve power coefficients and emission function coefficients. In order to show performances of the proposed approach, three cases are studied. In the first one, the classical EED with only thermal units generation is treated taking into account losses in the transmission lines. While in the second case, transmission power losses are neglected and two TUs generators are replaced by wind and PV cell generator of the same capacity as thermal ones 50 MW and 60 MW, respectively. The CDF of considered wind and PV generators are presented in Fig. 4. The data simulation are as follows. For wind power plant, the rated electrical power of the wind turbine generators is $P_r = 1$ MW, the cut-in, cut-off and rated speed wind are, respectively, $v_c = 3.6$ m/s, $v_f = 20$ m/s and $v_r = 12$ m/s. For PV plant, the maximum generated power by The PV panel is $P_{pv}^{max} = 100$kW, the beta distribution coefficients are $a = 5$ and $b = 2$. We assume that generators of the same nature and in the same plant parc are perfectly correlated.

In the first case, we present three optimization scenarios where each scenario represents two of the three objective functions of the multiobjective dispatch problem in order to present to the power system dispatcher all possibilities he can need dependently to the requirements of a particular system. For all cases, the obtained curves of Pareto fronts and the best solution of each objective function are presented to be compared and discussed. The first study is the optimization of the consumed fuel cost and the greenhouse gas emissions. This optimization allows the dispatcher to have the database of several compromise solutions between the minimal possible cost and the minimal environmental possible impact. Fig. 5a shows the Pareto fronts for fuel cost/gas emissions optimization by both MOPSO (•) and FMOPSO (▼). We observe that the curve obtained by FMOPSO is smooth and the solutions are distrib-

Table 1
Cost and emission coefficients of IEEE-30 generators.

		G1	G2	G3	G4	G5	G6
Cost coef	a ($/(hMW^2))	10	10	20	10	20	10
	b ($/(hMW))	200	150	180	100	180	150
	c ($/h)	100	120	40	60	40	100
	y ($/(hMW))	300	190	320	310	320	310
	x ($/h)	30	35	25	30	25	30
Emission coef	α (tons/(hMW^2))	4.091	2.543	4.258	5.326	4.258	6.131
	β (tons/(hMW))	−5.554	−6.047	−5.094	−3.550	−5.094	−5.555
	γ (tons/h)	6.490	5.638	4.586	3.380	4.586	5.151
	ψ (tons/h)	2.0e−4	5.0e−4	1.0e−6	2.0e−3	1.0e−6	1.0e−5
	λ ((MW)$^{-1}$)	2.857	3.333	8.000	2.000	8.000	6.667
Limits	P_{min} (MW)	5	5	5	5	5	5
	P_{max} (MW)	50	60	100	120	100	60

