Ain Shams Engineering Journal (2016) 7, 895–905

Ain Shams University

Ain Shams Engineering Journal

www.elsevier.com/locate/asej
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ELECTRICAL ENGINEERING

Multi-objective optimization in the presence of ramp-rate limits using non-dominated sorting hybrid fruit fly algorithm

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Received 7 September 2015; revised 30 December 2015; accepted 18 January 2016
Available online 4 February 2016

KEYWORDS

Optimal power flow;
Fruit fly algorithm;
Generation fuel cost;
Total power loss;
Voltage stability index;
Non-dominated sorting

Abstract A novel optimization algorithm is proposed to solve single and multi-objective optimization problems with generation fuel cost, total power losses and voltage stability index as objectives. Fruit fly Algorithm (FFA) along with real coded Genetic Algorithm (GA) cross-over operation treated as Hybrid Fruit fly Algorithm (HFFA) is proposed to select best value as compared with existing single-objective evaluation algorithms and the proposed non-dominated sorting hybrid fruit fly algorithm (NSHFFA) is used for the multi-objective optimal power flow problem. A fuzzy decision making tool is used to select the best Pareto front from the total generated solutions by the proposed algorithm. The effectiveness of the proposed algorithm is analyzed for various standard test systems such as Booth's function, Schaffer 2 function and IEEE 30 bus system. The obtained results using proposed algorithm are compared with the existing optimization methods. The results reveal better solution and computational efficiency of the proposed algorithm.

1. Introduction

Power flow studies are of great importance for reliable, stable and secure operation of a power system and for proper planning as well as designed for future extension. In the past few decades, optimal power flow (OPF) problem has received greater attention, because it is one of the most powerful tools to analyze static systems of electrical energy. The main aim of OPF problem solution was to optimize a selected objective function such as fuel cost, power loss and voltage stability index (L-index).

Santos and da Costa describe a new approach for the optimal-power-flow problem based on Newton's method which is operated with an augmented original problem [1]. Momoh and Zhu proposed an improved quadratic interior point (IQIP) method used to solve comprehensive OPF problem with a variety of objective functions, including economic dispatch, VAR planning and loss minimization [2]. AlRashidi and El-Hawary investigated the applicability of hybrid partial swam optimization (HPSO) in solving the OPF problem under different formulations and considering different objectives [3]. Capitanescu et al. proposed interior-point based algorithms

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Peer review under responsibility of Ain Shams University.

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http://dx.doi.org/10.1016/j.asej.2016.01.005

for the solution of optimal power flow problems for the minimization of overall generation cost, minimization of active power losses, maximization of power system loadability and minimization of the amount of load curtailment [4]. An approach for the multi-objective OPF problem using 'differential evolution' is presented by Varada Rajan and Swarup [5]. Bai et al. described new solution using the semi definite programming (SDP) technique to solve the OPF problems. This involves reformulating the OPF problems into a SDP model and developing an algorithm of interior point method (IPM) for SDP [6]. Yang and Deb intend to formulate a new meta-heuristic algorithm, called Cuckoo Search (CS), for solving optimization problems [7]. Niknam et al. [8] have proposed improved particle swarm optimization for multi-objective OPF considering cost, loss, and emission voltage stability index. Bakirtzis et al. proposed a Strength Pareto Evolutionary Algorithm (SPEA) [9] with strong-dominated solutions is used to form the Pareto optimal set.

In the literature several algorithms have been proposed for multi-objective optimization problem. One of these methods is converting multi-objective problem to single-objective problem by considering one object as main object and other as a constraint. Another technique is combining all objectives into one objective function and solving using weighted sum technique. All these techniques have drawbacks such as limitation of the available choices of solution. The above methods will give only one solution for the multi-objective problem and this is the major drawback in these methods. To overcome these problems some of the techniques are proposed in the literature [10–13]. These algorithms are population based methods, and multi-Pareto-optimal solutions can be found in one program run. In the proposed technique non-dominated sorting approach is used along with the hybrid fruit fly algorithm to solve multi-objective optimization problem.

2. Problem formulation

The aim of optimal power flow solution was to optimize a selective objective function through optimal adjustment of control variables by satisfying equality and inequality constraints. The OPF problem can be mathematically formulated as follows:

$$\text{Minimize } C(x,u) \tag{1}$$

$$\text{Subjected to constrain } g(x,u) = 0 \tag{2}$$

$$h_{\min} \leqslant h(x,u) \leqslant h_{\max} \tag{3}$$

where $C(x,u)$ is the objective function, x is the vector of dependent variables, u is the vector of independent or control variables, $g(x,u)$ represents equality constraints, and $h(x,u)$ represents inequality constraints.

Equality constraints: These constraints are usually load flow equations described as

$$P_{Gi} - P_{Di} - \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) = 0$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) = 0$$

In-Equality Constraints: These are generator, voltage, transformer tap setting, shunt VAr compensators and security constraints are considered [14].

Ramp-rate limits: The operating range of the generating units is restricted by their ramp-rate limits, which force the generators to operate continuously between two adjacent periods. The inequality constraints imposed by these ramp-rate limits are

$$\max(P_{Gi}^{\min}, P_i^0 - DR_i) \leqslant \min(P_{Gi}^{\max}, P_i^0 + UR_i)$$

where P_i^0 is the power generation of ith unit at previous hour. DR_i and UR_i are the respective decreasing and increasing ramp-rate limits of ith unit.

