Energy Conversion and Management 58 (2012) 197–206

Contents lists available at SciVerse ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

A new hybrid algorithm for optimal power flow considering prohibited zones and valve point effect

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ARTICLE INFO

Article history:
Received 30 September 2011
Received in revised form 23 January 2012
Accepted 25 January 2012
Available online 28 February 2012

Keywords:
Optimal power flow
Hybrid SFLA-SA
Evolutionary algorithm
Shuffle frog leaping algorithm

ABSTRACT

In this paper, an effective and reliable algorithm, based on Shuffle Frog Leaping Algorithm (SFLA) and Simulated Annealing (SA) is proposed for solving the optimal power flow (OPF) problem with non-smooth and non-convex generator fuel cost characteristics. Also, the proposed OPF formulation contains detailed generator constraints including active and reactive power generation limits, valve loading effects, and Prohibited Operating Zones (POZs) of units. OPF is spontaneously a complicate optimization problem, and becomes more and more complex considering the above constraints. Therefore, it needs to be solved with an accurate algorithm. Recently researchers have presented a new evolutionary method called SFLA algorithm. The original SFLA often converges to local optima. In order to avoid this shortcoming we propose a new method that profits from SA algorithm to improve local search near the global optima. The possibility of convergence to global optima is increased using the proposed method. For validating the proposed algorithm, it has been examined on the standard IEEE 30-bus test systems. The hybrid SFLA-SA provides better results compared to the original SFLA, SA, and other methods recently reported in the literature as demonstrated by simulation results.

1. Introduction

In the past two decades, much attention has been paid to the problem of optimal power flow (OPF). It is one of the current interests of many utilities and it has been marked as one of the most important of operational needs [1]. The OPF problem is an optimization tool through which the electric utilities strive to determine secure and operating conditions for a power system.

Many mathematical programming techniques [2] such as the Newton method [3], quadratic programming [4], linear programming [5], non-linear programming [6], and interior point methods [7] have been applied to successfully solve the OPF problem. The OPF problem is usually a large and difficult optimization problem for practical power systems. Mathematical approaches such as the above mentioned techniques have some drawbacks such as trapping in local solutions, applicability to a specific OPF optimization problem, and inconsistency with the characteristics of the OPF formulation [8,9]. All above shortcomings can be overcome if evolutionary methods are utilized to solve the optimization problem.

As previously mentioned, the OPF problem is spontaneously a complex problem, however this problem turns into a non-smooth non-convex optimization problem, in which finding the global optimum gets more challenge by considering some constraints such as valve-point effect and prohibited zones. Therefore, classical optimization algorithms are not capable of finding the global optimum solution. This paper focuses on the OPF problem with valve-point loading effect and Prohibited Operation Zones (POZs). Power plants usually have multiple valves that are used to control the power output of the units. When steam admission valves are first opened in thermal units, a sudden increase in losses is observed which leads to ripples in the curve of cost function. This phenomenon is known as the valve-point loading effect. Furthermore, this paper considers POZ constraint besides the valve point effect. The POZ arise from physical limitations of individual power plant components. Lee and Breipohl [10] give the example of the amplification of vibrations in a shaft bearing at certain operating regions. Because of the physical limitations of generation units, the generating units may not be able to operate in specific operating zones. For example, mechanical vibrations could cause cumulative metal fatigue in turbine blades and lead to premature turbine blade failures. The POZ could represent gaps on generation cost curves and cause discontinuity on curves [11]. These physical limitations may lead to instabilities in operation for certain loads. To avoid these instabilities, the concept of prohibited zones has been developed. The fuel cost curve of units with POZ is broken into several isolated feasible sub-regions which form multiple decision spaces. A decision space may be feasible or infeasible with respect to system demand and optimal solution of the dispatch problem will reside

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0196-8904/$ - see front matter
doi:10.1016/j.enconman.2012.01.017

in one of the feasible decision spaces. Generators that operate in these zones may experience amplification of vibrations in their shaft bearings, which should be avoided in practical application [12]. There are some models for handling valve-point effect and prohibited operating zones in the literature. There are two different forms in which the valve-point effects are modeled [13,14], One of them considers this effect as POZ [15–17] and formulates it as inequality constraints. The second model considers it by superimposing this effect as a rectified sinusoid component into the generating unit fuel cost function [18–20]. Lin and colleagues consider the piece-wise quadratic cost function for handling the valve point loading effect [21]. Walters and Sheble formulate the valve point phenomenon by adding circulating commutated sinusoidal function to cost function [13]. To get close to the real condition some articles consider valve point effect and prohibited operating zones simultaneously, which means that they consider these two effects as independent phenomena. Chakraborty and coworkers consider the valve-point effects by adding a rectified sinusoid component into the generating unit fuel cost function, also they handled the POZ by considering it as constraint [22]. Also, there are some approaches which considered valve point effect and prohibited operating zones simultaneously [23–27], meaning that they consider these two effects independently. Amjady and Nasiri-Rad solved the economic dispatch problem prohibited operating zones (POZs) and valve loading effects which are usually found simultaneously in realistic power systems [23,24]. Pereira-Neto and colleagues describe the cost because of valve-point loading and consider nonlinear generator characteristics, such as ramp rate limits and prohibited operating zones in the power system operation [28]. Praveena and coworkers handle the POZ by considering it as a constraint [29]. Orero and colleagues [30] presented a penalty function approach to handle the POZ constraint. Some solutions have been suggested to adequately solve the dispatch problem with POZ including Hopfield model of neural networks [31,32], genetic algorithm (GA) [30], and evolutionary programming (EP) [33]. Park and coworkers proposed an improved particle swarm optimization for economic dispatch with valve-point effect and quoted that, the practical ED problems should consider multiple fuels as well as prohibited operating zones [34]. From the above statements it is clear that for reaching real conditions in power system operation it is crucial to consider valve-point effect and prohibited zones simultaneously. Ciornei and Kyriakides considered the valve point effect and POZ to solve the ED problem which is novel in the literature in this sector [35]. In this paper valve point effect is added to the cost function as rectified sinusoid contribution and prohibited operating zones are considered as constraint. It is clear that considering these effects will increase the total generation cost. The above statement is proved in the numerical result section in this paper. Overall, considering the prohibited zones and valve point effect increases the complexity of the OPF problem and consequently the application of an accurate algorithm to solve this problem is more tangible than before. In recent years, many heuristic algorithms, such as evolutionary programming [36], particle swarm optimization [37], simulated annealing [38] genetic algorithms (GAs) [39], and Tabu search Algorithm (TSA) [40] have been proposed for solving the OPF problem, without any restrictions. In spite of the privileges of these algorithms they have some drawbacks as well. One way to cope with these drawbacks is combining these algorithms with each other. This paper proposes a Hybrid SFLA and SA (Hybrid SFLA-SA) algorithm to solve the OPF problem. The proposed algorithm profits from the abilities of both algorithms. Therefore, it has better behavior and has more authority to solve complex optimization problems. In recent years some hybrid algorithms have been proposed to solve optimization problems. The obtained results proved that their efficiency is better than algorithms that construct them [41–43]. Hybrid algorithms such as GA-ACO [44], hybrid particle swarm optimization [9], and hybrid evolutionary programming [45] are applied to solve some optimization problems. In the past few years, the SFLA algorithm which is one of the famous optimization algorithms has been applied in some optimization problems. The SFLA is very simple in concept, and is an accurate and fast optimization algorithm. However, the traditional SLFA often encounters some problems such as being trapped in local optima and takes a long time to converge to optimal. In order to avoid these problems, the SA algorithm is applied to increase the local search ability of the SFLA algorithm in this paper. It is worthwhile to note that the problem control variables to solve the OPF problem are generator real powers, generator bus voltages, transformer tap settings, and reactive power of switchable VAR sources. Also, to validate the obtained results, they are compared with original SLFA, genetic algorithm (GA), simulated annealing (SA), and particle swarm optimization (PSO) methods and other algorithms in the literature. Simulation results show that the proposed hybrid SFLA-SA algorithm is superior in comparison with other algorithms.

