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An optimal power flow problem incorporating stochastic wind and solar power through the modified competitive swarm optimization algorithm

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Abstract

Increasing power demand day by day is the primary concern for power system practitioners and researchers. Generating a large amount of power through thermal power plants is neither economical nor environmentally friendly. The cost of fuel (Coal) is growing gradually as the coal reserves are depleting exponentially. Moreover, the government is imposing strict environmental guidelines on power-generating utilities. All these circumstances restrict the generation of electricity through fossil fuel-based plants. It is of most importance to develop for an alternative to fulfill consumers' economic and clean energy demand. Based on it, this paper explains minimization fuel cost along with emission, power loss and voltage deviation. Modified competitive swarm optimization (MCSO) algorithm is used to determine optimization. The results obtained from the modified competitive swarm optimization algorithm are compared with the competitive swarm optimization (CSO) algorithm and successive history-based adaptive differential evolution (SHADE-SF) algorithm to verify the efficiency of modified competitive swarm optimization. The work is executed on a standard IEEE 30 bus system, and MATLAB is used as a simulation platform.

Subject Classification: *Primary 93A30, Secondary 49K15.*

Keywords: *Fuel cost, Emission, Power loss, Voltage deviation, Optimization, Hybrid power system.*

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1. Introduction

Fossil-powered electricity energy production has increased rapidly due to fast industrialization, population growth, and improved technologies in the last few decades. As per the ongoing 2017 report [1] of the International Energy Agency, the entire primary power resource of the world has arrived at 162,494 terawatt-hours (TWh) or proportionate to 13,972 million tons of oil equivalent (Mtoe) and out of which the thermal energy represents 80% of it. The graphical presentation of energy sources in 1971 and 2017 is provided in Figure 1.

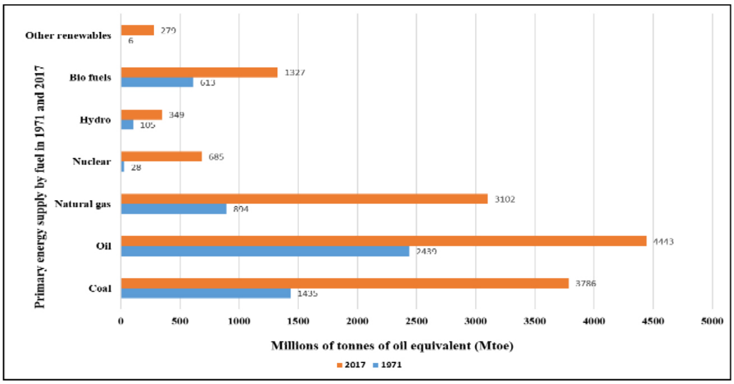

Figure 1

Estimation of fuel source in 1971 and 2017.

In traditional power system operation, emphasis was only given to optimizing the different forms of power generating rate by satisfying the operating constraints [2]. Gradually, optimization techniques based on intelligence come into the picture. Many researchers have tried to integrate wind and solar plants with traditional thermal power plants and develop exciting results. The optimization technique, which are mostly used for solving HPS problem are AI-based neural network (ANN) [3] and CI-based methods like GA [4-5], PSO [6], HS [7], SA [8], DE [24], GSA [25], BBO [26] and the nature motivated recent CI methods like BFA [26], ACO [27].

2. Mathematical Presentation

A 30 bus IEEE HPS problem comprised of thermal, solar, and wind generators are adapted for study. This asymmetrical tendency of the hybrid power system restrains engineers from the utmost exploitation of the renewable sources.

2.1 *Thermal generators fuel cost*

Thermal power plant required non-renewable bases like coal, natural oil, natural gas. The generated power (MW) from this type of plants is directly depend on value of fuel price. Therefore, the associated fuel cost (*$/h*) and generated power (*MW*) can be predicated by following quadratic equation as:

$$Fcost_{Total} = \sum_{i=1}^{N_T} \alpha_i + \beta_i P_{Ti} + \gamma_i P_{Ti}^2 \tag{1}$$

where P_{Ti} is the power output and α_i, β_i and γ_i are the coefficients of the i^{th} thermal generator.

$$VP\,Effect = \sum_{i=1}^{N_T} \alpha_i + \beta_i P_{Ti} + \gamma_i P_{Ti}^2 + |a_i \times \sin(b_i \times (P_{Ti}^{minimum} - P_{Ti}))| \tag{2}$$

where, a_i and b_i are the valve-point coefficients and $P_{Ti}^{minimum}$ is the least energy generation capacity of the i^{th} plant. The essential constraints of all the thermal generators are given in Table 1

2.2 *Direct cost of renewable energies*

The direct cost for the k^{th} wind power is revealed in terms of power generated as:

$$Dcost_{Wk}(P_{Wk}) = u_k P_{Wk} \tag{3}$$

where u_k represents direct cost coefficient of the linked k^{th} wind mill and P_{Wk} represents predictable power from the stated generator. Similarly, the direct cost for the l^{th} solar power plant is specified as:

$$Dcost_{Sl}(P_{Sl}) = v_l P_{Sl} \tag{4}$$

where, v_l represents the direct cost coefficient of the connected l^{th} solar Photovoltaic plant and P_{Sl} is output power.