3. Objective functions

The main objective of OPF problem was to minimize the generation fuel cost, total real power loss of a transmission line in a system and voltage stability index (L-Index).

3.1. Case 1. Generation fuel cost

The fuel cost curves of thermal generators are modeled as a quadratic cost curve which can be represented as,

$$C_T = \sum_{i=1}^{NG} C_i(P_{Gi}) \tag{4}$$

$$C_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + d_i \quad \$/\text{h} \tag{5}$$

where a_i, b_i and d_i are ith generating unit cost coefficients, P_{Gi} is real power generation of ith generating unit, and NG is total number of generating units.

3.2. Case 2. Total real power loss (TPL)

The total real power loss is

$$C_{Loss} = \sum_{i=1}^{nl} g_l[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)] \quad \text{MW} \tag{6}$$

where g_l is the conduction of lth line which connects buses i and j, and V_l, V_j and δ_i, δ_j are the voltage magnitude and angle of the lth and ith bus, respectively.

3.3. Case 3. Voltage stability index (VSI)

The significance of L-index of load buses in a power system is to monitor the voltage stability. It uses information from the normal load flow. It is in the range of 0–1. Voltage collapse can be controlled by minimizing the sum of squares of L-indices for a given operating condition.

$$C_{\text{L-Index}} = \sum_{j=NG+1}^{NB} L_j^2 \tag{7}$$

where NG is the number of generator buses and NB is the total number of buses in the system.

$$L_j = \left|1 - \sum_{i=1}^{NG} C_{ji} \frac{V_i}{V_j}\right| \quad (8)$$

where $j = NG + 1, \ldots, NB$, C_{ji} is obtained from Y_{bus} matrices.

4. Hybrid Fruit Fly Algorithm (HFFA)

Fruit fly algorithm is the meta-heuristic method suitable for solving continuous nonlinear optimization problems. This algorithm was developed from the lifestyle of fruit fly family. Fruit flies live in the temperate and tropical climate zones. They have very sensitive osphresis and vision organs which are superior to other species. They feed on rotten foods; it smells all kinds of scents in the air through their organs, and then flies toward the corresponding food location for searching food. In this paper the performance of existing fruit fly algorithm is improved by using real coded GA crossover operation. Due to this, the searching capabilities of particles in each iteration are improved. The detailed steps of hybrid fruit fly algorithm are given as follows.

4.1. Step-1: Initialization of fruit fly swarm location

Generate randomly '*ps*' number of populations

$$\delta_j = \delta_j^{\min} + rand\,(0,1) \times (\delta_j^{\max} - \delta_j^{\min}); \quad j = 1, 2, \ldots, n \quad (9)$$

where ps = number of populations, n = number of control variables, and $\delta_j^{\min}$ and $\delta_j^{\max}$ are minimum and maximum limits of control variable.

