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ELECTRO SEARCH ALGORITHM FOR PROBABILISTIC MULTI-OBJECTIVE OPTIMAL POWER FLOW CONSIDERING WIND POWER AND LOAD UNCERTAINTIES

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Abstract- Extending wind power and uncertain nature of loads in power networks stand troubles in system provision because of the probabilistic trait of them. In order to plan accurately, it is important to evaluate uncertainties in optimal managing the power network. As regards to this matter, this paper introduces a probabilistic multi objective optimal power flow (MO-OPF) taking in to account the uncertainties of wind power and the demand. In this paper, a point estimate method (PEM) that utilizes $2m+1$ points for estimation is used to handle uncertainties. In fact, the probability density function (PDF) of wind speed and demands pertaining to several locations are not accessible but statistical data is available in most cases, which helps to approximate the PDF. In this paper Electro Search algorithm, which is a new meta-heuristic algorithm in optimizing problems is used to solve MO-OPF considering uncertainties. In order to show effectiveness of the procedure, IEEE 30-bus standard test system with extension of wind farms is simulated. At last, the gained results are evaluated with the Monte Carlo simulation (MCS) results. The evaluation shows great precision of the used procedure.

Keywords: Optimal Power Flow, Load Uncertainties.

I. INTRODUCTION

Pollutant increase, decreasing power sources and growing load have addressed lots of notice to renewable power sources. In renewable power sources, wind energy has become more popular in power networks all over the world [1]. The extension of a high value of wind energy which has probabilistic character has extended necessary difficulties in power networks management and optimization [2]. The essential problem is that wind speed and produced energy of wind turbines vary stochastically.

Optimal power flow (OPF) is a useful tool for observing economic issues of the power system which makes balance among power networks security and economic [3]. This problem is made of two different problems [4, 5]. Probabilistic Optimal Power Flow (POPF) is a useful gadget for observing effect of uncertainties on optimal condition of power networks [6-8]. Solving POPF has 3 basic methods: simulation methods, analytical methods and approximation methods.

Simulation methods known as Monte Carlo simulation (MCS) need high simulation time but it is popular because of simple implementation and high accuracy [9-11]. Analytical methods use linearization so have less accuracy [12-14]. Ref. [15] proposes an analytical method based on cumulates and Gram-Charlier expansion which solves the probabilistic load flow (PLF) with correlation of loads.

One of the approximation methods is point estimate method (PEM) that is used to solve probabilistic optimal power flow in [3, 16, 17]. These methods have lesser simulation time and obtain precise results. Approximation methods provides good results in problems with low number of uncertain variables and have less accuracy in large scale problems. On the other hand, PEM methods need some modifications to solve problems which considers correlation in input Random Variables (RVs). Two kinds of PEMs i.e. $2m$ and $2m+1$ schemes, are proposed in [18] in solving the probabilistic optimal power flow problem.

An improved PEM is introduced in [19] to solve probabilistic optimal power flow problem with correlated wind energy, solar power and demand. Ref [20] provided a review of the techniques utilized to handle probabilistic optimal power flow and used a transformation known as unscented (UT) method to handle correlated variables. Zhao's point estimate method (PEM) improved with Nataf transformation used to solve probabilistic load flow with correlation is introduced in [21]. In [22] $2m+1$ PEM improved by a conversion is used to manage correlation in probabilistic optimal power flow problem. In [23], a method is introduced in order to observe the results of provisionally correlated input random variables using PEM for solving probabilistic optimal power flow problem. This method is utilized to solve multi-period probabilistic optimal power flow problem consisting correlated time periods.

It is notable that, in OPF problem it is important to discuss more than one objectives together, as is important in real problems [24]. As regards, it is necessary to observe results of random variables in multi objective probabilistic optimal power flow problem that may be more effective in projecting of network to optimize several objectives together.

In this approach, Electro Search algorithm and weighted sum is utilized to solve POPF problem and conventional PEM is used to manage uncertainty of wind power and loads. This research observes the results of uncertainties on control variables and costs of probabilistic multi-objective optimal power flow problem. The IEEE 30-bus test network with integration of 2 wind farms is utilized to simulate the introduced method.

Contributions of this approach are as below:

1. Solving probabilistic multi-objective optimal power flow taking into account wind energy and demands uncertainties.
2. Utilizing Electro Search algorithm as solving method.
3. Investigating result of uncertainties on the objectives and control variables of the MO-POPF.

The rest of the paper is formed as below: Section II formulates MO-POPF and proposes point estimate method. Section III illustrates ES algorithm. Section IV presents results of simulations of evaluating introduced method on IEEE 30-bus test network and Section V concludes the proposed method and the results.