2.3 *Uncertainty cost of renewable energies*

Renewable sources of energies keep changeable nature. When climatic condition is favorable, they can generate more than the required and during unfavorable climatic condition, they fail to generate the necessary power. The primary condition is called an overestimation situation. Hence, there is requirement of an isolated energy in standby to encounter the call.

The charge of engaging the reserve generators to fulfill the overestimated sum is called as reserve cost [13]. Therefore, the reserve cost for the wind-based plant is as given.

Reserve cost for overestimation of k^{th} wind generator is:

$$Rcost_{Wk}(P_{Wk}-P_{Wak})=K_{RWk}(P_{Wk}-P_{Wak}) \\ =K_{RWk}\int_0^{P_{Wk}}(P_{Wk}-p_{Wk})f_W(p_{Wk})dp_{Wk} \quad (5)$$

Reserve cost for overestimation of l^{th} solar photovoltaic is:

$$Rcost_{Sl}(P_{Sl}-P_{Sal})=K_{RSl}(P_{Sl}-P_{Sal}) \\ =K_{RSl}*f_S(P_{Sal}<P_{Sl})*[P_{Sl}-E(P_{Sal}<P_{Sl})] \quad (6)$$

where, K_{RWk} and K_{RSl} are the reserve cost coefficients of the k^{th} and l^{th} wind generator and solar photovoltaic plant respectively. P_{Wak} and P_{Sal} are the real obtainable power from the individual power units. f_W represent probability function for the wind. The probability function $f_S(P_{Sal}<P_{Sl})$ denotes the probabilities of scarcity situations than the planned power.

Penalty cost for underestimation of k^{th} wind generator is:

$$P\cos t_{Wk}(P_{Wak}-P_{Wk})=K_{PWk}(P_{Wk}-P_{Wk}) \\ =K_{PWk}\int_{P_{Wk}}^{P_{wr,k}}(P_{Wk}-P_{Wk})f_W(p_{Wk})dp_{Wk} \quad (7)$$

Penalty cost for l^{th} solar photovoltaic is:

$$Pcost_{Sl}(P_{Sal}-P_{Sl})=K_{PSl}(P_{Sal}-P_{Sl}) \\ =K_{PSl}*f_S(P_{Sal}>P_{Sl})*[E(P_{Sal}>P_{Sl})]-P_{Sl} \quad (8)$$

where, K_{PWk} and K_{PSl} are the penalty cost coefficients of the k^{th} and l^{th} windmill and solar photovoltaic plant respectively. P_{Wak} and P_{Sal} are the real obtainable power from the individual units. The probability density function $f_S(P_{Sal}>P_{Sl})$ denotes the excess occurrence probabilities than the estimated power. $E(P_{Sal}>P_{Sl})$ denotes the prospect of existing power greater than the planned power for the photovoltaic plant.

2.4 *Emission cost*

The power produced from thermal power plants released toxic and harmful gases like as SO_x and NO_x, which pullulate our atmosphere.

$$E=\sum_{i=1}^{N_T}[(a_i+b_iP_{Ti}+c_iP_{Ti}^2)\times 0.01+\delta_i e^{(\theta_i P_{Ti})}] \quad (9)$$

where, a_i, b_i, c_i, δ_i and θ_i are the coefficients of the i^{th} thermal based generator.

Now a day, many countries impose taxes, which is known as carbon taxes on thermal based power plants for release of harmful gases in atmosphere. Therefore, for encouraging green energy sources, a carbon tax factor (C_{tax}) imposed on emission of harmful toxic gases to signify emission as cost. So, emission cost ($/h) is represented as:

$$E_{\cos t} = C_{tax} * E \tag{10}$$

2.5 *Power loss and voltage deviation*

Other essential features in hybrid power planning problem are the real system voltage deviation and power loss. The power loss is projected as:

$$P_{Loss} = \sum_{j=1}^{nl} \sum_{k \neq i}^{nl} G_{jk} V_j^2 + V_k^2 - 2V_j V_k \cos(\delta_{jk}) \tag{11}$$

where $\delta_{jk} = \delta_j - \delta_k$ is the angles change among *j* and *k* bus. G_{jk} is the transfer conductance and *nl* is total number of transmission lines.

In taken model, voltage variation is the grade of voltage excellence. The voltage deviation constraint is measured as an acquisitive distinction of voltage of all load buses. It can be expressed as

$$V_{Deviation} = (\sum_{p=1}^{NL} | V_{L_p} - 1 |) \tag{12}$$

where *NL* is the total load buses and V_{L_p} is the voltage at loss bus.

3.1 *Objective functions and study cases*

In the present work, for solving IEEE 30 bus hybrid power system, eight cases studies are carried out to extend the analysis of the MCSO optimization technique.