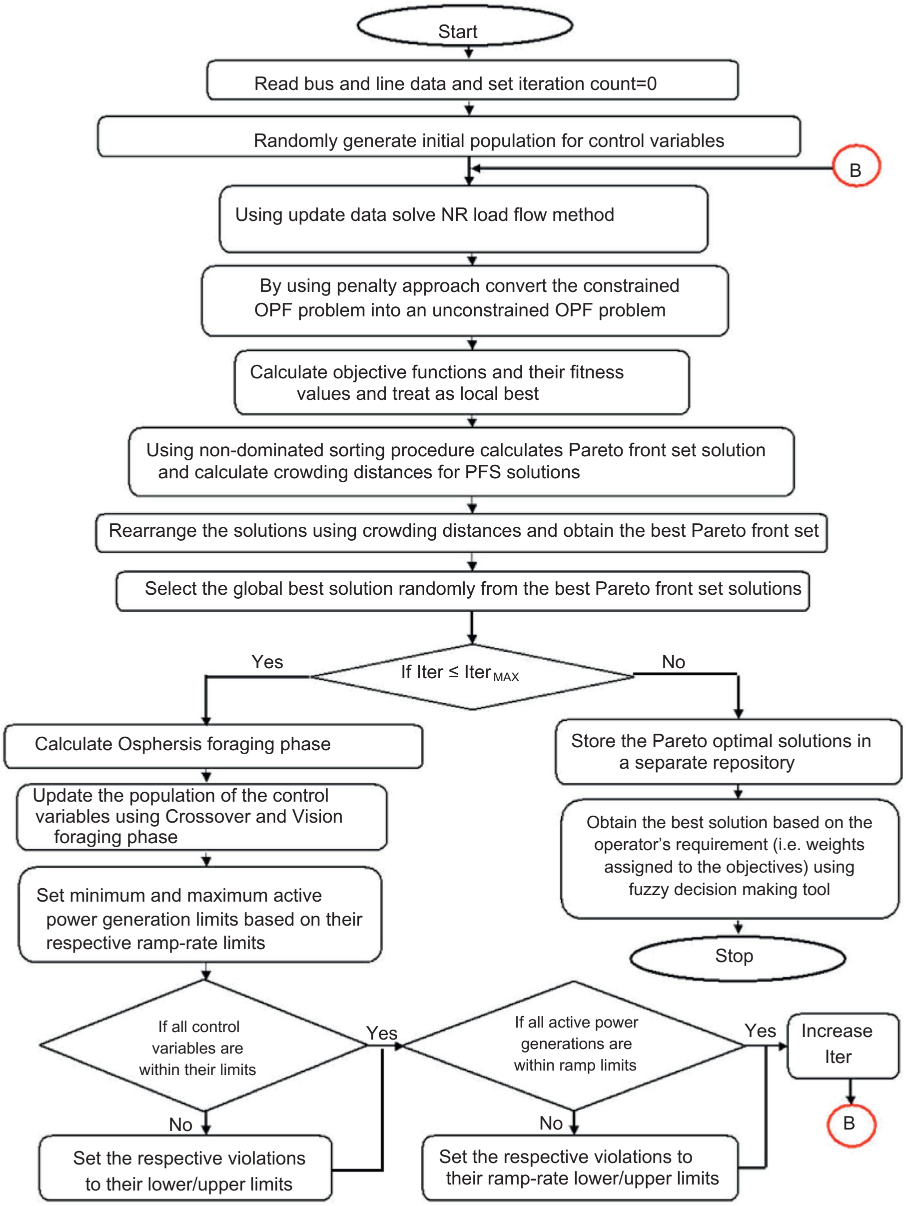

Figure 1 Flowchart of the multi-objective solution strategy.

Table 1 Comparison of optimal solution for Booths function.

Parameters	Existing PSO [14]	Existing CSA [14]	Existing FFA	Proposed HFFA
x	1.012698676	1.002249267	1.000	1.000
y	2.989245453	2.991978006	3.000	3.000
Min. function value	0.000292035	0.000202709	2.2845e−5	1.2364e−8
Time (s)	8.232991	6.95472	3.42322	2.8321

4.2. Step-2: Start loop: Set Generation = 1

Perform operations on randomly generated population vector to get best population vector [PV] vector. Operations to be performed are listed below.

4.3. Step-3: Osphresis foraging phase

In this phase a population of 'ps' food sources are generated randomly around the current fruit fly swarm locations Δ where Δ is set of the randomly initialized swarm location $\Delta = (\delta_1, \delta_2, \ldots, \delta_n)$

Let $\{x_1, x_2, \ldots, x_{ps}\}$ are the generated food sources

$$x_{ij} = \delta_j \pm \lambda \cdot rand\ (), \quad j = 1, 2, \ldots, n \tag{10}$$

In osphresis foraging food sources generated around its swarm location within a radius equals to one. This radius is fixed and cannot be changed during iterations. For optimal solution this search region is too small and considerable increase needed in iterations. Hence search radius can be changed dynamically with iteration number.

$$\lambda = \lambda_{\max} \cdot \exp\left[\log\left(\frac{\lambda_{\min}}{\lambda_{\max}}\right) \cdot \frac{itr}{itr_{\max}}\right]$$

4.4. Step-4: Crossover

It is an efficient recombination operator has been used to search swarm food location in certain long range. Recombination crossover generates new swarm locations by using the following crossover equation.

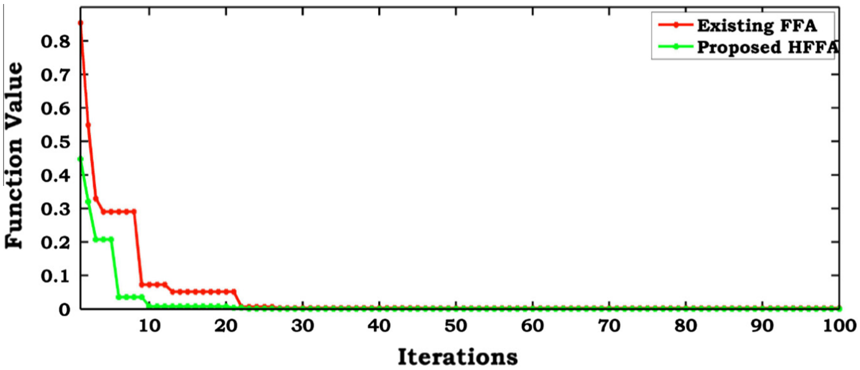

Figure 2 Convergence characteristics of Booth's function.

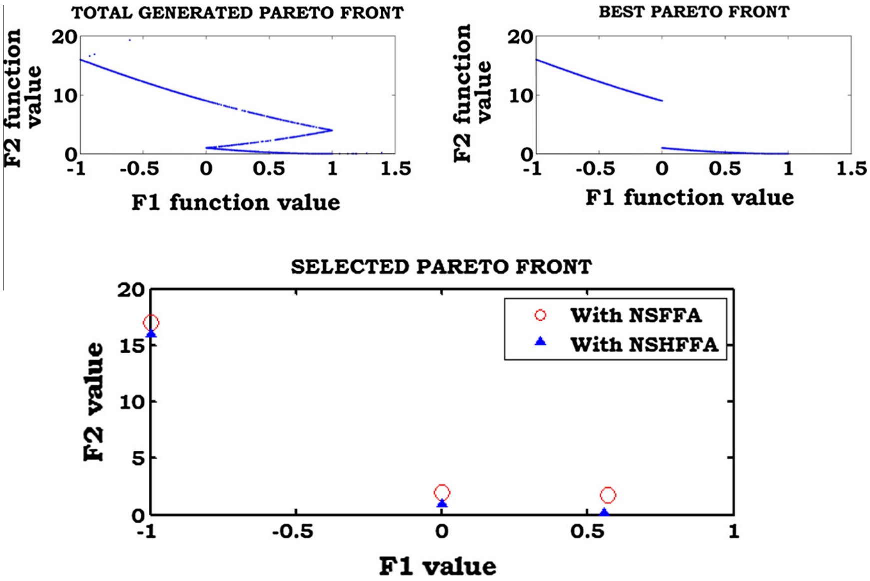

Figure 3 Multi-objective Pareto solutions for Schaffer 2 function.

$$x_{i,j} = (1-\lambda)\times x_{(1,j)} + \lambda \times x_{(i,j)} \quad \begin{array}{l} i = 1,2,\ldots,ps \\ j = 1,2,\ldots,n \end{array} \tag{11}$$

After getting new values of control variables for total number of food sources, whose limits have to be checked, new population vector is obtained and its fitness vector is evaluated.