II. PROBLEM FORMULATION

Optimal power flow is a non-linear, non-convex and constrained problem. This problem can be solved considering more than one objective as multi objective problem and taking into account uncertain input variables which is known as multi-objective probabilistic optimal power flow. MO-POPF problem can be formulated generally as follows:

$$\begin{aligned} &\min F(X,Y)=\{F_1(X,Y),F_2(X,Y)\} \\ &\text{s.t. } G(X,Y)\geq 0\ ,\ H(X,Y)=0 \end{aligned} \tag{1}$$

where, $F_1(X,Y)$ and $F_2(X,Y)$ refer to objective functions of POPF problem, X and Y are set of control variables and input variables with uncertain nature of POPF problem, respectively, and $H(X,Y), G(X,Y)$ refer to the equality and inequality constraints of the POPF problem, respectively. This research considers the fuel cost and released emission of the generation units of network as goals of MO-POPF problem [25]. The objectives are formulated as follows:

- *Fuel cost function:*

$$F_1(X,Y)=\sum_{i=1}^{N_g} a_i + b_i P_{gi} + c_i P_{gi}^2 \tag{2}$$

where, $F_1(X,Y)$ refers to the fuel cost object function of problem in \$/h, N_g refers to the number of generators, P_{gi} (MW) refer to the ith generator's produced active power and a_i, b_i, c_i are the coefficients of fuel cost objective function.

- *Emission cost function:*

$$F_2(X,Y)=\sum_{i=1}^{N_g} (\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2 + \varepsilon_i \exp(\lambda_i P_{gi})) \tag{3}$$

where, $F_2(X,Y)$ is pollutants released from ith generator (ton/h) and $\alpha_i, \beta_i, \gamma_i, \varepsilon_i, \lambda_i$ are the emission objective function coefficients.

In this paper, in order to solve multi-objective optimal power flow weighted sum method is utilized. The following expression presents the objective function which is made of weighted fuel cost and emission:

$$F = k_1 \frac{F_1(X,Y)}{F_{1\min}} + k_2 \frac{F_2(X,Y)}{F_{2\min}} \tag{4}$$

where, k_1 and k_2 are the weighting factors of total cost and released emission objective functions, and $F_{1\min}, F_{2\min}$ are the least amount of the objectives that could be reached by solving OPF as single objective problem. In this paper, for equivalent weighting of objective functions k_1 and k_2 are assumed to be equal.

- *Control variables:*

$$X=[P_g, V_g, T, Q_c]_{1\times N} \tag{5}$$

$$P_g=[P_{g1}, P_{g2}, \ldots, P_{g(N_g-1)}]_{1\times(N_g-1)} \tag{6}$$

$$V_g=[V_{g1}, V_{g2}, \ldots, V_{gN_g}]_{1\times N_g} \tag{7}$$

$$T=[T_1, T_2, \ldots, T_{N_t}]_{1\times N_t} \tag{8}$$

$$Q_c=[Q_{c1}, Q_{c2}, \ldots, Q_{cN_c}]_{1\times N_c} \tag{9}$$

where, vector X refers to decision variables vector including active power of generators besides slack generator (P_g), V_g refers to voltage altitude of generating buses, T refers to tap of tap transformers and Q_c refers to the reactive power injected by capacitors.

- *Equality constraints (power flow constraints):*

$$P_{gi} + P_{wi} - P_{di} = \sum_{j=1}^{N_b} V_i V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \tag{10}$$

$$Q_{gi} + Q_{ci} - Q_{di} = \sum_{j=1}^{N_b} V_i V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) \tag{11}$$

where, P_{gi}, Q_{gi} are the generated active and reactive powers, P_{di}, Q_{di} are the active and reactive power of loads in the ith bus, P_{wi}, Q_{ci} are the active power generated by wind farms and reactive power generated by shunt capacitors of ith bus, respectively and N_b is the buses numbers. It is notable that, reactive power injected by wind farms is not considered in this research as [22]. $(V_i,\theta_i),(V_j,\theta_j)$ are the voltage magnitude and angle at the ith and jth buses and $\theta_{ij}=\theta_i-\theta_j$.

- *Inequality constraints:*

$$P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max}\ ,\ i=1,2,\ldots,N_g \tag{12}$$

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max}\ ,\ i=1,2,\ldots,N_g \tag{13}$$

$$V_{gi}^{\min} \leq V_{gi} \leq V_{gi}^{\max}\ ,\ i=1,2,\ldots,N_g \tag{14}$$

$$T_i^{\min} \leq T_i \leq T_i^{\max}\ ,\ i=1,2,\ldots,N_t \tag{15}$$

$$Q_{ci}^{\min} \leq Q_{ci} \leq Q_{ci}^{\max}\ ,\ i=1,2,\ldots,N_c \tag{16}$$

$$V_{Li}^{\min} \leq V_{Li} \leq V_{Li}^{\max}\ ,\ i=1,2,\ldots,N_{pq} \tag{17}$$

$$|S_{ij}| \leq S_{ij}^{\max}\ ,\ i,j=1,2,\ldots,N_l \tag{18}$$

where, N_L, N_{pq} are the connecting branches and PQ buses numbers, S_{ij} is power passing the branch which connects bus i to bus j, and V_{Li} is the magnitude of voltage of PQ buses. It is notable that min and max superscripts refer to lower and upper range of each variable.