The present paper is organized as follows: Section 2 describes the problem formulation and constraints. Section 3 declares the original SLFA, original SA, and hybrid SLFA-SA algorithms. Section 4 shows the implementation of the proposed algorithm on the OPF problem. Section 5 depicts numerical examples for solving the approached problem.

2. Problem formulation

2.1. Objective function

The OPF problem is considered as a general minimization problem with constraints, and can be written in the following form:

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

$$X = [Pg_i, Vg_i, Tap_i, Qc_i] \tag{2}$$

where $f(X)$ is the total generation cost, a_i, b_i and c_i are the cost function coefficients of the ith unit, P_{gi} is the real power generation of ith unit, N_g is the number of generators, Vg_i is the voltage magnitude of ith generator, Tap_i is the tap of ith transformer, Qc_i is the reactive power of ith compensator capacitor.

2.2. valve point effect and prohibited zones

Fig. 1 depicts the cost function of generators with and without the valve point effect. However, in practice, the fuel cost function

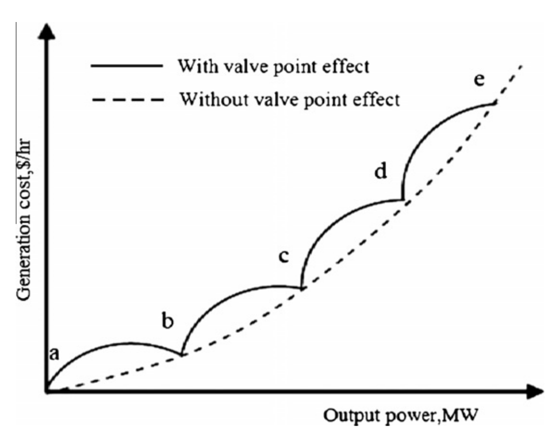

Fig. 1. Cost function with and without valve point effect.

of units has non differentiable points due to the valve-loading point effect and change of fuels. For considering the valve-loading effects of units, a recurring rectifying sinusoidal term is added to the basic quadratic cost function, as follows [44]:

$$\min f(X) = \sum_{i=1}^{N_g} a_i P_{gi}^2 + b_i P_{gi} + c_i + |d_i \times \sin(e_i \times (P_{gi}^{\min} - P_{gi}))| \tag{3}$$

The cost curves of practical generators have prohibited operating zones due to some faults in the shaft bearing or vibration of machines or their accessories such as pumps or boilers [46]. A unit with POZ has discontinuous input–output characteristics, since it is difficult to determine the actual POZ by real performance testing or operating records, so normally the best economy is achieved by avoiding operation in areas that are in actual operation. Therefore it is necessary to determine a mathematic formulation for prohibited zones. Each generator with $K-1$ prohibited zones is characterized by K disjoint operating sub-regions (P_{gik}^L, P_{gik}^U). The mathematic formulation for prohibited zones is considered as follows:

$$P_{gik}^L \leqslant P_{gi} \leqslant P_{gik}^U \quad \forall i \in \omega \quad k = 1, 2, \ldots, K \tag{4}$$

Note that $P_{gi1}^L = P_{gi}^{\min}$ and $P_{giK}^L = P_{gi}^{\max}$ where K is the number of prohibited zones for each generator. The cost function with prohibited zones is shown in Fig. 2.

The procedure of considering POZ in this paper is determined in the following section. In this regard at first the delimitation point divides the POZ into two sub-zones, that is the left and right prohibited sub-zones. The delimitation point is set in the middle point of each prohibited zone in this study. When a unit operates in one of these POZs, the strategy is to force the unit to move either towards the lower bound of that zone from the left sub-zone or towards the upper bound of that zone from the right sub-zone [12].

2.3. Constraints

The OPF equality constraints reflect the physics of the power system. Equality constraints are expressed in following equations [47]:

$$P_i = P_{gi} - P_{di} = \sum_{j=1}^{n} V_i V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \tag{5}$$

$$Q_i = Q_{gi} - Q_{di} = \sum_{j=1}^{n} V_i V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) \tag{6}$$

where $i = 1, 2, \ldots, n$ and $\theta_{ij} = \theta_i - \theta_j$, that θ_i and θ_j are the voltage angles of the two ending bus of an arbitrary branch, and n is expressed as the number of the buses.