4.5. Step-5: Vision foraging phase

In this phase fruit fly optimization carries a greedy selection procedure. Finding best food source with lowest fitness was given by

$$X_{best} = \arg(\min f(X_i)), \quad i = 1,2,\ldots,ps \tag{12}$$

If X_{best} is better than the current fruit fly swarm location, swarm will replace the new position. Otherwise swarm location will not change.

4.6. Step-6: Stopping criteria

Stop the process, if the maximum number of generations is reached. Otherwise, go to step 2 and repeat the process up to specified maximum number of generations. Here we set the maximum of generations is 100.

5. Multi-objective solution strategy

Multi-objective optimization with two and more objectives is optimized simultaneously, while satisfying equality, inequality and ramp rate limit constraints using proposed non-dominated hybrid fruit fly algorithm (HFFA).

The multi-objective optimization with different n number of objectives is optimized as follows

$$Minimize\ [F_1(x,u), F_2(x,u),\ldots,F_n(x,u)]; \quad n = 1,2,\ldots,n \tag{13}$$

To perform this, sequence of step is given in flowchart shown in Fig. 1.

5.1. Non-dominated sorting

A non-dominated sorting procedure is applied to the multi-objective optimization solutions to obtain a Pareto front set. Let us consider two solutions, F_1 and F_2, in one Pareto front set. They are checked for the following possibilities: one of them dominates the other or none of them dominates each other. A vector u_1 dominates u_2, when the following conditions are met [15]

$$\forall\ i = 1,2,\ldots,n, \quad F_i(u_1) \leqslant F_i(u_2)$$

$$\exists\ j = 1,2,\ldots,n, \quad F_j(u_1) \leqslant F_j(u_2),$$

where n is the number of objective functions. Solutions that are non-dominated over the entire search space are called Pareto optimal set. We follow the sorting procedure from [16,17], based on crowding distance, to obtain the best Pareto front set solutions.

5.2. Fuzzy decision making tool

To extract the best compromised solution from best Pareto front based on the decision of operator we follow the fuzzy decision making approach to obtain the optimal solution. The linear membership value, μ is initially calculated for the ith objective in the jth Pareto solution using [16,18]

$$\mu_i^j = \begin{cases} 1; & F_i^j \leqslant \min(F_i) \\ \frac{\max(F_i)-F_i^j}{\max(F_i)-\min(F_i)}; & \min(F_i) \leqslant F_i^j \leqslant \max(F_i) \\ 0; & F_i^j \geqslant \max(F_i) \end{cases}$$

By using normalized membership values, the favored degree of the Pareto optimal solution can be identified and this value for qth Pareto front set solution can be calculated using

Table 2 Multi-objective Pareto solutions for the Schaffer 2 function.

S. no.	W1	W2	Existing NSFFA		Proposed NSHFFA	
			F1 value	F2 value	F1 value	F2 value
1	0.9	0.1	−1.000	17.000	−1.000	16.000
2	0.8	0.2	−1.000	17.000	−1.000	16.000
3	0.7	0.3	−1.000	17.000	−1.000	16.000
4	0.6	0.4	0.000	2.000	0.000	1.000
5	0.5	0.5	0.000	2.000	0.000	1.000
6	0.4	0.6	0.000	2.000	0.000	1.000
7	0.3	0.7	0.000	2.000	0.000	1.000
8	0.2	0.8	0.001	2.000	0.000	1.000
9	0.1	0.9	0.568	1.7	0.555	0.198

Table 3 Comparison of optimal power flow solution for cost minimization objective.

Control variables	Existing TS [23]	Existing FFA	Proposed HFFA
P_{G1} (MW)	176.0400	177.7152	179.3122
P_{G2} (MW)	48.7600	45.46423	48.26495
P_{G5} (MW)	21.5600	22.24322	20.9265
P_{G8} (MW)	22.0500	20.59715	19.86292
P_{G11} (MW)	12.4400	14.70965	12.3402
P_{G13} (MW)	12.0000	12	12
V_{G1}- (p.u.)	1.0500	1.098934	1.1
V_{G2} (p.u.)	1.0389	1.082836	1.057657
V_{G5} (p.u.)	1.0110	0.919706	1.065718
V_{G8} (p.u.)	1.0198	1.1	1.070609
V_{G11} (p.u.)	1.0941	0.961242	1.025229
V_{G13} (p.u.)	1.0898	1.062683	1.092478
$T_{6\text{–}9}$ (p.u.)	1.0407	1.006858	1.045322
$T_{6\text{–}10}$ (p.u.)	0.9218	0.993187	0.980038
$T_{4\text{–}12}$ (p.u.)	1.0098	0.990804	1.096105
$T_{28\text{–}27}$ (p.u.)	0.9402	0.981178	1.02131
Q_{C10} (MVAr)	–	28.98477	5
Q_{C24} (MVAr)	–	20.53278	29.67086
Cost ($/h)	802.2900	802.3834	800.9964