Case 1: Minimization of total cost

In this section, hybrid power system accumulates entire cost functions of generating is expressed as the sum of the cost functions, which is provided as follows.

$$\begin{aligned} F_1 = Minimum\{ & Fcost_T(P_T) \\ & + \sum_{k=1}^{N_W} [Dcost_{Wk}(P_{Wk}) + Rcost_{Wk}(P_{Wk} - P_{Wak}) + Pcost_{Wk}(P_{Wak} - P_{Wk})] \\ & + \sum_{l=1}^{N_S} [Dcost_{Sl}(P_{Sl}) + Rcost_{Sl}(P_{Sl} - P_{Sal}) + Pcost_{Sl}(P_{Sal} - P_{Sl})]\} \end{aligned} \tag{13}$$

Here, N_W and N_S signify the quantities of wind and solar based plants respectively.

Case 2: Minimization of fuel cost with valve point effect

The valve point effect needs to be reflected in the fuel cost. Hence, the objective of this case is to minimize the producing fuel cost bearing in mind the valve point effect, which is expressed as follows.

$$F_2 = Minimum\ (F_1 + VP\,Effect) \tag{14}$$

Case 3: Minimization of power loss

The occurrence of usual resistance in the transmission lines makes it hard to neglect transmission losses altogether. So, this case reflects diminishing the actual power loss (in MW) described as follows.

$$F_3 = Minimum(P_{Loss}) \tag{15}$$

Case 4: Minimization of voltage deviation

In order to retain the voltage quality and security under limit in the HPS, it is important to regulator the voltage deviations. Hence, the cumulative distinction of all the load buses voltages needs to be minimized. So, the objective of this case study given as follow.

$$F_4 = Minimum\ (V_{Deviation}) \tag{16}$$

Case 5: Minimization of the total cost with the addition of emission cost

Recently, now a day many developed countries have imposed taxes on emission of greenhouse gases to avoid global warming. So, to encourage production of green energies like hydro, wind, solar, the carbon tax factor (C_{tax}) is imposed on individual unit of toxic gasses production. Hence, the objective of this case study given as follows.

$$F_5 = Minimum\ (F_1 + C_{tax} * E) \tag{17}$$

Case 6: Minimization of total cost with power loss

In this case, the power loss and cost are converted into a single objective by multiplying appropriate weight factor $(\lambda_p = 40)$ available in the literature [6]. Hence, the goal of this case is to discover the finest results for both objectives at the same time, which is given as follows.

$$F_6 = Minimum(F_1 \times \lambda_p P_{Loss}) \tag{18}$$

Case 7: Minimization of total cost with voltage deviation

In this case, objective is to minimize the cost of the fuel as well as the collective voltage deviation simultaneously. Therefore, the aim for this case is to designed with the help of a appropriate weight value $(\lambda_{VD} = 100)$ available in the literature [14,15]. The objective function is given as follows.

$$F_7 = Minimum\ (F_1 + \lambda_{VD} \times V_{Deviation}) \tag{19}$$

Case 8: Minimization of total fuel cost with emission, voltage deviation and power loss

This case study associates all the 4 prime aims at once for assessing the global outcome. Hence, the objective function is formed by taking suitable weights $(\lambda_E, \lambda_{VD}, \lambda_P)$ available in the literature [14]. The objective function is described as follows.

$$F_8 = Minimum(F_1 + \lambda_E \times E + \lambda_{VD} \times V_{Deviation} + \lambda_P \times P_{Loss}) \tag{20}$$

4. Optimization algorithm and application

The CSO is a swarm-based metaheuristic algorithm introduced by Cheng and Jin [16]. The technique is inspired by the behavior of birds, ants, and fishes. The enhanced accuracy in the solution excellence and greater rate of convergence steadiness needed to be spoken. Hence, a modified CSO (MCSO) was projected in [19] to upgrade two-thirds of the swarm members in place of 50% of the swarm members in the CSO algorithm. The modernized technique of MCSO allows a tri-competitive scenario in each iteration. This minor modification in CSO marks a massive variance in the solution superiority. This tri-competitive tool of the MCSO and the update process of losers are presented in Figure 2 and Figure 3.