The inequality constraints of the OPF reflect the limits on physical devices in the power system as well as the limits created to ensure system security, presented in following inequalities:

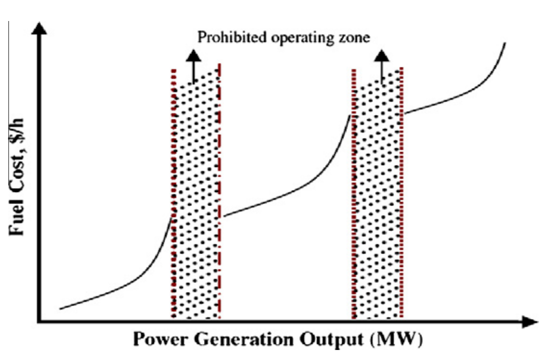

Fig. 2. Cost function with prohibited zones.

$$P_{gi\min} \leqslant P_{gi} \leqslant P_{gi\max}, \quad i = 1, 2, \ldots, N_g \tag{7}$$

$$Q_{gi\min} \leqslant Q_{gi} \leqslant Q_{gi\max} \tag{8}$$

$$|P_{ij}| \leqslant P_{ij\max} \tag{9}$$

$$V_{i\min} \leqslant V_i \leqslant V_{i\max}, \quad i = 1, 2, \ldots, Nl \tag{10}$$

$$Qc_{\min} \leqslant Qc_i \leqslant Qc_{\max}, \quad i = 1, 2, \ldots, NC \tag{11}$$

$$Tap_{\min} \leqslant Tap_i \leqslant Tap_{\max}, \quad i = 1, 2, \ldots, NT \tag{12}$$

where Nl is the number of load bus and P_{ij} is the power that flows between bus i and bus j. $V_{i\max}$ and $V_{i\min}$ voltages are the maximum and minimum valid voltages for each bus, respectively. $P_{ij\max}$ is the maximum power that flows through the branch. $P_{gi\max}$ and $P_{gi\min}$ are the maximum and minimum active power values of ith generator, respectively. $Q_{gi\max}$ and $Q_{gi\min}$ are maximum and minimum reactive power values of ith bus, respectively.

3. Hybrid shuffle frog leaping algorithm and simulated annealing

3.1. Overview of SFLA algorithm

SFLA is a descending based stochastic search method that begins with an initial population of frogs that represent the decision variables. An initial population of F frogs is created randomly. For K-dimensional problems (K variables), a frog i is represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{ik})$. Afterwards, the frogs are sorted in a descending order according to their fitness. In SFLA, the total population is divided into groups (memeplexes) that search independently. In this process, the first frog goes to the first memeplex, the second frog goes to the second memeplex, frog m goes to the Mth memeplex, and frog M + 1 goes to the first memeplex, and so on. In each memeplex, the frogs with the best and the worst fitness are identified as X_b and X_w, respectively. Also, the frog with the best fitness in all memeplexes is identified as X_g. Then, a process is applied to improve only the frog with the worst fitness in each iterate. Correspondingly, the location of the frog with the worst fitness is regulated as follows:

Change in the location

$$Velocity_i = rand() \times (X_b - X_w) + rand() \times (X_g - X_w) \tag{13}$$

$$\text{New location of } X_w = \text{current location of } X_w + Velocity_i \tag{14}$$

$$-Velocity_{\max} \leqslant Velocity_i \leqslant Velocity_{\max} \tag{15}$$

where rand () is a random number between 0 and 1, and $Velocity_{\max}$ is the maximum permitted change in a frog's location. If this process generates a better solution, it replaces the worst frog. Otherwise, the calculations in Eqs. (13) and (14) are repeated. Moreover, to provide the opportunity for random generation of improved information, random virtual frogs are generated and substituted in the population if the local search cannot find better solutions respectively in each iterate. After a number of iterations, the different groups combine and share their ideas with each other through a shuffling process. The local search and the shuffling processes continue until the defined convergence criteria are satisfied.

3.2. Overview of SA algorithm

Simulated annealing (SA) was first described by Metropolis et al. [48]. SA is a randomized gradient descent algorithm that permits uphill moves with some probability so that it can escape local minima. This optimization technique acts on the basis of a condensed material behavior at low temperatures, which in fact simulates the annealing process in nature like freezing and crystallizing liquid or cooling and annealing metal [41]. This algorithm starts with an initial solution (X_0). Temperature (T) is a parameter that controls the process, this parameter takes an initial value (T_0) and decreases during the optimization process. Other solutions search in the problems' search space as follows. In each step with the reduction of temperature, the optimization process stops to obtain a thermal balance which represents a better solution. Meanwhile, a new solution (Sn) is created in the neighborhood of the previous solution (X). If the amount of the new objective function ($f(X_{new})$) is better than the previous one ($f(X)$), the previous solution is replaced with the new solution. Otherwise the new solution will be accepted with a probability of P to escape from the local optimum. P is computed as follows:

$$P = \exp\left(\frac{-\Delta}{T}\right) \tag{16}$$

$$\Delta = \frac{f(X_{new}) - f(X)}{f(X_{new})} \tag{17}$$

The process repeats until the algorithm reaches a desired state. SA is an enhanced local search algorithm, which accepts not only better but also worse neighborhood solutions with a certain probability, instead of absolute rejection of the worse ones in traditional local search methods. The probable acceptance of the worse solutions is determined by the temperature of SA, which decreases during the algorithm's process.