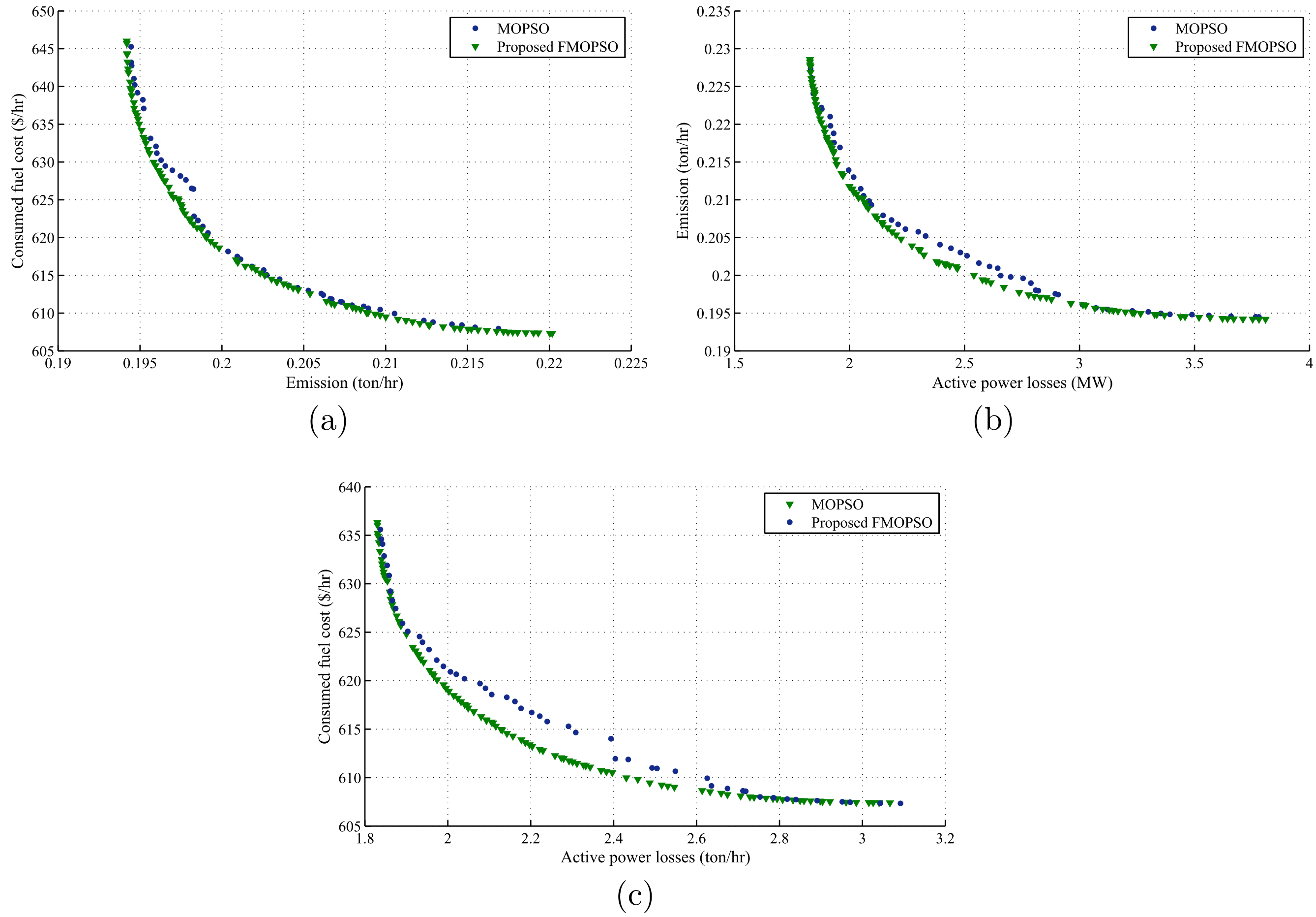

Fig. 5. Pareto front of (a) consumed fuel cost/greenhouse gas emissions, (b) greenhouse gas emissions/active power losses and (c) consumed fuel cost/active power losses.

Table 2
Best consumed fuel cost.

	NPGA [40]	SPEA [40]	NSGA-II [39]	MOPSO	Proposed
P_{G1}	0.1425	0.1279	0.1136	0.1559	0.1114
P_{G2}	0.2693	0.3163	0.3052	0.3203	0.3001
P_{G3}	0.5908	0.5803	0.6009	0.5279	0.5959
P_{G4}	0.9944	0.9580	0.9810	0.9650	0.9784
P_{G5}	0.5315	0.5258	0.5122	0.5399	0.5384
P_{G6}	0.3392	0.3589	0.3557	0.3582	0.3405
Cost ($/h)	608.06	607.86	608.12	607.95	**607.33**
Emission (ton/h)	0.2207	0.2176	0.2199	0.2168	0.2201
Losses (MW)	3.3700	3.3200	3.4658	3.3364	3.1025
	–	–	–	$R = 0.46$	

Table 3
Best greenhouse gas emissions.