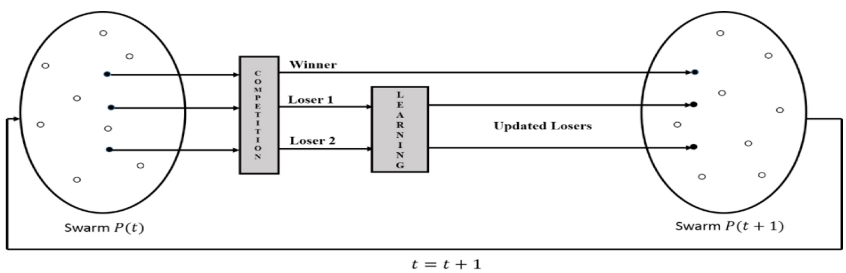

Figure 2

The pair-wise competition scheme in MCSO

MCSO Algorithm

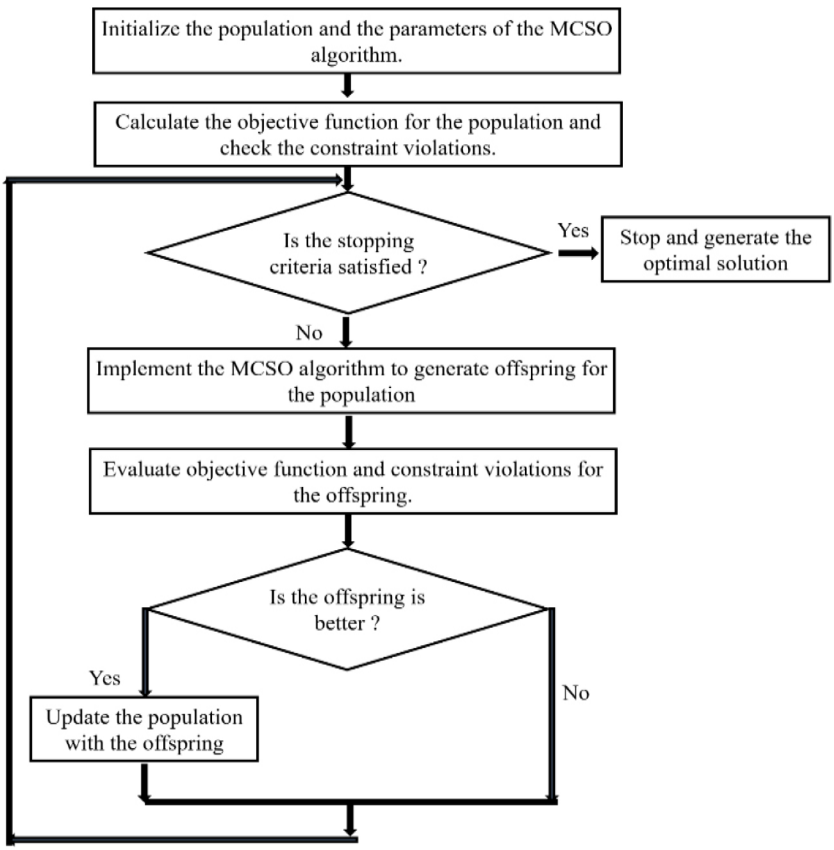

Figure 3

Flowchart of the MCSO algorithm.

5. Case Studies

In this section, the MCSO, CSO, and the SHADE-SF algorithm are implemented to get the finest fitness result for all the eight cases. Table 1 (a) and Table 1 (b) give the best fitness values, parameters and control variables. Case 1 stands for optimum fuel cost, and from Case 1, it is perceived that the fuel cost is 781.8465, 782.37829 $/h, and 782.6638 $/h for MCSO, CSO, and SHADE-SF algorithm respectively. The MCSO algorithm can provide a better fuel cost value than the CSO and SHADE-SF algorithms by accomplishing all the inequality and equality equations.

The valve point effect is accepted in Case 2 to sign an upsurge in cost than Case 1 for all the algorithms. Though, the sovereignty of the MCSO algorithm remains unaffected. Case 3 reflects the routine of all the algorithms in terms of actual power losses. The real power loss for the algorithms MCSO, CSO, and SHADE-SF are 2.0754 MW, 2.07682W, and 2.1037 MW, respectively. Power loss is an essential factor for optimal power flow problems. The MCSO algorithm's performance cannot be disregarded with respect to the CSO and SHADE-SF algorithms. The voltage deviation limitation studied in case 4 achieves comparable results as 0.37523, 0.37576, and 0.37577 for the SHADE-SF, CSO, and MCSO.

Last four cases studies are based on multi-objective situations. Case 5 signifies the minimization of the cost of the fuel together with the addition of cost due to emission. The present reflection with MCSO shows a healthy and improved cost of 810.6560 $/h than the cost of 810.7148 $/h and 811.15413 $/h of the CSO and SHADE-SF algorithms, respectively. Its efforts to offer the optimal result for both objectives. Case 6 to case 8 are the other multi-objective cases of the considered problem. Case 6 and 7 reflect fuel cost and power loss and voltage deviation, while case 8 reflects all the four prime aims fuel cost, power loss, emission, and voltage variation at the same time. The MCSO algorithm's outcome is far better than the CSO and SHADE-SF algorithms for all these multi-objective cases. It can be observed from the above analysis that the results of the MCSO algorithm are promising and encouraging in all the 8 cases which are taken into consideration. The convergence graphs of eight case studies are drawn in Figure 4, which also confirm the superiority of the MCSO algorithm in all the cases.

5.1 Statistical analysis

The $t-test$ is performed on mean and standard deviation of MCSO, CSO and SHADE -SF algorithms, the value is mentioned in Table 2. It is clear from Table 2 that value of MCSO algorithm is better then CSO and SHADE-SF algorithms.

Table 1(a)

Best computational results of the considered system from case 1 to case 4.