3.3. Hybrid SFLA-SA

Despite the privileges SFLA algorithm, it has some drawbacks such as being trapped in local optima or converging to global optima in a long time. One reason for this phenomenon is that all particles in each memeplex have the tendency to go forward to the current best solution in each memeplex and the best solution among all memeplexes may be a local optimum or a solution near the local optimum. Therefore, all particles will concentrate to a small region and the global exploration ability will weaken. The most significant character of SA is the probabilistic jumping property, a worse solution has a probability to be accepted as the new solution, therefore by combining the SFLA and SA algorithms, SA can eliminate the SFLA drawback by jumping property. As a result of combining these algorithms, an accurate algorithm would be produced which can search in the problems' search space easily and converge to the global optima with a high probability. For better explanation, the flowchart of this algorithm is shown in Fig. 3.

4. Implementation of the proposed algorithm to the OPF problem

This part demonstrates the application of the proposed algorithm for solving the OPF problem. To implement the proposed algorithm in the OPF problem, it is necessary to execute the following steps:

Step 1: Define the input data.

Step 2: convert the constraint problem to an unconstraint one.

To apply the proposed algorithm in the presented OPF problem, it should be transformed into an unconstrained one by constructing an augmented objective function incorporating penalty factors for any value violating the constraints, as follows:

$$J(X) = \left[f(X) + L_1\left(\sum_{j=1}^{N_{eq}}(h_j(X))^2\right) + L_2\left(\sum_{j=1}^{N_{ueq}}(\max[0, -g_j(X)])^2\right)\right] \tag{18}$$

$$h_j(X) = 0, \quad j = 1, 2, \ldots, N_{eq} \tag{19}$$

$$g_j(X) < 0, \quad j = 1, 2, \ldots, N_{ineq} \tag{20}$$

where $f(X)$ is an objective function related to Eq. (3). N_{eq} and N_{ueq} are the number of equality and inequality constraints, respectively. Also, $h_j(X)$ and g_j are the equality and inequality constraints which are shown in Eqs. (5)–(12). L_1 and L_2 are the penalty factors. Since the constraints should be met, the values of the parameters should be high. In this paper the values have been considered as 10,000.

To this end at first, the optimal power flow is run based on the control variables. According to the obtained results of optimal power flow, the objective function value $f(X)$ is calculated and the constraints are checked. Then the augmented objective function is calculated by using the values of function and constraints. In other words, the penalty factor method is utilized for handling the inequalities constraints. In this regard, each control vector which violates constraints will be fined by these penalty factors. Therefore, step this control vector will be deleted automatically in the next step.

Step 3: an initial population X_j which must meet constraints is generated randomly, as follows:

$$\text{Population} = \begin{bmatrix} X_1 \\ X_2 \\ \ldots \\ X_F \end{bmatrix} \tag{21}$$

$$X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,N}] \tag{22}$$

where F is the number of frogand N is the number of variables.

$$X_i = [Vg_i, Pg_i, Qc_i, Tap_i] \tag{23}$$

where

$$Vg_i = [Vg_{i,1}, Vg_{i,2}, \ldots, Vg_{i,Ng}]_{1\times Ng} \tag{24}$$

$$Pg_i = [Pg_{i,1}, Pg_{i,2}, \ldots, Pg_{i,j}, \ldots, Pg_{i,Ng}]_{1\times(Ng-1)}, \quad j \neq \textit{slack bus} \tag{25}$$

$$Qc_i = [Qc_{i,1}, Qc_{i,2}, \ldots, Qc_{i,Nc}]_{1\times Nc} \tag{26}$$

$$\text{Tap}_i = [\text{tap}_{i,T1}, \text{tap}_{i,T2}, \ldots, \text{tap}_{i,Tm}]_{1\times Tm} \tag{27}$$

$$x_{i,j} = rand() * (x_{j,\max} - x_{j,\min}) + x_{j,\min}, \quad j = 1, 2, 3, \ldots, N; \quad i = 1, 2, 3, \ldots, N_F \tag{28}$$

where x_j is the position of the jth state variable, $rand()$ is a random function generator between 0 and 1 and N_F is the number of frogs.

Step 4: Calculate the objective functions.

Step 5: Sort the initial population based on the objective function values with descending manner.

Step 6: Dividing the sorted generated population in the memeplexes using the following process, the first individual goes to the first memeplex, the second individual goes to the second memeplex, the Mth individual goes to the Mth memeplex, and the $(M + 1)$th individual goes back to the first memeplex, etc.

Step 7: Select the best and worst individual in each memeplex, called X_b and X_w, respectively. Also the frog with the global best fitness in all memeplexes is identified as X_g.

Step 8: apply the SA algorithm, and compare the obtained results of the SA algorithm with X_g if the obtained result is better than X_g then, X_g is replaced by the SA result.

Step 9: A process is applied to improve only the frog with the worst fitness according to Eq. (13), if this process produces a better solution, it replaces the worst frog. Otherwise, a new population is randomly generated to replace that population. This process continues for a specific number of iterations (itetation$_{\max1}$).