	NPGA [40]	SPEA [40]	NSGA-II [39]	MOPSO	Proposed
P_{G1}	0.4064	0.4145	0.4111	0.3913	0.4066
P_{G2}	0.4876	0.4450	0.4652	0.4257	0.4546
P_{G3}	0.5251	0.5799	0.5415	0.5944	0.5499
P_{G4}	0.4085	0.3847	0.3955	0.3755	0.392
P_{G5}	0.5386	0.5348	0.5370	0.5672	0.5526
P_{G6}	0.4992	0.5051	0.5168	0.5156	0.5153
Cost ($/h)	644.23	644.77	645.48	645.26	646.01
Emission (ton/h)	0.19430	0.1943	0.1942	0.1944	**0.1941**
Losses (MW)	3.1400	3.0000	3.3313	3.5942	3.7765
	–	–	–	$R = 0.46$	

Table 4
Extreme solutions of Pareto front of greenhouse gas emissions/active power losses.

	MOPSO		Proposed	
	Best emission	Best losses	Best emission	Best losses
P_{G1}	0.3991	0.06900	0.4106	0.0610
P_{G2}	0.4788	0.2879	0.4611	0.2819
P_{G3}	0.6023	1.0000	0.5454	1.0000
P_{G4}	0.3440	0.5380	0.3911	0.5193
P_{G5}	0.5203	0.7966	0.5486	0.8288
P_{G6}	0.5270	0.1607	0.5151	0.1610
Cost ($/h)	650.88	634.05	646.63	635.99
Emission (ton/h)	0.1944	0.2273	**0.1941**	0.2285
Losses (MW)	3.7802	1.8309	3.809	**1.8278**
		$R = 0.43$		

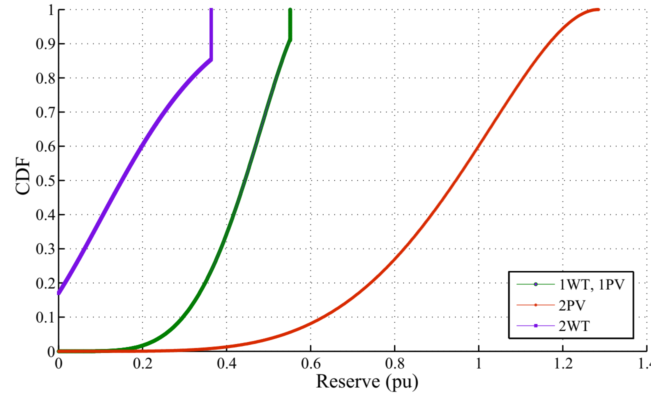

Fig. 7. Cumulative distribution function of required reserve.

Table 5
Extreme solutions of Pareto front of active power losses/consumed fuel cost.

	MOPSO		Proposed	
	Best cost	Best losses	Best cost	Best losses
P_{G1}	0.0824	0.0768	0.1036	0.0951
P_{G2}	0.3055	0.3260	0.3091	0.2588
P_{G3}	0.6112	0.9927	0.6004	1.0000
P_{G4}	0.9885	0.5128	0.9816	0.5140
P_{G5}	0.5385	0.7929	0.5313	0.8268
P_{G6}	0.3384	0.1510	0.3386	0.1575
Cost ($/h)	607.40	635.60	**607.34**	636.33
Emission (ton/h)	0.2220	0.2257	0.2225	0.2276
Losses (MW)	3.0665	1.8375	3.0919	**1.8302**
		$R = 0.49$		