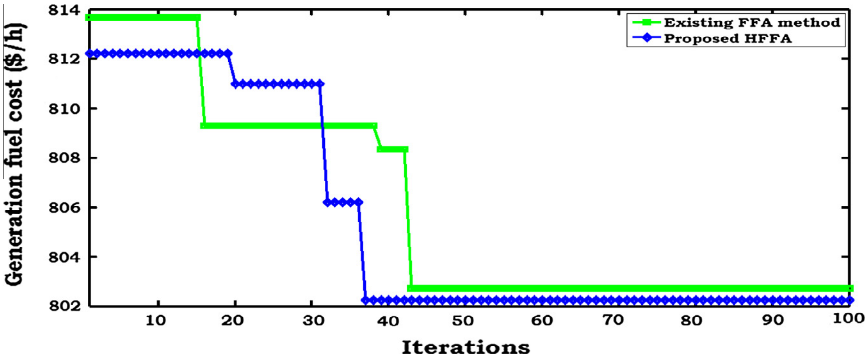

Figure 4 Convergence characteristics of generation fuel cost.

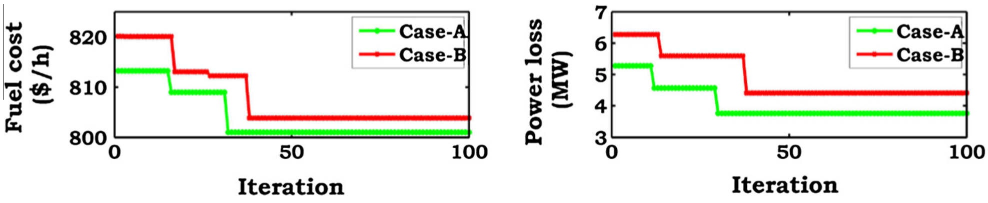

Figure 5 Convergence characteristics of fuel cost and total power losses.

Table 4 Summary of test results for generation fuel cost.

Methods	Generation fuel cost ($/h)
HCSA [14]	802.0347
EP [24]	802.907
TS/SA [25]	802.788
ITS [26]	804.556
IEP [27]	802.465
GA [28]	803.05
PSO [29]	802.41
GSO [30]	802.092
Chaotic self-adaptive differential HSA (CDHSA) [31]	801.5888
Imperialist competitive algorithm (ICA) [32]	801.843
Enhanced genetic algorithm (EGA) [33]	802.06
Artificial bee colony (ABC) [34]	802.1649
Tabu search (TS) [20]	802.29
Differential HSA (DHSA) [31]	802.2966
Modified differential evolution algorithm (MDEA) [35]	802.376
Refined genetic algorithm (RGA) [36]	804.02
Gradient projection method (GPM) [37]	804.853
Proposed HFFA	800.9964

$$\mu_{opt} = \sup \frac{\sum_{p=1}^{n} W_p \mu_p^q}{\sum_{q=1}^{N_{PFS}} \sum_{p=1}^{n} W_p \mu_p^q}; \tag{14}$$

where $W_p \geqslant 0; \sum_{p=1}^{n} W_p = 1$; W_p is the weight of the pth objective function, and N_{PFS} is the total number of solutions in the best Pareto front set. The Pareto front set solution that has the highest normalized membership for the weight coefficients is considered to be the most optimal solution. The complete methodology of the proposed multi-objective optimization strategy is shown in Fig. 1.

6. Results and analysis

This section clearly describes the results of standard test system Booth's function, Schaffer 2 function and IEEE-30 bus test systems. For electrical test systems, primarily single objectives are optimized individually using proposed HFFA and multi-objectives are optimized simultaneously using proposed NSHFFA method; corresponding results are analyzed. The proposed and existing methods are solved using Matlab-9 software (coding) on a PC with Intel core i3-370 M Pentium processor with 2.40 GHz frequency and 3 GB RAM.

6.1. Illustrative example

6.1.1. Booth's function

The first example is Booth's function [19] given by Eq. (15). The solution for this function was obtained using existing Partial Swam Optimization (PSO), and Cuckoo Search Algorithm (CSA) [14], Fruit fly method and proposed method. The preferred solution for this function is $f(1,3) = 0$ in the operating range of $-10 \leqslant x, y \leqslant 10$.

$$f(x,y) = (x + 2y - 7)^2 + (2x + y - 5)^2 \tag{15}$$

The comparison of optimal parameters for booth's function is given in Table 1. From Table 1 it is observed that proposed method gives the better solution than the existing methods. And it is also observed that the computation time is also less as compared to existing methods.

The convergence characteristic of booth's function is shown in Fig. 2. From this figure it is observed that existing Fruit fly method starts highest function value and converges to optimal best value with more number of iterations, whereas proposed HFFA starts with less function value and reaches best optimal