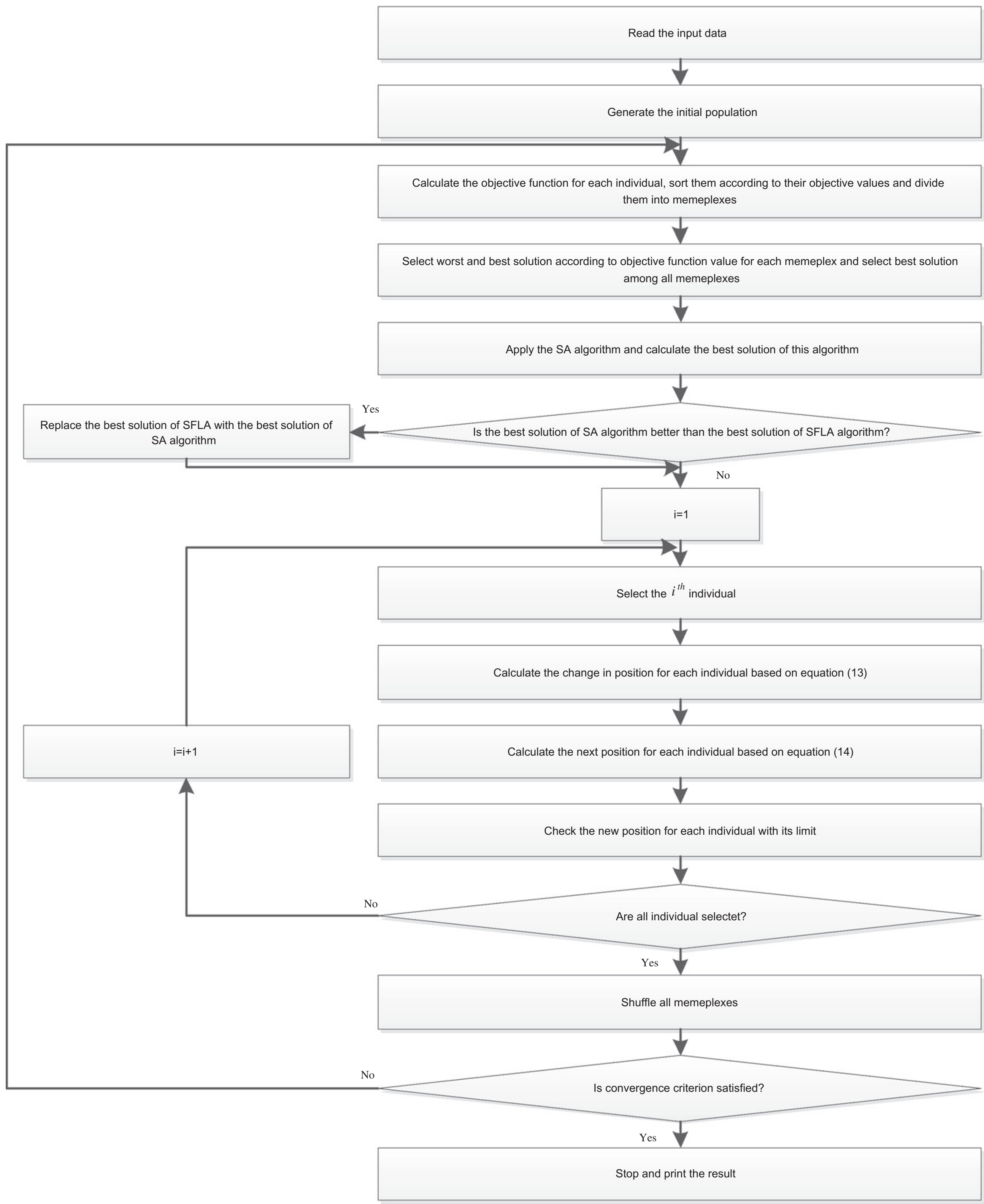

Fig. 3. Flowchart of the proposed hybrid SFLA-SA algorithm.

Step 10: If any element of an individual breaks its inequality constraints then the position of the individual is fixed to its maximum or minimum operating point. Therefore, this can be formulated as:

$$X_{i,j}^{k+1} = \begin{cases} x_{i,j}^{k+1} & \text{if } x_{j,\min} < x_{i,j}^{k} < x_{j,\max} \\ x_{j,\min} & \text{if } x_{i,j}^{k} < x_{j,\min} \\ x_{j,\max} & \text{if } x_{i,j}^{k} > x_{j,\max} \end{cases} \tag{29}$$

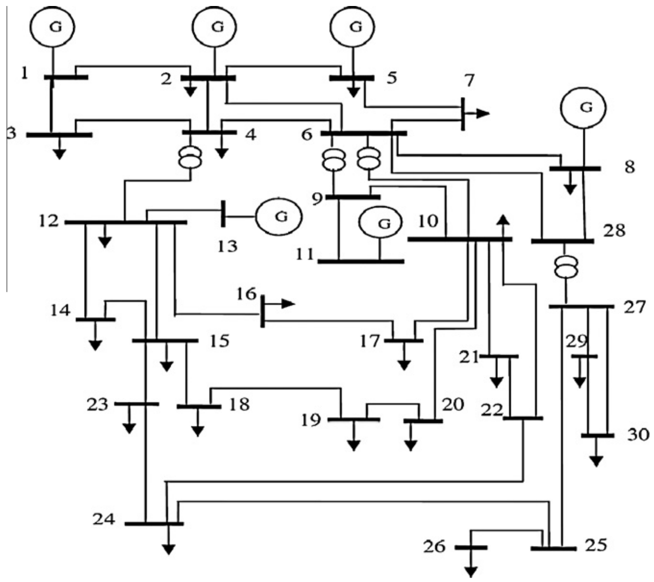

Fig. 4. One line diagram of 30-bus IEEE test system.

Step 11: in this section all memeplexes are combined and sorted again.

Step 12: If the current iteration number (iteration$_{max2}$) reaches the predetermined maximum iteration number, the search procedure is stopped; otherwise it goes to Step 6.

5. Simulation results

The proposed work is implemented in MATLAB 7.6 computing environment with Pentium IV, 2.66 GHz computer with 512 MB RAM. MATPOWER [49] is a package of MATLAB m-files for solving power flow and optimal power flow problems. It is a simulation tool for researchers and educators which is easy to use and modify. In this paper we have changed MATPOWER by adding hybrid SLFA-SA codes to execute the OPF in power systems. To validate performance of the proposed method, this method has been tested on the IEEE 30-bus test system. Detailed data about IEEE 30-bus test system can be derived from [50]. The 30-bus system consists of six generators at buses #1, #2, #5, #8, #11, and #13. Also bus #1 is considered as the slack bus and the voltage magnitude limits of all buses are set to $0.95 \leqslant V \leqslant 1.05$. The system schematic diagram is shown in Fig. 4.

All fuel cost coefficients, prohibited zones, and power generation limits of all generators are shown in Table 1.

This paper includes four case studies to show the effectiveness of valve point effect and prohibited zones on the OPF problem, as follows:

Case1: Presents the OPF problem without prohibited zones and valve point effect.