uted uniformly along the curve unlike the front obtained by MOPSO which presents points more crowded in the middle than in the edges. Besides, we have some points from the curve of MOPSO which are above the FMOPSO curve which means that those points are dominated by those of FMOPSO. In order to show the advantage of the proposed method, several background meta-heuristic methods, namely NSGA2 [39], SPEA [40] and NPGA [40] besides the classic MOPSO were applied to resolve this problem and comparative results are presented in Tables 2 and 3 (bold values present the best obtained values relatively to methods comparison). We note that the value of the minimum cost obtained by FMOPSO (607.33 $/h) and of the minimum emissions amount obtained by FMOPSO (0.19419 ton/h) are the least ones comparing with background methods. Besides, we have enhanced the running time also with a ratio of 0.46 (the FMOPSO running time is less than a half of MOPSO running time). The second study is the optimization of greenhouse gas emissions and active power losses. This scenario provides a database to be used as a decision support in the case where the system cannot bear high level of power losses in the transmission lines and, at the same time, the power system is aware of pollution impact of its own production. Fig. 5b shows the Pareto front of gas emissions/active losses. We note that the solutions obtained by FMOPSO (▼) are better distributed than those obtained by MOPSO (•). Table 4 gives the two extreme points of the Pareto curves. The minimum values obtained by FMOPSO are less than those obtained by MOPSO and with a good running time ratio. The third study is the optimization of active power losses and consumed fuel cost. If the environmental aspect is not considered, this study is enough for giving trade-off solutions for optimal economic dispatch while taking into consideration the minimization of power losses. Fig. 5c shows the Pareto front of active losses/fuel cost. We note that the solutions obtained by FMOPSO (▼) are more uniformly distributed than those obtained by MOPSO (•). Table 5

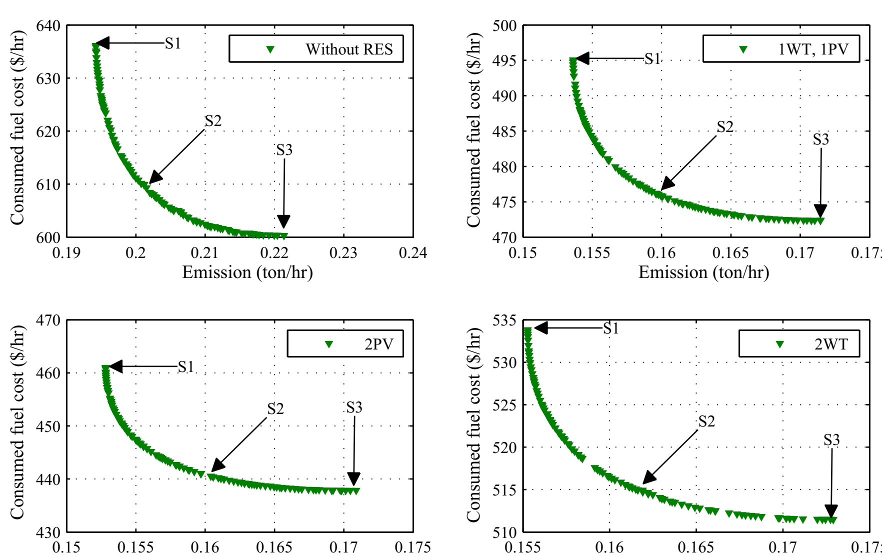

Fig. 6. Economic emission dispatch solutions.

Table 6
Particular EED solutions for different RES integration scenarios.

		P_{G1} (pu)	P_{G2} (pu)	P_{G3} (pu)	P_{G4} (pu)	P_{G5} (pu)	P_{G6} (pu)	Cost ($/h)	Emission (ton/h)
Without RES	S_1	0.0951	0.2900	0.5611	0.9871	0.5544	0.3462	600.30	0.2214
	S_2	0.2585	0.3536	0.5044	0.7235	0.5591	0.4349	608.44	0.2020
	S_3	0.3924	0.4537	0.5370	0.3986	0.5423	0.5100	636.10	0.1942
1PV, 1WT	S_1	–	–	0.4813	0.9876	0.4821	0.3426	472.37	0.1715
	S_2	–	–	0.5616	0.7534	0.5487	0.4299	476.87	0.1589
	S_3	–	–	0.6184	0.4770	0.6208	0.5773	495.05	0.1536
2PV	S_1	–	–	0.5408	1.0241	0.5405	0.3652	511.49	0.1729
	S_2	–	–	0.6223	0.7607	0.6265	0.4611	517.20	0.1594
	S_3	–	–	0.6651	0.5274	0.6646	0.6136	533.82	0.1553
2WT	S_1	–	–	0.4297	0.9540	0.4288	0.3214	437.83	0.1709
	S_2	–	–	0.5157	0.6983	0.5011	0.4188	443.17	0.1575
	S_3	–	–	0.5797	0.4303	0.5796	0.5445	460.99	0.1528