A. Uncertainty Modeling

The first and important step of uncertainty modeling is to introduce proper statistical patter for the uncertain input variables of the network. Following sub-sections present method of modeling wind power and load uncertainties permanent-magnet synchronous motors in the rotor reference frame:

A.1. Load Modelling

Uncertainty in demands of network is modeled with normal distribution in this research [15, 26]. As regards, normal distribution is utilized to model the active load demand with constant power factor [26]. The PDF of the normal distribution used to this model is as follows:

$$f(P_d) = \frac{1}{\sqrt{(2\pi)}\sigma} \exp\left(-\frac{(P_d-\mu)^2}{2\sigma^2}\right) \tag{19}$$

where, P_d refers to the active power demand, and σ, μ are standard deviation and mean value of P_d, respectively

A.2. Wind Speed Modelling

Wind speed statistical data follow Weibull distribution rather than normal distribution. Refs. [27, 28] show that two parameter Weibull distribution could be utilized to model wind speed observations. Weibull distribution mathematically could be shown as below [28]:

$$f(v) = \frac{h}{c}\left(\frac{v}{c}\right)^{(h-1)} \exp\left(-\left(\frac{v}{c}\right)^h\right) \tag{20}$$

where, v is wind speed, c and h are the shape and scale parameters of the distribution. Dependence of the generated power of wind turbines to the wind speed could be modeled by special curves. Following expression presents an example of power-speed characteristic for a wind turbine [29].

$$P_{wi} = \begin{cases} 0 & , \quad 0 \le v_i \le v_{in,i} \\ P_{n,i}\dfrac{v_i - v_{in}}{v_{n,i} - v_{in,i}} & , \quad v_{in,i} \le v_i \le v_{n,i} \\ P_{n,i} & , \quad v_{n,i} \le v_i \le v_{o,i} \\ 0 & , \quad v_{o,i} \le v_i \end{cases} \tag{21}$$

where, v_i is the wind speed in the location of ith turbine and $P_{n,i}$ is its nominal output power, and $v_{o,i}, v_{n,i}, v_{in,i}$, and $v_{o,i}, v_{n,i}, v_{in,i}$ are the cut-out, nominal and cut-in speed of the ith turbine. A speed-power curve for a sample wind turbine is shown in Figure 1 [30].

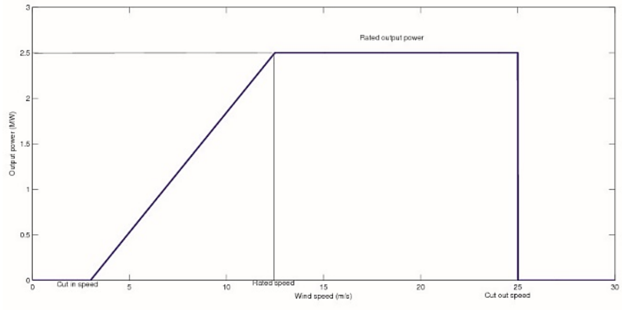

Figure 1. A speed-power characteristic for a sample wind turbine

A.3. Point Estimate Method

In this research, $2m$+1 PEM which proposed in [17] is utilized to solve MO-POPF problem. The main concept of the PEM is estimation of uncertain input variables with many spatial points reached from statistical data. In $2m$+1 PEM, when the problem has m random variables, each output variable of the problem should be evaluated $2m$+1 times. As mentioned in formulation section, in MO-POPF model the output variables could be shown with:

$$Z = F(X, Y) \tag{22}$$

In this expression, vector X refers to control variables and vector Y refers to uncertain input variables.

$$X = [P_G, V_G, T, Q_G]\ ,\ Y = [P_w, P_d] \tag{23}$$

For solving probabilistic MO-OPF problem, in first step on the standard normal distribution $2m$+1 points are determined for the uncertain input variables according to PEM method. Then a transformation is used to transfer the samples from standard normal distribution to other distributions following wind speed or loads. The last step is applying the inputs to the introduced model $2m$+1 times and obtaining mean and standard deviation of object functions i.e. total fuel cost, released emission and control variables of POPF problem. In $2m$+1 PEM method, each RV is determined with 3 weights and locations that can be expressed as:

$$y_{ik} = \mu_i + \xi_{ik}\sigma_i\ ,\ (i = 1, 2, ..., m; k = 1, 2, 3) \tag{24}$$

where, σ_i and μ_i are the standard deviation and mean of y_i and ξ_{ik} is the coefficient referring to the kth location on its probability distribution which can be calculated using following expression. Standard locations ξ_{ik} are calculated using Equation (25).

$$\xi_{ik} = \frac{\lambda_{i3}}{2} + (-1)^{3-k}\sqrt{\lambda_{i4} - \frac{3}{4}\lambda_{i3}^2}\ ,\ (k = 1, 2) \qquad \xi_{i3} = 0 \tag{25}$$

where, λ_{i3} and λ_{i4} are the skewness and kurtosis of y_i. For each location y_{ik} a weighting factor is calculated using Equation (26).