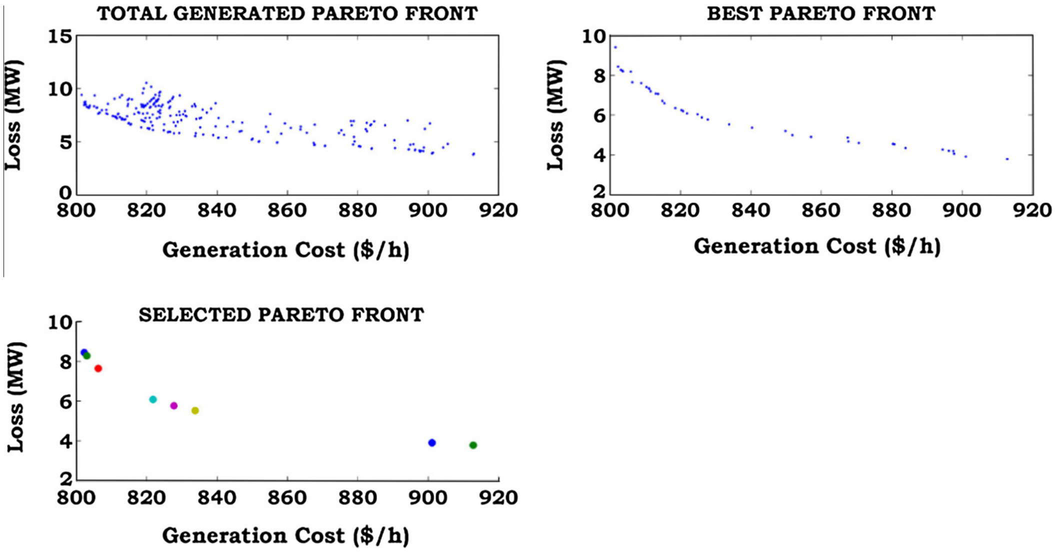

Figure 6 Multi-objective Pareto front solution for cost-loss combination.

value with less number of iterations. This shows the effectiveness of the proposed method.

6.1.2. Schaffer 2 function

To sophisticated performance of the proposed NSFFA technique for solving the multiobjective optimization problem, we consider the standard Schaffer 2 test function which is given in Eq. (16). Using Section 5 procedure the total solutions, best Pareto front and selected Pareto front solutions with proposed method and compared with existing methods are shown in Fig. 3. From this figure it is observed that total generated Pareto fronts and best Pareto fronts solutions coincide with the existing methods [19]. The selected Pareto solutions obtained using the fuzzy decision making tool are given in Table 2. From this table it is observed that function values are minimized by increasing the weights assigned to the corresponding objectives.

$$Minimize = \begin{cases} f_1(x) = \begin{cases} -x, & \text{if } x \leqslant 1 \\ x-2, & \text{if } 1 < x \leqslant 3 \\ 4-x, & \text{if } 3 < x \leqslant 4\,; \\ x-4, & \text{if } x > 4 \end{cases} \quad -5 \leqslant x \leqslant 10 \\ f_2(x) = (x-5)^2 \end{cases} \tag{16}$$

Table 5 OPF results of generation fuel cost, total power loss and L-index without and with ramp-rate limits.

Control variables	Generation cost ($/h)		Total power loss (MW)		L-index	
	Case-A	Case-B	Case-A	Case-B	Case-A	Case-B
P_{G1} (MW)	179.3122	168.7113	64.5787	86.105	133.7418	70.004
P_{G2} (MW)	48.26495	48.1673	73.1716	63.000	37.5136	62.458
P_{G5} (MW)	20.9265	25.9548	49.1044	49.000	46.7400	50.000
P_{G8} (MW)	19.86292	22.2982	34.6496	27.712	23.7323	35.000
P_{G11} (MW)	12.3402	13	29.3441	28.000	26.5676	30.000
P_{G13} (MW)	12	14	36.3133	34.999	21.3126	40.000
V_{G1-} (p.u.)	1.1	1.100	1.0350	1.056	1.0351	1.100
V_{G2} (p.u.)	1.057657	1.084	1.0295	1.067	1.0214	0.994
V_{G5} (p.u.)	1.065718	1.037	1.0297	0.940	1.0369	1.034
V_{G8} (p.u.)	1.070609	1.029	1.0217	1.008	1.0093	1.100
V_{G11} (p.u.)	1.025229	1.049	1.0249	1.030	1.0227	1.100
V_{G13} (p.u.)	1.092478	1.100	1.0293	0.900	1.0870	0.974
$T_{6\text{–}9}$ (p.u.)	1.045322	1.001	1.0648	1.100	0.9832	1.034
$T_{6\text{–}10}$ (p.u.)	0.980038	0.936	0.9786	0.900	0.9629	1.100
$T_{4\text{–}12}$ (p.u.)	1.096105	1.097	0.9810	0.951	1.0300	0.996
$T_{28\text{–}27}$ (p.u.)	1.02131	0.900	0.9597	0.900	0.9428	1.045
Q_{C10} (MVAr)	5	30.000	13.13752	14.591	30	5.000
Q_{C24} (MVAr)	29.67086	11.024	17.13742	17.238	6.334336	5.000
Cost ($/h)	**800.9964**	**803.8556**	940.4399	914.4714	862.5843	938.6717
TPL (MW)	8.36415	8.7317	**3.7618**	**4.4159**	6.2080	4.0621
L-Index	0.1815	0.1923	0.1562	0.1676	**0.1287**	**0.1328**

Bold values shows the optimal values in the corresponding minimization objects.