Control variables	Min	Max	Case No 1			Case No 2			Case No 3			Case No 4		
Algorithms			SHADE-SF	CSO	MCSO	SHADE-SF	CSO	MCSO	SHADE-SF	CSO	MCSO	SHADE-SF	CSO	MCSO
PT1 (MW)	50	140	134.90791	134.90024	134.91149	71.12885	71.116183	71.12762	50	50.04076	50.00192	74.857706	75.22654	76.23085
PT2 (MW)	20	80	28.3272	28.550759	28.486	20	20.01221	20.0003	31.8285	24.932402	25.4771	79.94748	80	79.9978
PT3 (MW)	10	35	10	10.015584	10.0063	10	10.000057	10	35	34.92185	34.9899	34.999816	35	34.9945
PT1 (MW)	0	75	43.6428	43.555297	43.7873	75	75	75	75	74.975468	74.9894	74.923849	75	74.9285
PT2 (MW)	0	60	36.8502	36.948183	36.8945	60	60	60	60	59.908404	59.9493	23.0885	22.5678	22.0055
PS (MW)	0	50	35.4503	35.21285	35.0902	50	50	50	40.4759	40.697946	40.0678	0.0014038	0	0.0047
V1 (p.u)	0.95	1.1	1.0716	1.0719105	1.0718	1.0611	1.0611538	1.0614	0.9627	1.057647	1.058	1.0516138	1.0376	1.0609
V2 (p.u)	0.95	1.1	1.0566	1.0564837	1.0567	1.0531	1.052998	1.0534	1.0546	1.0526214	1.0523	1.0889817	1.1	1.0867
V5 (p.u)	0.95	1.1	1.0347	1.0358865	1.0339	1.0427	1.0427961	1.0429	1.0454	1.0430145	1.0428	0.9959306	0.9961	0.9826
V8 (p.u)	0.95	1.1	1.0998	1.0464559	1.059	1.1	1.0457751	1.0449	1.0633	1.0840552	1.0722	1.0713753	1.1	1.0759
V11 (p.u)	0.95	1.1	1.0981	1.0969177	1.097	1.0998	1.0967173	1.095	1.0995	1.0973884	1.0988	1.0955744	1.0926	1.0952
V13 (p.u)	0.95	1.1	1.0492	1.0479046	1.0498	1.0591	1.0599094	1.0617	1.0631	1.0587388	1.0588	1.0750206	1.0594	1.0717
QT1 (MVAr)	-20	150	-2.36903	-1.2919616	-2.00046	-4.8205	-4.4356387	-4.59444	-20	-6.2963023	-4.6795	-20	-20	-8.57156
QT2 (MVAr)	-20	60	11.75363	10.002838	12.17394	7.25194	6.8133326	7.94189	19.03618	7.2052748	5.47876	60	60	60
QT3 (MVAr)	-15	40	40	40	40	40	39.504704	37.76328	40	40	40	40	40	40
QW1 (MVAr)	-30	35	22.42428	23.827282	21.66628	20.59645	20.802403	20.85419	20.74472	20.043877	20.05189	-19.676158	-19.63253	-30
QW2 (MVAr)	-25	30	30	29.664674	29.63473	30	30	30	30	30	30	30	30	30
QS (MVAr)	-20	25	15.20965	14.810852	15.50949	19.33425	19.676602	20.38886	19.54293	18.379048	18.45636	25	25	25
Total cost ($/h)			782.6638	782.37829	781.8465	864.9168	865.12465	864.7023	903.6583	880.61875	881.0496	961.02668	961.3115	962.1575
Emission (t/h)			1.76212	1.7612338	1.76247	0.12623	0.1262039	0.12623	0.09731	0.0990032	0.09883	0.1344177	0.13533	0.13785
Ploss (MW)			5.7784	5.782916	5.7758	2.7288	2.7284069	2.7279	2.1037	2.0768298	2.0754	4.4335461	4.4504	4.7618
VD (p.u)			0.45455	0.4518526	0.45341	0.4955	0.4978631	0.50264	0.54659	0.516698	0.51557	0.3757709	0.37576	0.37524

Table 1(b)

Best computational results of the considered system from case 5 to case 8.