$$w_{ik} = \frac{(-1)^{3-k}}{\xi_{ik}(\xi_{i1} - \xi_{i2})}\ ,\ (k = 1, 2) \tag{26}$$

$$w_{i3} = \frac{1}{m} - \frac{1}{\lambda_{i4} - \lambda_{i3}^2} \tag{27}$$

In this regard all the concentrations for all uncertain input variables (y_{ik}, w_{ik}) are calculated. Then, 2*m*+1 vectors are formed as input variables (*Y*):

$$Y_j(i,k) = [\mu_1, \mu_2, ..., \mu_{i-1}, y_{ik}, \mu_{i+1}, ..., \mu_m] \quad (k=1,2;\ j=1,2,...,2m) \tag{28}$$

$$Y_{2m+1} = [\mu_1, \mu_2, ..., \mu_m] \tag{29}$$

Deterministic MO-OPF simulation is run considering every Y_j vector as input. Then MO-OPF is solved 2*m*+1 times and 2*m*+1 proper solution is gained (*Z*). At last, weighting factors are used to calculate statistical moments of output variables of *Z* as follows:

$$\mu_n = E[Z_n(i,k)] = \sum_{i=1}^{m}\sum_{k=1}^{3} w_{ik}(Z_n(i,k)) \tag{30}$$

$$E[Z_n(i,k)^2] = \sum_{i=1}^{m}\sum_{k=1}^{3} w_{ik}(Z_n(i,k)^2) \tag{31}$$

$$\sigma_n = \sqrt{E[Z_n(i,k)^2] - (E(Z_n))^2} = \sqrt{E(Z_n^2) - \mu_n^2} \tag{32}$$

where, n is output variables number, σ_n and μ_n are standard deviation and mean value of *n*th output variable.

III. ELECTRO SEARCH ALGORITHM

Electro Search (SE) algorithm is a new optimization algorithm inspired from nature based on the spinning of electrons around the nucleus of an atom [31]. Electro search (ES) algorithm utilizes physical principals such as Bohr model and Rydberg formula in solution searching method. Electro search algorithm presents 3 phases for solution searching procedure. First phase is spreading phase; the atoms are randomly distributed in the molecular space (spreading the candidate solutions in the search space). The second phase is orbital transition phase in which the electrons go to larger orbits in order to reach higher energy levels (searching for better fitness values). The third phase is relocation phase; the atoms move towards the best location of the whole atoms. The important feature of the ES algorithm is that ES algorithm do not need parameter tuning in the global optimal searching process:

A. Structure of an Atom

Atoms are made of nucleus and one or more electrons orbiting around the nucleus, this is the Bohr's atomic model. The basic feature of the Bohr's atomic model is that the energy of electrons orbiting in the atom are discrete values known as quantized levels. According to Bohr's model only certain radii for orbits are allowed and the orbits between them are not stable. According to quantum mechanics, electrons can transit between the orbits by absorption or emission of the difference energy.

When an electron goes to a large orbit, it may return to the initial orbit by emitting a photon. In hydrogen atom, the energy of the emitted photon can be calculated using Rydberg formula which is as follows:

$$E = E_i - E_f = R_E\left(\frac{1}{n_f^2} - \frac{1}{n_i^2}\right) \tag{33}$$

where, n_f and n_i are the final and initial orbits, respectively, and R_E is the Rydberg energy. According to $E = hc/\lambda$, wavelength of the emitted photon can be calculated by following expression:

$$\frac{1}{\lambda} = R\left(\frac{1}{n_f^2} - \frac{1}{n_i^2}\right) \tag{34}$$

where, R is Rydberg constant $(R = R_E / hc)$. In the ES algorithm, searching for solutions with better fitness function value is analogous to electrons searching for higher energy levels and the domain of infeasible solutions is analogous to the molecular space that atoms are stated. The electrons spinning the nucleus of each atom change their orbits until obtaining molecular states with highest energy level that is analogous to the global optimal solution.

B. The ES Algorithm Phases

As mentioned, ES algorithm can be introduced in three phases as below:

B.1. Atom Spreading; The First Phase

In this phase, the candidate solutions are randomly spread in the infeasible domain of the problem solutions. Each of the candidate solutions is analogous to an atom. Each atom has electrons which orbit the nucleus. According to Bohr's model the electrons can transit between the orbits by absorbing or emitting photons.

B.2. Atom Spreading; The Second Phase

In this phase, the electrons rotating nucleus go to higher energy levels. The ES algorithm inspired solutions local search from the concept of the quantized energy levels in hydrogen atom. This process can be formulated as following expressions:

$$e_i = N_i + (2 \times \text{rand} - 1)\left(1 - \frac{1}{n^2}\right)r \quad n \in 2,3,4,5,\ \text{rand} \in [0,1] \tag{35}$$

where, N_i is the current position of the nucleus, rand is a random number in the range [0,1] with uniform distribution, n is the energy level and the orbital number in which electrons can rotate, r is the orbital radius defined by using D_k (r is defined randomly in the first iteration). In every iteration the electrons are located in the orbitals using Equation (35). Then the fitness of electrons are evaluated and the electrons with the best fitness (highest energy) is known as e_{best}. In the next step the e_{best} is used to relocating the nucleus in global searching process.