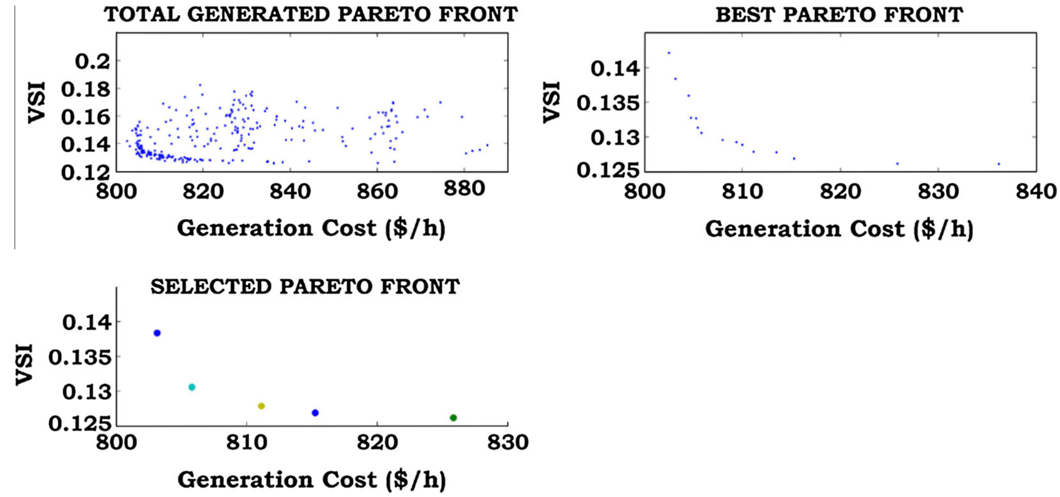

Figure 7 Multi-objective Pareto front solution for cost-VSI combination.

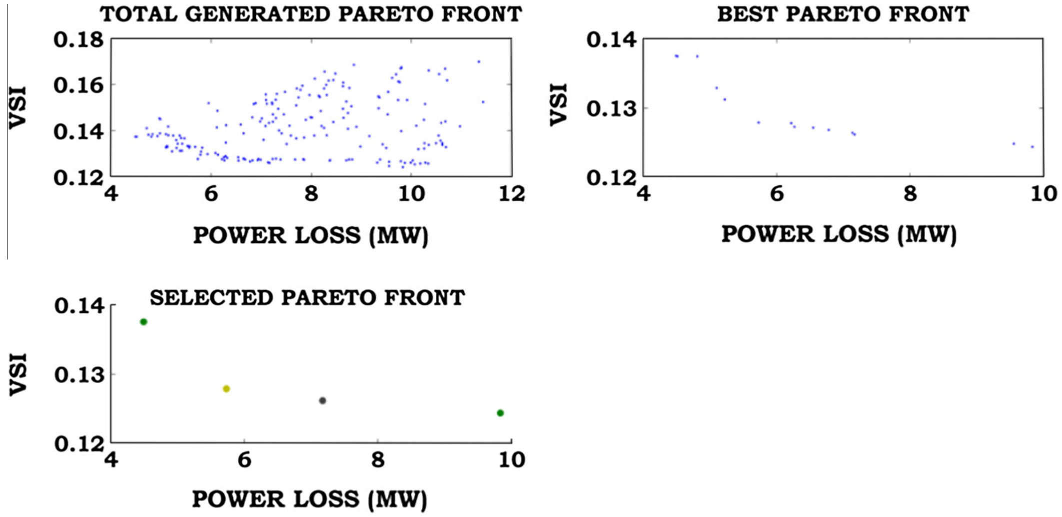

Figure 8 Multi-objective Pareto front solution for loss-VSI combination.

Table 6 Consolidated results for multi-objective optimization for all three cases.

Set no.	W1	W2	Case-I		Case-II		Case-III	
			Cost ($/h)	Loss (MW)	Cost ($/h)	VSI	Loss (MW)	VSI
1	0.9	0.1	802.2387	8.4478	803.120	0.138	4.487	0.138
2	0.8	0.2	802.9737	8.2841	805.789	0.131	4.487	0.138
3	0.7	0.3	806.2689	7.6453	805.789	0.131	5.727	0.128
4	0.6	0.4	821.7963	6.0954	805.789	0.131	5.727	0.128
5	0.5	0.5	827.6991	5.7787	811.108	0.128	5.727	0.128
6	0.4	0.6	833.7969	5.5350	811.108	0.128	5.727	0.128
7	0.3	0.7	901.0323	3.9105	815.247	0.127	7.168	0.126
8	0.2	0.8	901.0323	3.9105	815.247	0.127	9.832	0.124
9	0.1	0.9	912.7326	3.7974	825.817	0.126	9.832	0.124

6.2. Electrical test system

We consider the IEEE-30 bus test system with forty-one transmission lines [20–22] to extend the features of the proposed HFFA technique to solve single objective OPF problems and proposed NSHFFA for multi-objective optimization problems. There are eighteen control variables for this system, which include six active power generations and respective voltage magnitudes, two shunt compensators and four tap setting transformers.

6.2.1. Single objective optimization

The generation fuel cost, total power loss and voltage stability index are considered as objective functions. The solution of the individual objective function is determined using proposed HFFA method and the results are compared with existing methods.

The optimal solution obtained using existing Tabu Search (TS) and Fruit fly algorithm (FFA) methods and proposed (HFFA) method is compared. Table 3 gives the comparisons of existing methods and proposed method. From Table 3, it is observed that the generation fuel cost is minimum for the proposed method compared with the existing methods.

The convergence characteristics of the existing method FFA and proposed HFFA are shown in Fig. 4. From this figure it is observed that proposed method starts with good initial value and reaches its final value with less number of iterations as compared with existing FFA method. This shows the effectiveness of the proposed method. Also comparing the proposed method with different existing methods in Table 4, it is observed that the proposed method gives the best solution.