Control variables	Min	Max	Case No 5			Case No 6			Case No 7			Case No 8		
Algorithms			SHADE-SF	CSO	MCSO	SHADE-SF	CSO	MCSO	SHADE-SF	CSO	MCSO	SHADE-SF	CSO	MCSO
PT1 (MW)	50	140	123.66783	123.52164	123.4424	50.08324	50.258497	50.00107	134.90791	134.91168	134.9081	99.23769	97.982243	100.84876
PT2 (MW)	20	80	33.4397	32.9718	32.82406	35.7387	35.839557	35.4357	28.8777	27.9983	28.74184	28.8072	28.830344	28.9234
PT3 (MW)	10	35	10	10.0001	10	35	34.94294	34.2687	10	10.0176	10.00535	12.9509	13.432311	13.9569
PT1 (MW)	0	75	46.2246	46.042	45.90569	74.5868	74.597048	73.9672	43.99	43.5327	43.85217	60.9558	60.925797	61.2116
PT2 (MW)	0	60	38.9127	38.7926	38.65407	49.346	49.49521	49.2763	36.7834	36.363	36.73044	45.1554	45.150001	45.3239
PS (MW)	0	50	36.4315	37.3499	37.84941	40.8375	40.458867	42.6603	34.8023	36.5408	35.12927	40.1605	40.903383	37.0255
V1 (p.u)	0.95	1.1	1.0707	1.0699	1.070545	1.0587	1.0589007	1.0589	1.0566	1.0569	1.055584	1.068	1.0679514	1.0686
V2 (p.u)	0.95	1.1	1.0572	1.0566	1.057035	1.0536	1.0541476	1.0539	1.0448	1.0444	1.044724	1.0566	1.0564572	1.0568
V5 (p.u)	0.95	1.1	1.0361	1.0355	1.035907	1.0434	1.0436155	1.0436	1.0131	1.0136	1.014109	1.0393	1.0393548	1.0394
V8 (p.u)	0.95	1.1	1.0404	1.0597	1.04036	1.0912	1.049412	1.0488	1.1	1.0869	1.062411	1.0969	1.0439956	1.0431
V11 (p.u)	0.95	1.1	1.0992	1.0994	1.098936	1.1	1.0999423	1.0999	1.1	1.0945	1.099891	1.0961	1.0975927	1.0973
V13 (p.u)	0.95	1.1	1.0556	1.0503	1.056108	1.0556	1.0565768	1.06	1.1	1.0974	1.084822	1.0416	1.0418187	1.0412
QT1 (MVAr)	-20	150	-2.63733	-3.33257	-2.69282	-5.4751	-5.8181665	-5.27475	-10.5863	-9.32484	-12.7799	-1.58153	-1.2455088	-0.80813
QT2 (MVAr)	-20	60	12.35438	11.21907	12.29203	5.79256	7.6282832	6.77417	21.78418	19.7032	22.92539	10.40612	10.255036	11.03499
QT3 (MVAr)	-15	40	35.3153	40	35.24449	40	37.803357	36.6064	40	40	40	40	39.421021	38.38229
QW1 (MVAr)	-30	35	22.95762	22.22908	22.96808	20.10696	20.332895	20.72833	12.54977	13.33909	13.62033	20.67877	20.84401	20.85311
QW2 (MVAr)	-25	30	30	30	30	30	30	29.98132	30	30	30	30	30	30
QS (MVAr)	-20	25	17.662	15.55908	16.79614	18.56216	17.289071	12.56706	25	25	25	12.59223	12.698641	12.59223
Total cost (\$/h)			792.8309	792.6821	792.9124	871.1039	871.82706	870.3521	783.8867	782.7189	782.7942	823.0902	824.80526	821.8129
Emission (t/h)			0.89867	0.89121	0.887179	0.09668	0.0967502	0.09672	1.76199	1.76261	1.762039	0.26494	0.2519249	0.28284
Ploss (MW)			5.2763	5.2781	5.275616	2.1922	2.1921201	2.2094	5.9613	5.9641	5.967118	3.8676	3.8240782	3.8901
VD (p.u)			0.46863	0.46005	0.469569	0.51008	0.5092833	0.52124	0.41559	0.4171	0.415786	0.45034	0.4502143	0.44684

Table 2

Statistical summary of *t-test* among MCSO vs CSO and MCSO vs SHADE-SF.

Cases no.	MCSO				CSO					SHADE-SF				
	Best	Worst	Mean	Std	Best	Worst	Mean	Std	*t*-value	Best	Worst	Mean	Std	*t*-value
Case 1 121No 1	781.846	782.193	7.82E+02	0.14824	782.378	782.841	7.82E+02	0.20703	-4.74E+00	782.663	783.136	7.83E+02	0.1853	-8.67E+00
Case 2 No 2	249.243	249.256	2.49E+02	0.00155	249.245	249.345	2.49E+02	0.11946	-1.12E+00	249.245	249.246	2.49E+02	0.00006	0.00E+00
Case 3 No 3	2.0750	2.07603	2.08E+00	0.00041	2.0768	2.0914	2.0805	0.00653	-1.67E+00	2.10371	2.10642	2.10E+00	0.00118	-5.14E+01
Case 4 No 4	0.37523	0.37546	3.75E-01	0.0001	0.37576	0.37577	0.3758	0	-1.12E+01	0.37577	0.37578	3.76E-01	0	-1.12E+01
Case 5 No 5	810.656	810.841	8.11E+02	0.08268	810.714	811.144	8.11E+02	0.18097	-1.69E+00	811.154	811.614	8.11E+02	0.19106	-6.55E+00
Case 6 No 6	958.808	959.179	9.59E+02	0.16067	959.511	959.725	9.60E+02	0.0897	-8.51E+00	959.626	959.817	9.60E+02	0.07367	-1.01E+01
Case 7 No 7	824.372	825.125	8.25E+02	0.30374	824.418	825.487	8.25E+02	0.41347	-1.00E+00	825.140	825.598	8.25E+02	0.18839	-4.38E+00
Case 8 No 8	922.716	923.343	9.23E+02	0.2394	923.176	923.518	9.23E+02	0.13727	-2.35E+00	923.608	923.842	9.24E+02	0.8911	-1.65E+00
					$w/t/l = 4/4/0$									