B.3. Atom Spreading; The Third Phase

In this phase, the nucleus is relocated based on the energy of an emitted photon. The formulated nucleus relocation based on Rydberg formula is as follows:

$$\vec{D}_k = (\vec{e}_{best} - \vec{N}_{best}) + Re_k \otimes \left(\frac{1}{\vec{N}_{best}^2} - \frac{1}{\vec{N}_k^2}\right) \tag{36}$$

$$\vec{N}_{new,k} = \vec{N}_k + Ac_k \times \vec{D}_k \quad (37)$$

where, k is iteration number, $\vec{D}_k$ is the relocation distance, $\vec{N}_{best}$ is the current best nucleus position, $\vec{e}_{best}$ refer to the best electron around the nucleus, $\vec{N}_k$ refers to the current position of the nucleus, Re_k is Rydberg's energy constant, Ac_k is accelerator coefficient. Note that presented equations are in vector form and the symbol $\otimes$ denotes element by element vector multiplication. This procedure is performed on all nuclei in order to replace all of the atoms towards the global optimum solution. Detailed information about parameter tuning and about algorithm can be found in [31].

IV. SIMULATION RESULTS

The IEEE 30-bus standard test system is utilized to evaluate the ES algorithm. This network has 30 buses, 41 transmission branches, 6 generators, 4 tap transformers and 9 capacitors. Network data of the IEEE 30-bus system can be reached in [32]. Emission objective function coefficients could be found in [25]. Matpower 4.1 is utilized in power flow computations. Voltage magnitude and transformers tap can be varyied in the limit of [0.95,1.1] pu and [0.9,1.1] pu. Reactive power generated by capacitors can be raised up to 0.05 pu.

A. ES Algorithm for Solving Deterministic OPF Problem

In this section, the assessment of ES is examined in solving deterministic OPF on IEEE 30-bus test system. In this case no uncertainty and wind turbines are considered in order to examine and compare the performance of ES algorithm with some other methods. This case considers fuel cost and released emission of generation units of system as objectives. In this case, ES algorithm hired 100 atoms for solving deterministic and probabilistic optimal power flow. The results of solving single objective deterministic optimal power flow are tabulated in Table 1 and are compared with results of other research results. According to this table ES algorithm has good performance in comparison with other meta-heuristic algorithms in solving OPF problem. In this regard, Table 2 compares power generation of results of ES algorithm with ABC and MSA algorithm.

In order to show performance of ES algorithm in solving multi objective OPF, Table 3 compares results of ES algorithm with many other meta-heuristic algorithms used to solve MO-OPF. According to this table results obtained by ES algorithm cannot be dominated by results of other algorithms. In this regard, ES algorithm has acceptable performance in solving MO-OPF problem.

Table 1. Results of solving deterministic single objective OPF

Algorithm	Fuel cost ($/h)	Emission (ton/h)
ES	799.2446	0.2047
ABC [34, 40, 41]	800.66	0.204826
LTLBO [33]	799.4369	0.2047
MSFLA [36]	802.287	0.2056
SFLA [36]	802.21	0.2063

Table 2. Comparison of power generated in deterministic single objective OPF

variables	ES		ABC [34]		MSA [36]	
	Fuel cost	Emis	Fuel cost	Emis	Fuel cost	Emis
P_{G1} (MW)	177.444	63.9202	176.791	64.062	177.213	64.99
P_{G2} (MW)	48.601	67.4310	48.502	67.584	48.732	67.63
P_{G5} (MW)	21.368	50	21.507	50	21.457	50
P_{G8} (MW)	21.145	34.9999	21.329	35	21.063	35
P_{G11} (MW)	11.541	30	12.30	30	11.965	30
P_{G13} (MW)	12	40	12	40	12.002	40
Cost ($/h)	799.244	943.4054	800.660	944.439	800.509	944.50
Emis (ton/h)	0.3672	0.2047	0.3651	0.20482	0.3664	0.204

Table 3. Comparison of fuel cost and emission in MO-OPF solution

Method	Total fuel cost ($/h)	Emission (ton/h)
ES	803.1542	0.2503
NSMOOGSA [37]	836.978	0.2236
BSO [38]	835.0199	0.2425
MOEA/D [39]	833.72	0.2438
NSGA-II [39]	835.59	0.2449

B. Probabilistic MO-OPF

As mentioned, the active load demands are considered to follow normal distribution. In this model, mean values are the rated demand at load buses and standard deviations are 5% of the mean demands [21]. The load buses supposed to have constant power factor equal to 0.85 and reactive power demand assumed to vary according to power factor and active power [21]. In this paper, two wind farms are added to buses 29 and 30. Each of the connected wind farms consist of 4 wind turbines and both of the wind turbines are connected to the network via a transmission line with the impedance of 0.01+j0.01 pu. Table 4 presents information of the utilized wind turbines. As mentioned, the speed of wind is modeled with 2 parameter Weibull distribution. The shape and scale parameters are considered 2.01 and 7.28 [21].