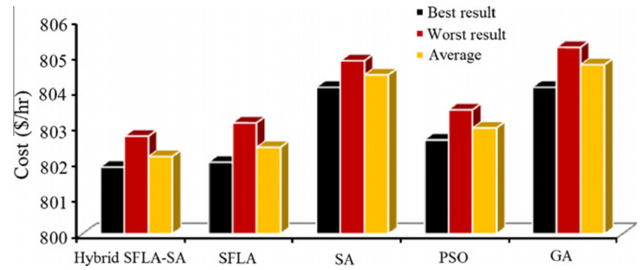

Fig. 5. Best, worst and average of different algorithm.

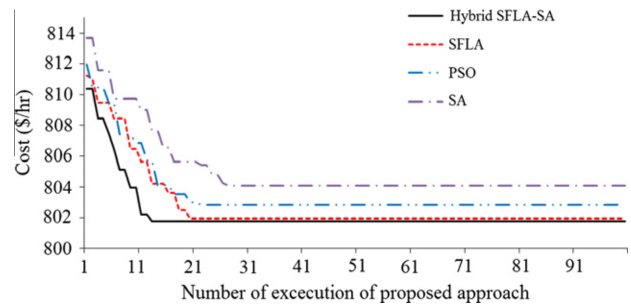

Fig. 6. convergence plot for different algorithms for case1.

Case2: Solves the OPF problem by considering the valve point effect.

Case3: Proposes the OPF problem by considering the prohibited zones.

Case4: Solves the OPF problem by considering the prohibited zones and valve point effect.

Comparisons of the proposed optimization algorithm with other corresponding methods confirm the effectiveness of the proposed method.

5.1. Case1: OPF without considering the valve point effect and prohibited zones

In this case the conventional OPF without considering the valve point effect and prohibited zone is proposed. The obtained results are compared with the original SFLA and other algorithms in the literature. The cost obtained by the proposed technique is less than the existing results while satisfying basic demand and generation limit constraints. The obtained result with hybrid SFLA-SA algorithm is 801.79 which is less than other algorithms. It also proves that the proposed algorithm can converge to better results and it is suitable for solving the OPF problem.

For more validation of the proposed algorithm, the original SFLA, SA, Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) are applied 50 times to solve the OPF problem. Fig. 5 depicts the best, worst, and average values of these algorithms to verify the

Table 1
Fuel cost coefficient and prohibited zones for 30-bus IEEE test system.

Generator number	*a*	*b*	*c*	*d*	*e*	P_{max}	P_{min}	Prohibit zones
G1	0.00375	2	0	18	0.037	250	50	[55–66], [80–120]
G2	0.0175	1.75	0	16	0.038	80	20	[21–24], [45–55]
G5	0.0625	1	0	14	0.04	50	15	[30–36]
G8	0.0083	3.25	0	12	0.045	35	10	[25–30]
G11	0.025	3	0	13	0.042	30	10	[25–28]
G13	0.025	3	0	13.5	0.041	40	12	[24–30]

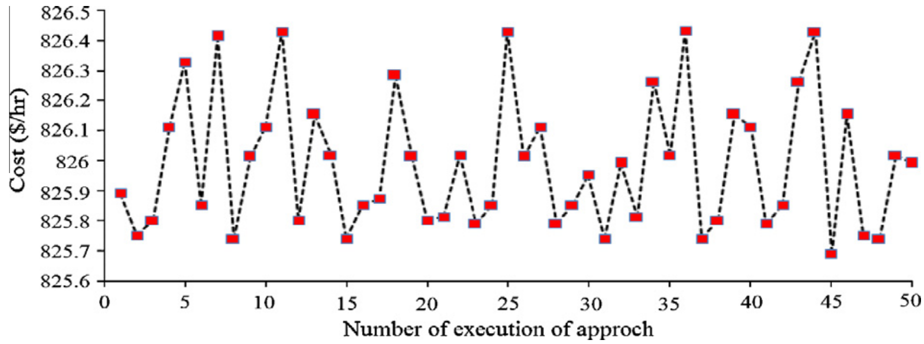

Fig. 7. Variation range of best results obtained by proposed algorithm for case2.

Table 2
Comparison of different OPF methods for the IEEE 30-bus test system.

	PG1 (MW)	PG2 (MW)	PG3 (MW)	PG4 (MW)	PG5 (MW)	PG6 (MW)	Losses (MW)	Cost ($/h)
NLP [51]	176.26	48.84	21.51	22.15	12.14	12	9.48	802.4
EP [36]	173.84	49.998	21.386	22.63	12.928	12	–	802.62
TS [40]	176.04	48.76	21.56	22.05	12.44	12	–	802.29
IEP [52]	176.23	49.0093	21.5023	21.8115	12.3387	12.012	–	802.46
DE-OPF [46]	176.009	48.801	21.334	22.262	12.46	12	9.466	802.39
MDE-OPF [46]	175.974	48.884	21.51	22.24	12.251	12	9.459	802.37
GA [53]	192.510	48.3951	19.5506	11.6204	10	12	–	804.10
SA [53]	192.510	48.3951	19.5506	11.6204	10	12	–	804.10
SGA [54]	179.367	44.24	24.61	19.9	10.71	14.09	–	803.69
EGA [55]	176.2	48.75	21.44	21.95	12.42	12.02	–	802.06
ACO [56]	181.945	47.001	20.553	21.146	10.433	12.173	–	802.57
FGA [57]	175.137	50.353	21.451	21.176	12.667	12.11	–	802.00
GA-OPF [58]	174.833	48.8845	23.7843	20.1961	13.1373	12.2196	–	803.91
EP-OPF [58]	175.029	48.9522	21.42	22.702	12.904	12.1035	–	803.57
SFLA	181.16	52.11	22.82	15.59	10	12.18	–	801.97
Hybrid SFLA_SA	172.78	48.02	23.94	23.85	12.60	12	–	801.79

Table 3
CUP time of different algorithms in solving the OPF problem without valve point effect and prohibited zones.