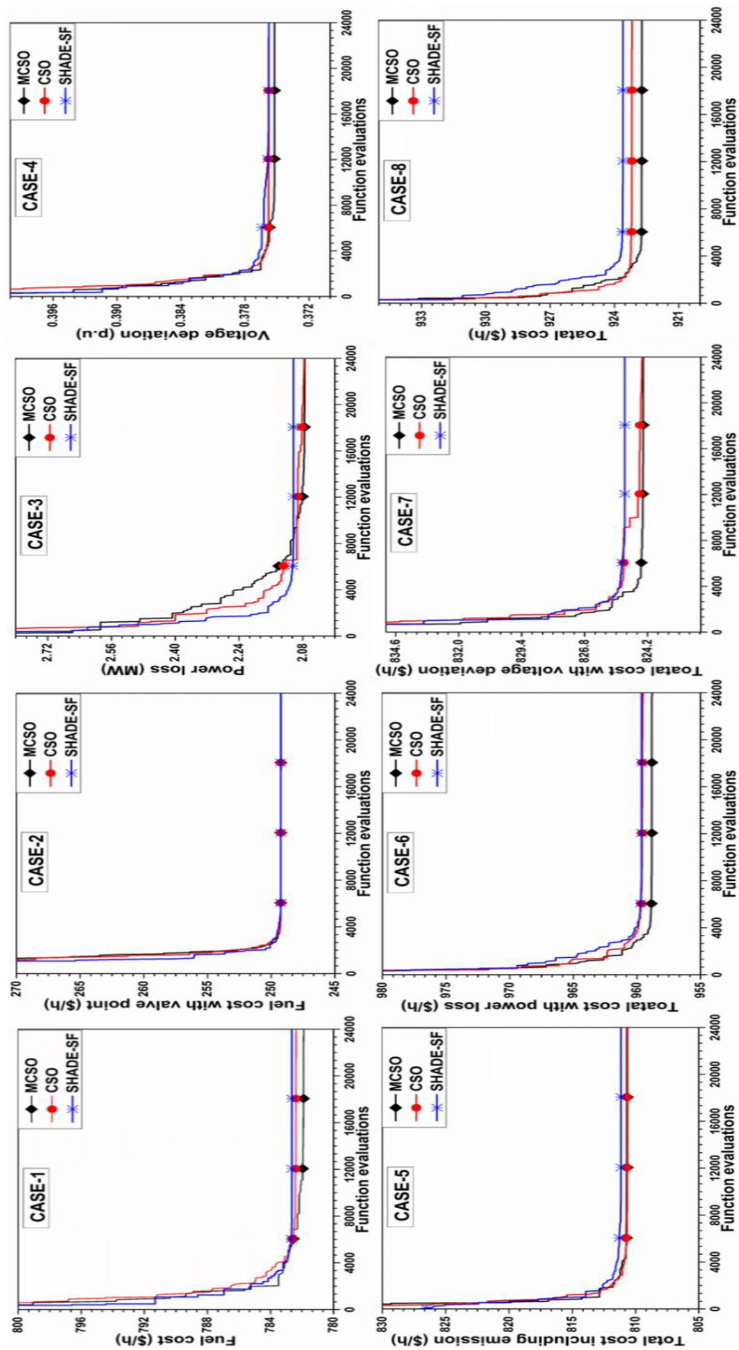

Figure 4
Convergence graph between SHADE-SF, CSO and MCSO algorithm.

6. Variations in voltage deviations

For establishing security and keeping voltage quality, constraints are very essential in HPS. It is usual nature that the operating voltage lie closer to the boundary limit. In the present work, load bus voltage are maintained between 0.95 p.u to 1.05 p.u. to fulfill both the objectives of voltage quality and security. Figure 5 show the variation of voltage quality by keeping voltage limitation. It is clearly sheen from the figure that voltage pf each bus falls inside the recommended limits.