Table 4. Wind turbine parameters

Parameter	Rating Capacity (MW)	Cut in speed (m/s)	Cut out speed (m/s)	Rating speed (m/s)
Value	2.5	3	25	12.5

Table 5. Comparison of results for single objective OPF for different cases

Variables	Fuel cost		Emission		Multi-Objective	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
P_{G1} (MW)	177.4445	2.6145	63.9751	2.5421	118.2513	2.7121
P_{G2} (MW)	48.6013	1.2156	67.3542	1.3235	56.5421	1.2541
P_{G5} (MW)	21.3682	0.5321	49.8214	0.6512	59.8124	0.3541
P_{G8} (MW)	21.1452	1.24e^{-9}	34.9514	0.00001	35.0000	2.01e^{-10}
P_{G11} (MW)	11.5412	1.2342	29.9621	0.3214	23.4152	0.9214
P_{G13} (MW)	12	1.4523	38.9951	1.3214	23.1214	0.8421
Cost ($/h)	799.2446	21.7124	942.1422	34.1254	804.2143	23.1214
Emis (ton/h)	0.3672	0.00235	0.2047	0.000012	0.2514	0.00041

In this case, OPF problem is solved probabilistically as single objective and multi objective problem. Table 5 presents standard deviation and mean values of generated power, fuel cost and emission released in probabilistic single objective and multi objective OPF. According to this table uncertain input variables caused increase in costs. It shows that mean values are close to deterministic OPF results where the standard deviations are noticeable.

C. Accuracy

Monte Carlo Simulations (MCS) is very accurate when using high number of simulation runs and can be used as reference method in evaluation of other methods. In this paper MCS is used to illustrate performance and accuracy of the employed method. In this regard, mean and standard deviation of output variables, resulted by employed method are evaluated with mean and standard deviation resulted by 2000 runs of MCS. The errors of mean and standard deviation for proposed method can be expressed using following equations.

$$\varepsilon_{\mu} = \left| \frac{100(\mu_{MCS} - \mu)}{\mu_{MCS}} \right| [\%] \tag{38}$$

$$\varepsilon_{\sigma} = \left| \frac{100(\sigma_{MCS} - \sigma)}{\sigma_{MCS}} \right| [\%] \tag{39}$$

Table 6 presents the errors of mean and standard deviation of generated power, fuel cost and emission for POPF results. This table presents average error for all generation units. Figures 2 and 3 present convergence characteristics of MCSs with 2000 runs for standard deviation and mean values. Good convergence of the MCS shown in Figures 2 and 3 determine that MCS with 2000 iterations is a good reference for error evaluations. According to Table 6, proposed method has low error and has acceptable accuracy in solving POPF problem.

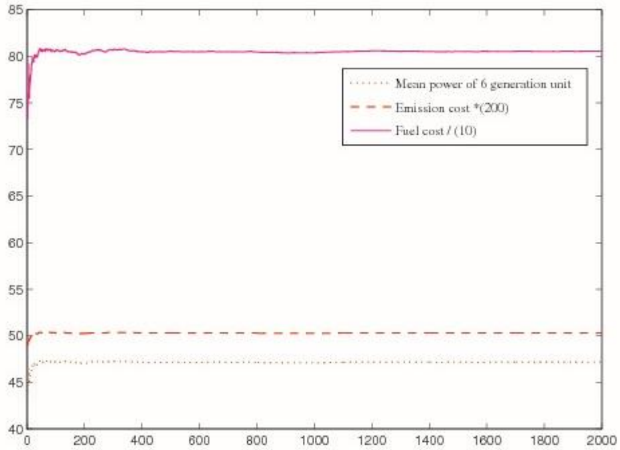

Figure 2. MCS results convergence for mean values

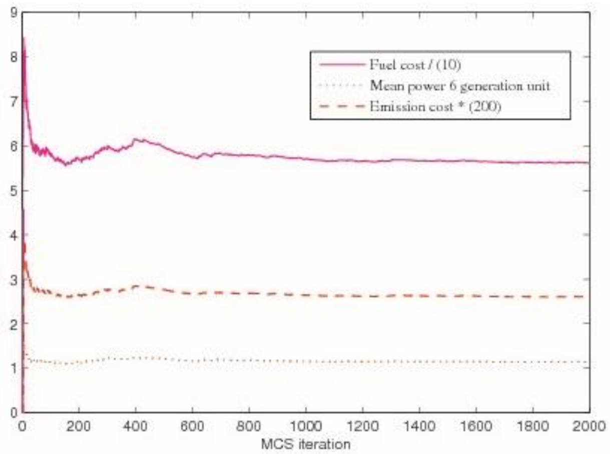

Figure 3. MCS results convergence for standard deviation

Table 6. Mean and standard deviation average error by 2000 run MCS

Output variables	Mean error ε_{μ}	Std error ε_{σ}
P_G (%)	0.2414	2.0167
Fuel Cost (%)	0.0264	1.0562
Emission (%)	0.0621	0.5376

V. CONCLUSIONS

This paper, proposes ES algorithm using PEM to solve multi-objective optimal power flow considering released emission and fuel cost as objective function with uncertainties in wind power and load demands. The basic idea of the research proposed in this paper is to utilize electro search algorithm combined with point estimate method to solve probabilistic multi-objective optimal power flow problem. In this paper it is shown that uncertainties in the input variables affect both control variables and all objectives and this effect are more considerable in standard deviation than mean values. This paper surveys the accuracy of the proposed method using MCS with high number of iteration. The efficiency of the method is shown by simulating on IEEE 30-bus test network.

REFERENCES

[1] N. Hatziargyriou, A. Zervos, "Wind Power Development in Europe", Proceedings of IEEE, Vol. 89, N. 12, pp. 1765-1782, 2001.