Algorithm	IEP	DE-OPF	MDE-OPF	SA	PSO	SFLA	Hybrid SFLA_SA
CPU time	594.08	36.61	23.07	98.74	21.84	19.22	18.93

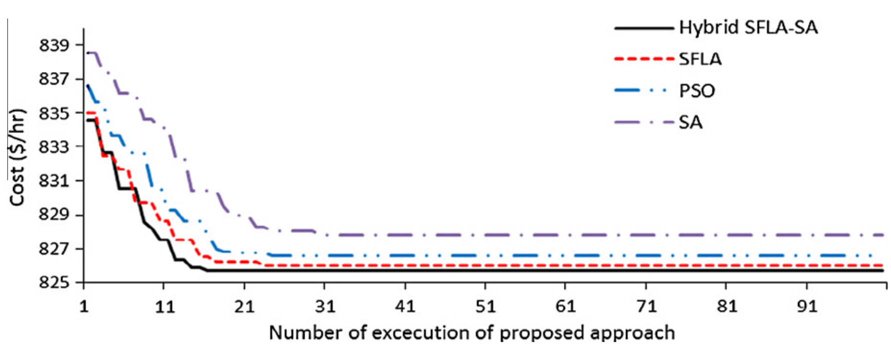

Fig. 8. convergence plot for different algorithms for case2.

proposed algorithm introduced in this paper. As shown, it is clear that proposed algorithm can converge to global optima or near it at different times of executing. Also the obtained best and worst result of the proposed algorithm are better than other algorithms in this figure which proves the superiority of the proposed algorithm once again. Also, Fig. 6 shows the convergence plot of different algorithms, which is clear that the proposed algorithm can converge to its global optima in lesser iteration compared with other algorithms. It is a very important characteristic for optimiza-

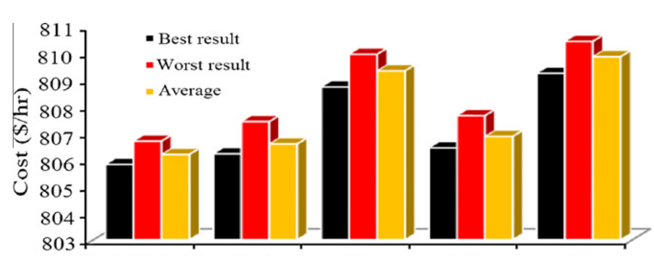

Fig. 9. Best, worst and average of different algorithm.

Table 4
Obtained results with different algorithms for case2.

Algorithm	PG1	PG2	PG3	PG4	PG5	PG6	Cost ($/h)
RCGA [59]	198.81	38.96	19.16	10.64	13.56	12.03	831.04
DE [59]	199.13	38.32	20.17	11.43	10.43	12.66	826.54
GA	222.1640423	22.9945922	15	10	10	17.15675679	829.4493073
PSO	227.0398743	20	16.70704004	10	10.3475555	12	826.5897702
SA	216.8178354	25.54906545	15.98774734	15.98756272	10	12.01699904	827.8262923
SFLA	223.4772943	22.10005449	17.11635285	10.98852899	10.17789811	12.46966811	825.9906126
Hybrid SFLA-SA	223.2516412	24.31206227	17.04793226	10	10.00003734	12.0293528	**825.6921669**

Table 5
Obtained cost with different algorithm for case3.

Algorithm	PG1	PG2	PG3	PG4	PG5	PG6	Cost ($/h)
GA	175.1155303	44.59472658	23.39201586	23.65051819	11.52781703	15.93642031	809.2314784
PSO	174.2634047	57.02641982	23.53917875	14.15582196	11.00304308	14.5145281	806.4331434
SA	181.6963186	57.91776223	17.10627026	16.51932769	10	12	808.7174786
SFLA	182.8236009	45	21.03986385	20.48529067	12.03383101	13.30211909	806.2155404
Hybrid SFLA-SA	181.4529678	45	21.52698226	22.07859788	11.98543771	12	**805.8152356**

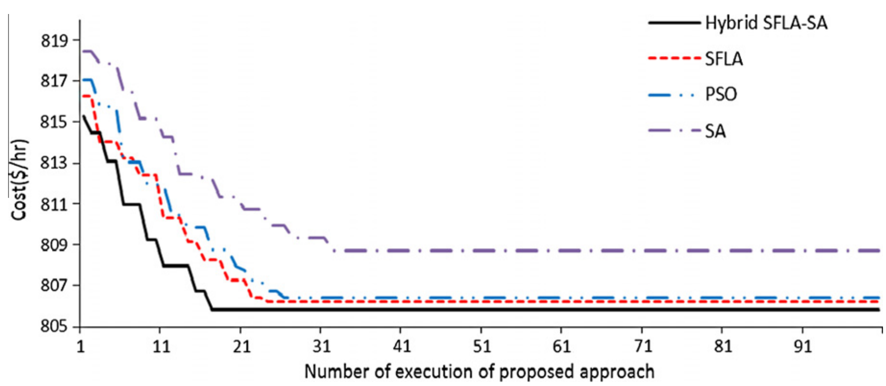

Fig. 10. convergence plot for different algorithms for case3.

Table 6
Obtained results with different algorithms for case4.

Algorithm	PG1	PG2	PG3	PG4	PG5	PG6	Cost ($/h)
GA	226.1783156	24.33444771	16.9393486	10	10.15253559	12	838.1727153
PSO	221.147092	30.8367047	15	10	10	12	835.4785807
SA	217.6116578	32.77084147	16.51772172	10	10	12	836.5364494
SFLA	219.4201277	31.1173131	15.85351826	10.0415162	10	12	834.8165531
Hybrid SFLA-SA	219.8159983	29.77073737	16.6669505	10.00002787	10	12.00000008	**834.6339404**

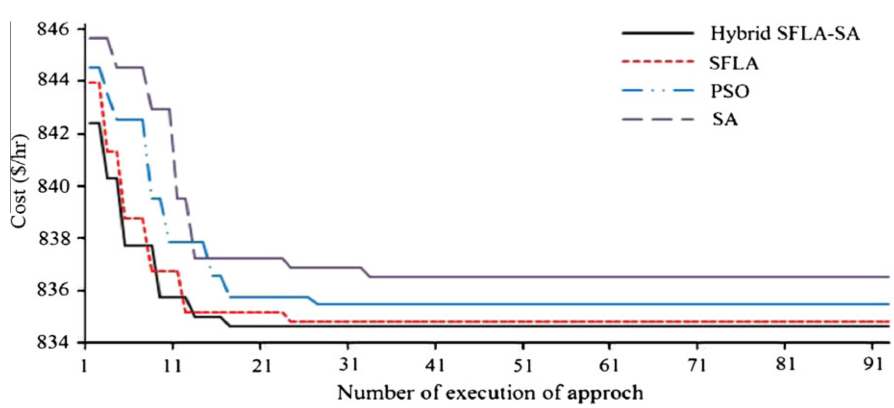

Fig. 11. convergence plot for different algorithms for case4.