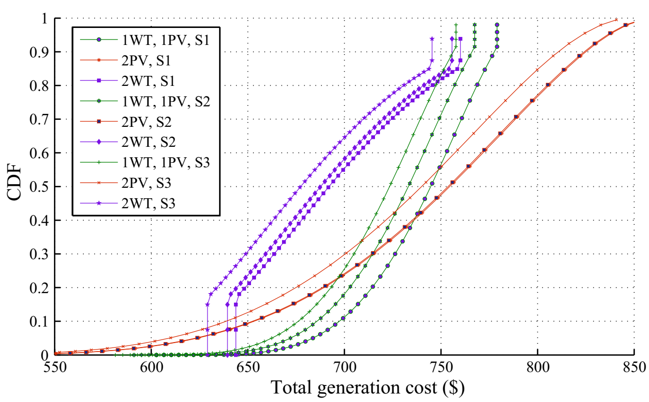

Fig. 8. Cumulative distribution function of three particular solutions.

gives the two extreme points of Pareto curve. The minimum cost obtained by FMOPSO, once again are less than those obtained by MOPSO which makes evident that the proposed method has higher performance.

In the second case, four integration scenarios are presented. In deed, it is aimed to compare the obtained Pareto fronts of EED with only conventional resources (without RES) on the one hand and with considering the expected values of wind and PV generators as shown in Fig. 4 on the other side. And that for two PV generators, (2PV), two wind generators (2WT) and finally for one PV and one wind generators (1PV, 1WT). Fig. 6 shows the obtained curves for the four studied scenarios. Then, comparing these curves, it is well observed that the cost and emission functions get better values. But, it is important to note that this curve reflect only the expected values of RES generations. Then the CDF of required reserve is calculated based on the two CDF corresponding to each generation plant. Fig. 7 shows the CDF of required reserve for each plant scenario. Then, three particular solutions are chosen, especially the extreme points and middle one in order to show the CDF of all possible total costs in terms of the CDF of RES generation. Indeed, Table 6 gives obtained evaluations of cost and emission values based on the expected values of RES plants generation while Fig. 8 illustrates the CDF of the total production cost corresponding to the obtained cost using expected RES generation added to the cost of required reserve.

6. Conclusion and perspectives

This paper extends the classical multiobjective economic emission dispatch of power system with only thermal units production to a probabilistic EED of a system with renewable energy sources. The proposed approach considers the operating cost as the sum of two parts. The first one is the solution to the classical EED which represents the renewable energy sources (RES) by their expected values. However, the second part of operating cost takes into account the stochastic behaver of the EEC production. The calculus of the stochastic part is based on determining the CDF of the required reserve in order to determine the CDF of all the problem random variables and finally to determine the CDF of the total operating cost. First, a new optimization algorithm, called FMOPSO, is proposed. This algorithm is based on PSO that uses matrix computation in order to handle multiobjective problems. By means of successive motion strategies, a uniform motion followed by a relative one. First, this algorithm has been applied to solve multiobjective economic environmental power dispatch problem of the IEEE-30 bus test network. It allows to minimize the production cost taking into consideration environmental constraints and transmission power losses. Results analysis shows that the proposed algorithm outperforms the classical MOPSO in terms of convergence, distribution and computing time and gives extreme points better than NSGA-II and SPEA. After that, this FMOPSO is applied to generate Pareto fronts of four RES integration scenarios and added to the probabilistic cost or required reserve. Obtained CDF curves allow to treat the EED problem as a probabilistic problem. This study can be extended to analyze and find the optimal probabilistic dispatch of a power system with more RES diversity such as biomass, CSP with and without storage, geothermal and heliostat. And also in the case of combined heat and power. In addition, the current study has supposed renewable energy sources integration, it is important to study the policy implications impact on the progress of these sources integration rate.

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