[2] M. Moradi Dalvand, B. Mohammadi Ivatloo, N. Amjady, H. Zareipour, A. Mazhab Jafari, "Self-Scheduling of a Wind Producer Based on Information Gap Decision Theory", Energy, Vol. 81, pp. 588-600, 2015.

[3] G. Verbic, C.A. Canizares, "Probabilistic Optimal Power Flow in Electricity Markets Based on a Two-Point Estimate Method", IEEE Transactions on Power Systems, Vol. 21, No. 4, pp. 1883-1893, 2006.

[4] S.M. Mohseni Bonab, A. Rabiee, B. B. Mohammadi Ivatloo, "Voltage Stability Constrained Multi-Objective Optimal Reactive Power Dispatch under Load and Wind Power Uncertainties: A Stochastic Approach", Renewable Energy, Vol. 85, pp. 598-609, 2016.

[5] S. Mohseni Bonab, A. Rabiee, S. Jalilzadeh, B. Mohammadi Ivatloo, S. Nojavan, "Probabilistic Multi-Objective Optimal Reactive Power Dispatch Considering Load Uncertainties Using Monte Carlo Simulations", Journal of Operation and Automation in Power Engineering, Vol. 3, No. 1, pp. 83-93, 2015.

[6] X. Li, Y. Li, S. Zhang, "Analysis of Probabilistic Optimal Power Flow Taking Account of the Variation of Load Power", IEEE Transactions on Power Systems, Vol. 23, No. 3, pp. 992-999, 2008.

[7] M. Madrigal, K. Ponnambalam, V. Quintana, "Probabilistic Optimal Power Flow", IEEE Canadian Conference on Electrical and Computer Engineering, Vol. 1, pp. 385-388, 1998.

[8] H. Yu, W. Rosehart, "An Optimal Power Flow Algorithm to Achieve Robust Operation Considering Load and Renewable Generation Uncertainties", IEEE Transactions on Power Systems, Vol. 27, No. 4, pp. 1808-1817, 2012.