Table 7
Comparison of best results for different cases.

	PG1	PG2	PG3	PG4	PG5	PG6	Cost ($/h)
Case1	172.78303	48.026356	23.947456	23.855225	12.607924	12	**801.79692**
Case2	223.25164	24.312062	17.047932	10	10.000037	12.029353	**825.69217**
Case3	181.45297	45	21.526982	22.078598	11.985438	12	**805.81524**
Case4	219.816	29.770737	16.66695	10.000028	10	12	**834.63394**

tion algorithms because the speed of these algorithms is a significant feature in solving optimization problems.

Table 3 shows the CPU time for different algorithms. As shown, the proposed algorithm can converge to its global optima in lesser time compared other algorithm. Therefore, the proposed algorithm not only converges to a better solution, but also has a high convergence speed which is helpful for solving the complex optimization problems.

5.2. Case2: OPF with considering valve point effect

This case considers the valve point effect in optimal power flow. From the results it is clear that by considering the valve point effect, the generation cost is increased. Also for more validation, the obtained results are compared with other algorithms.

The results of some different number of runs are displayed in Fig. 7. As shown, these results are very identical; of course, some small differences exist between them, which indicate the convergence of the proposed algorithm in different iterations.

By comparing Tables 2 and 3 it is clear that valve point effect increases generation cost. Without considering the valve point effect the generation cost is 801.79 but by considering this phenomenon, the generation cost is increased to 825.69. Fig. 8 displays a convergence plot of different algorithms related to case2, it is clear that the proposed algorithm can converge to global optima in less iteration irrespective of the complexity of problem.

5.3. Case3: OPF with considering prohibited zones

Solving the OPF problem with considering the prohibited zones is proposed in this section. Table 5 and Fig. 9 show the obtained results, and similar to other sections they are compared with other algorithms.

By comparing Tables 2 and 4 it is clear that prohibited zones like valve point effect increase the generation cost. If prohibited zones have a wide overlap with the areas which are near the optimal work point area obtained in case1 then the drastic increase in the generation cost is inevitable; otherwise generation cost is little. For more validation, the convergence plot of the proposed algorithm in terms of case3 is depicted in Fig. 10. Similar to other convergence plots, in this figure, the proposed algorithm converges to global optima in lesser iteration compared with other algorithms such as SFLA, PSO and SA.

5.4. Case4: OPF with considering valve point effect and prohibited zones

This section considers the valve point effect and prohibited zones simultaneously. The related results of this case are depicted in Table 6. By comparing the results with to the results of other sections, it is clear that the amount of generation cost is higher and more predictable.

Also, the convergence plots of hybrid SFLA-SA, SFLA, PSO, and SA are shown in Fig. 11. As shown, the hybrid SFLA-SA is faster and it has better convergence compared with other algorithms. Moreover, the value of the objective function settles at the minimum point after about 17 iterations, and does not vary thereafter while other algorithms converge to global point in about at least 23 iterations.

Table 8
Comparison of CPU time of different algorithms for different cases.

	SA	PSO	SFLA	Hybrid SFLA-SA
Case1	98.74	21.84	19.22	18.93
Case2	119.48	24.75	22.83	21.48
Case3	123.86	24.94	24.74	22.19
Case4	152.32	31.62	30.72	27.57

Table 9
Comparison of number of function evaluation of different algorithms for different cases.

	SA	PSO	SFLA	Hybrid SFLA-SA
Case1	3956	2194	1985	647
Case2	4572	2426	2317	873
Case3	4829	2631	2391	937
Case4	5084	3418	2579	1029

For more depiction of valve point effect and prohibited zones on generation cost in power system the best results of each case is shown in the Table 7. It is clear that by considering these constraints the generation cost is increased.

Table 8 depicts the CPU time of different algorithms for solving different cases. As shown, the proposed algorithm can converge to its global solution in lesser time. In other words, the proposed algorithm has higher speed of convergence. Once again the superiority of proposed algorithm in solving optimization problem is proved.

Table 9 shows the comparison of the number of function evaluations for different methods. The simulation results in the tables demonstrate that the proposed hybrid evolutionary algorithm converges to global optimum with less function evaluations and leads naturally to the conclusion that the Hybrid SFLA-SA algorithm is a viable and robust technique for optimization problems such as OPF.

With comparing Tables 7 and 8 it is clear that proposed Hybrid SFLA-SA can converge to global optima with a less number of function evaluation respect to other optimization algorithms, but the CPU time of this algorithm in comparison with SFLA's CPU time is negligible. This proves the fact that SA algorithm is slow in convergence. Also, CPU time and number of function evaluation related to SA algorithm proves previous statement.

6. Conclusion

In this paper, a novel hybrid SFLA-SA based approach to the OPF problem in power systems is presented. Objective function has been considered to minimize fuel cost. The proposed algorithm is suitable for solving the complex problems like OPF because it benefits from the advantages of both SFLA and SA algorithms. The outcome of this research helps not only to determine the optimal generation cost in power systems, but also helps consider the practical constraint like valve point effect and prohibited zones. The proposed algorithm turns out to be effective since the obtained solutions have some superior characteristics compared with other approaches in the literature. This paper is significant for two reasons: 1. The efficiency of the proposed algorithm which is proved when compared with other algorithms, 2. It solves the OPF problem considering the generator constraints.

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