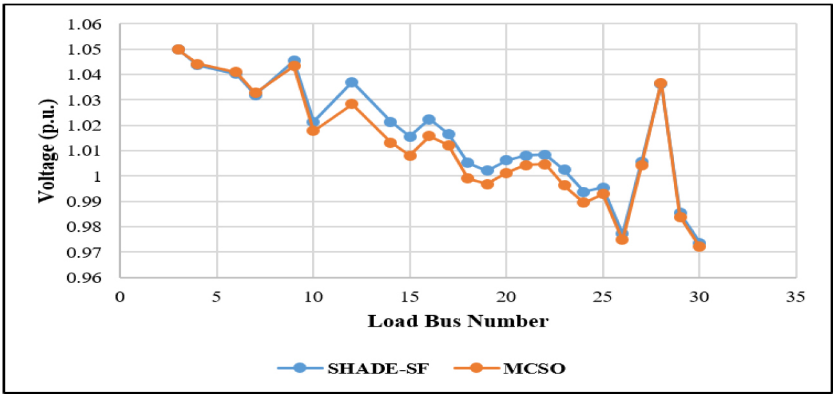

Figure 5
Voltage distribution of load bus

Conclusions

This paper proposed MCSO algorithm for finding optimal power flow solution with multi objective function incorporating stochastic wind and solar photovoltaic power sources. Uncertain underestimation and overestimation situation of renewable energies sources are also addressed with different measures such as penalty and reserve cost. In this work, eight case studies are considered. The first four case studies undergo single objective function, which refers total fuel cost minimization, fuel cost minimization with valve point effect, power loss minimization and voltage deviation minimization. The last four case studies undergo multi objective function, which refers fuel cost with emission minimization, fuel cost with voltage deviation minimization and fuel cost with emission, power loss and voltage deviation minimization. These objective functions are optimized using modified competitive swarm optimization and the results are compared with CSO and SHADE-SF. Rigorous statical analysis has been accomplished for different case studies and the outcome suggest that MCSO dominants over CSO and SHADE-SF, thereby keeping its efficiency in solving complex nonlinear optimization problems.

References

[1] Key World Energy Statistics, International Energy Agency (2019).

[2] A. Kadir, Y. Volkan, Differential search algorithm for solving multi-objective optimal power flow problem, *Int. J. Electr. Power Energy Syst.* 79, 1–10 (2016).

[3] B. Kar, K.K. Mandal, D. Pal, N. Chakraborty, combined economic and emission dispatch by ANN with backprop algorithm using variant learning rate & momentum coefficient, in: 2005 International Power Engineering Conference, pp. 1–235 (2005).

[4] K. Chandrasekaran, S.P. Simon, NP. Padhy, Cuckoo search algorithm for emission reliable economic multi-objective dispatch problem, *IETE J Res*. 6,0 128–138 (2014).

[5] B. Ramesh, V. Chandra, V.C. Reddy, Application of bat algorithm for combined economic load and emission dispatch, *J Electr Eng*. 13, 214-219 (2013).

[6] J.P. Zhan, Q.H. Wu, C.X. Guo, XX. Zhou, Fast lambda-iteration method for economic dispatch, *IEEE Trans Power Syst*. 29, 990-991 (2014).

[7] K. Chandrasekaran, S.P. Simon, Firefly algorithm for reliable/emission/economic dispatch multi objective problem, *Int Rev Electr Eng-Iree.* 7, 3414–3425 (2012).

[8] A.Y. Abdelaziz, E.S. Ali, SM. Abd Elazim, Implementation of flower pollination algorithm for solving economic load dispatch and combined economic emission dispatch problems in power systems, *Energy.* 101, 506–518 (2016).

[9] A.A. Abou El Ela, M.A. Abido, S.R. Spea, Differential evolution algorithm for emission constrained economic power dispatch problem, *Electr Power Syst Res,* 80, 1286–1292 (2010).

[10] U. Güvenç, Y. Sönmez, S. Duman, N. Yörükeren, combined economic and emission dispatch solution using gravitational search algorithm, *Sci Iran*, 19, 1754-1762 (2012).

[11] A. Bhattacharya, P.K. Chattopadhyay, Application of Biogeography-based Optimization for Solving Multi-objective Economic Emis-

sion Load Dispatch Problems, *Electr Power Compon Syst*, 38, 340–365 (2010).

[12] I. Karakonstantis, A. Vlachos, Ant colony optimization for continuous domains applied to emission and economic dispatch problems, *J Inform Optim Sci.* 36, 23–42 (2015).

[13] A. Panda, M. Tripathy, Security constrained optimal power flow solution of wind-thermal generation system using modified bacteria foraging algorithm, *Energy*. 93, 816–827 (2015).

[14] J.P. Zhan, Q.H. Wu, C.X. Guo, XX. Zhou, Fast lambda-iteration method for economic dispatch, *IEEE Trans Power Syst.* 29, 990-991 (2014).

[15] P.K. Singhal, R. Naresh, V. Sharma, N. Goutham Kumar, Enhanced lambda iteration algorithm for the solution of large-scale economic dispatch problem, In: Recent Adv Innov Eng (ICRAIE), IEEE, pp : 1–6 (2014).

[16] R. Cheng, Y. Jin, A competitive swarm optimizer for large scale optimization problems. *IEEE Trans.* 45 (2), 191–204 (2014).

[17] P. Mohapatra, K.N. Das, S. Roy, R. Kumar, A. Kumar, CSO Technique for Solving the Economic Dispatch Problem Considering the Environmental Constraints, *Asian Journal of Water, Environment and Pollution*. 16(2), 43-50 (2019).