[9] A.B. Rodrigues, M.G. Da Silva, "Probabilistic Assessment of Available Transfer Capability Based on Monte Carlo Method with Sequential Simulation", IEEE Transactions on Power Systems, Vol. 22, No. 1, pp. 484-492, 2007.
[10] H. Zhang, P. Li, "Probabilistic Analysis for Optimal Power Flow under Uncertainty", IEE Proceedings on Generation, Transmission and Distribution, IET, Vol. 4, No. 5, pp. 553-561, 2010.
[11] G. Carpinelli, P. Caramia, P. Varilone, "Multi-Linear Monte Carlo Simulation Method for Probabilistic Load Flow of Distribution Systems with Wind and Photovoltaic Generation Systems", Renewable Energy, Vol. 76, pp. 283-295, 2015.
[12] A. Schellenberg, W. Rosehart, J. Aguado, "Cumulant-Based Probabilistic Optimal Power Flow (P-OPF) with Gaussian and Gamma Distributions", IEEE Transactions on Power Systems, Vol. 20, No. 2, pp. 773-781, 2005.
[13] L. Shi, C. Wang, L. Yao, Y. Ni, M. Bazargan, "Optimal Power Flow Solution Incorporating Wind Power", IEEE Journal of Systems, Vol. 6, No. 2, pp. 233-241, 2012.
[14] A. Schellenberg, W. Rosehart, J. Aguado, "Introduction to Cumulant-Based Probabilistic Optimal Power Flow (P-OPF)", IEEE Transactions on Power Systems, Vol. 20, No. 2, pp. 1184-1186, 2005.
[15] D. Villanueva, A.E. Feijoo, J.L. Pazos, "An Analytical Method to Solve the Probabilistic Load Flow Considering Load Demand Correlation Using the DC Load Flow", Electric Power Systems Research, Vol. 110, pp. 1-8, 2014.
[16] E. Rosenblueth, "Point Estimates for Probability Moments", Proceedings of the National Academy of Sciences, Vol. 72, No. 10, pp. 3812-3814, 1975.
[17] H. Hong, "An Efficient Point Estimate Method for Probabilistic Analysis", Reliability Engineering & System Safety, Vol. 59, No. 3, pp. 261-267, 1998.
[18] X. Li, J. Cao, D. Du, "Probabilistic Optimal Power Flow for Power Systems Considering Wind Uncertainty and Load Correlation", Neurocomputing, Vol. 148, pp. 240-247, 2015.
[19] M. Aien, M. Fotuhi Firuzabad, M. Rashidinejad, "Probabilistic Optimal Power Flow in Correlated Hybrid Wind-Photovoltaic Power Systems", IEEE Transactions on Smart Grid, Vol. 5, No. 1, pp. 130-138, 2014.
[20] M. Aien, M. Rashidinejad, M.F. Firuz Abad, "Probabilistic Optimal Power Flow in Correlated Hybrid Wind-PV Power Systems: A Review and a New Approach", Renewable and Sustainable Energy Reviews, Vol. 41, pp. 1437-1446, 2015.
[21] C. Chen, W. Wu, B. Zhang, H. Sun, "Correlated Probabilistic Load Flow Using a Point Estimate Method with Nataf Transformation", International Journal of Electrical Power & Energy Systems, Vol. 65, pp. 325-333, 2015.
[22] Y. Li, W. Li, W. Yan, J. Yu, X. Zhao, "Probabilistic Optimal Power Flow Considering Correlations of Wind Speeds Following Different Distributions", IEEE Transactions on Power Systems, Vol. 29, No. 4, pp. 1847-1854, 2014.
[23] C.S. Saunders, "Point Estimate Method Addressing Correlated Wind Power for Probabilistic Optimal Power Flow", IEEE Transactions on Power Systems, Vol. 29, No. 3, pp. 1045-1054, 2014.
[24] M Li, Q. Wu, T. Ji, H. Rao, "Stochastic Multi-Objective Optimization for Economic Emission Dispatch with Uncertain Wind Power and Distributed Loads", Electric Power Systems Research, Vol. 116, pp. 367-373, 2014.
[25] A. Shabanpour Haghighi, A.R. Seifi, T. Niknam, "A Modified Teaching-Learning Based Optimization for Multi-Objective Optimal Power Flow Problem", Energy Conversion and Management, Vol. 77, pp. 597-607, 2014.
[26] R. Azizipanah Abarghooee, T. Niknam, M. Malekpour, F. Bavafa, M. Kaji, "Optimal Power Flow Based TU/CHP/PV/WPP Coordination in View of Wind Speed, Solar Irradiance and Load Correlations", Energy Conversion and Management, Vol. 96, pp. 131-145, 2015.
[27] D. Lalas, H. Tselepidaki, G. Theoharatos, "An Analysis of Wind Power Potential in Greece", Solar Energy, Vol. 30, No. 6, pp. 497-505, 1983.
[28] A. Garcia, J. Torres, E. Prieto, A. De Francisco, "Fitting Wind Speed Distributions: A Case Study", Solar Energy, Vol. 62, No. 2, pp. 139-144, 1998.
[29] A. Rabiee, A. Soroudi, B. Mohammadi Ivatloo, M. Parniani, "Corrective Voltage Control Scheme Considering Demand Response and Stochastic Wind Power", IEEE Transactions on Power Systems, Vol. 29, No. 6, pp. 2965-2973, 2014.
[30] A. Soroudi, B. Mohammadi Ivatloo, A. Rabiee, "Energy Hub Management with Intermittent Wind Power", Large Scale Renewable Power Generation. Springer, pp. 413-438, 2014.
[31] A. Tabari, A. Ahmad, "A New Optimization Method: Electro-Search Algorithm", Computers & Chemical Engineering Vol. 103, pp. 1-11, 2017.
[32] O. Alsac, B. Stott, "Optimal Load Flow with Steady-State Security", IEEE Transactions on Power Apparatus and Systems, Vol. 3, pp. 745-751, 1974.
[33] M. Ghasemi, S. Ghavidel, M. Gitizadeh, E. Akbari, "An Improved Teaching-Learning-Based Optimization Algorithm Using Levy Mutation Strategy for Non-Smooth Optimal Power Flow", International Journal of Electrical Power & Energy Systems, Vol. 65, pp. 375-384, 2015.
[34] M. Rezaei Adaryani, A. Karami, "Artificial Bee Colony Algorithm for Solving Multi-Objective Optimal Power Flow Problem", Int. J. Electr. Power Energy Syst., Vol. 53, pp. 219-230, 2013.
[35] T. Niknam, M. Jabbari, A.R. Malekpour, et al., "A Modified Shuffle Frog Leaping Algorithm for Multi-Objective Optimal Power Flow", Energy, Vol. 36, No. 11, pp. 6420-6432, 2011.
[36] A.A.A. Mohamed, Y.S. Mohamed, A.A. El-Gaafary, A.M. Hemeida, "Optimal Power Flow Using Moth Swarm Algorithm", Electric Power Systems Research, Vol. 142, pp. 190-206, 2017.

[37] A.R. Bhowmik, A.K. Chakraborty, "Solution of Optimal Power Flow Using Non Dominated Sorting Multi-Objective Opposition Based Gravitational Search Algorithm", International Journal of Electrical Power & Energy Systems, Vol. 64, pp. 1237-1250, 2015.
[38] A. Chaib, H. Bouchekara, R. Mehasni, M. Abido, "Optimal Power Flow with Emission and Non-Smooth Cost Functions Using Backtracking Search Optimization Algorithm", International Journal of Electrical Power & Energy Systems, Vol. 81, pp. 64-77, 2016.
[39] J. Zhang, Q. Tang, P. Li, D. Deng, Y. Chen, "A Modified MOEA/D Approach to the Solution of Multi-Objective Optimal Power Flow Problem", Applied Soft Computing, Vol. 47, pp. 494-514, 2016.
[40] H. Gozde, M.C. Taplamacioglu, I. Kocaarslan, "Application of Artificial Bees Colony Algorithm in an Automatic Voltage Regulator (AVR) System", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 4, Vol. 2, No. 3, pp. 88-92, September 2010.
[41] H. Shayeghi, H.A. Shayanfar, A. Ghasemi, "A Robust ABC Based PSS Design for a SMIB Power System", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 8, Vol. 3, No. 3, pp. 86-92, September 2011.

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