To show the effect of ramp-rate limit constraint, the OPF problem was solved for the following two cases:

Case-A: Without ramp-rate limits; Case-B: With ramp-rate limits

The same analysis is carried out for Case-A and Case-B with the proposed HFFA of generation fuel cost, total power loss and voltage stability index objectives. The detailed results for three objectives with two different cases are tabulated in Table 5. From this table it is observed that, the three objective values are increasing from Case-A to Case-B with inclusion of additional constraint ramp-rate limits. Generation fuel cost has increased from 800.9964 $/h to 803.8556 $/h of Case-A to Case-B. Similarly, it is also observed that total power loss from 3.7618 MW to 4.4159 MW and voltage stability index change from 0.1287 to 0.1328 from Case-A to Case-B. As the number of constraints increases, the objective function values also increase, and minimization of one objective, increases the values of the other objectives. This is due to the objectives being contradictory. Due to the restrictions imposed by practical constraint such as ramp-rate limits on power generation, the generation is rescheduled and some generators increase the generation and some decrease the generation. Thus the total generation and losses also vary from without considering ramp-rate limits and with considering ramp-rate limits.

Convergences for the objectives in the two cases are shown in Fig. 5. From these figures it is observed that, all

Table 7 Multi-objective optimization results for three objective combinations.

S. no.	W1	W2	W3	Cost ($/h)	Loss (MW)	VSI
1	0.1	0.1	0.8	850.4035	6.5452	**0.1295**
2	0.1	0.8	0.1	883.7378	**5.1369**	0.1394
3	0.8	0.1	0.1	**804.0934**	10.3095	0.1394
4	0.5	0.4	0.1	813.1923	7.7085	0.1348
5	0.5	0.1	0.4	818.7691	7.5061	0.1314
6	0.4	0.5	0.1	832.0813	6.4482	0.1409
7	0.1	0.5	0.4	879.9792	5.7349	0.1314
8	0.1	0.4	0.5	870.1570	6.2228	0.1291
9	0.4	0.1	0.5	818.7691	7.5061	0.1314

Bold values shows the optimal values in the corresponding minimization objects.

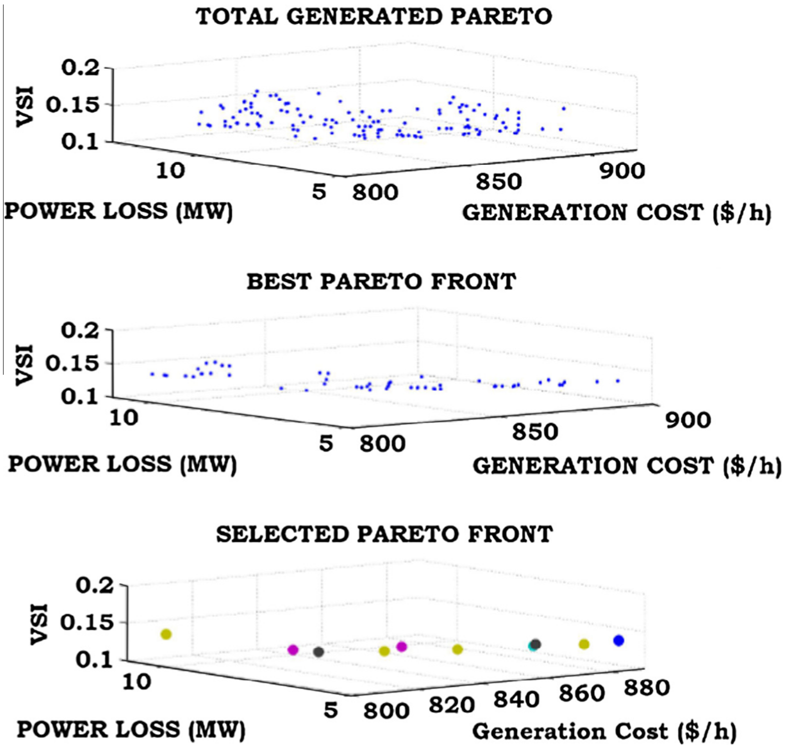

Figure 9 Multi-objective Pareto front solution for Cost-loss-VSI combination.

the objective function values with the proposed method started with best starting value for Case-A and reaches less number of iterations for final best value. On the other hand in Case-B i.e. by incorporation of ramp-rate limits to all the objectives with proposed method the function value starts with high value and time taken to reach final value required more number of iterations.

6.2.2. *Multi-objective optimization*

In this case, combination of two and three objectives is considered at a time for analysis using the proposed NSHFFA method. From the single objective analysis discussed in previous section, it is observed that the objective function value variations are more with ramp rate limit. Hence, the multi-objective analysis has been carried out by considering ramp rate limits.

To show the effectiveness of the proposed method multi-objective optimization with ramp-rate limits is solved for the following three combinations

- Case-1: Generation fuel cost and total power loss objectives.
- Case-2: Generation fuel cost and voltage stability index objectives.
- Case-3: Total power loss and voltage stability index objectives.

By using Section 5 procedure the total generated solutions, best Pareto fronts and selected Pareto fronts for all three cases are shown in Figs. 6–8. Fuzzy decision making tool is used to calculate the selected Pareto front from best Pareto front. From these figures it is observed that the proposed NSHFFA method provides the best Pareto front that confines the entire solutions region. The selected Pareto fronts for three cases of two objectives with different weights are tabulated in Table 6.

From Table 6, it is observed that the cost is less and total power loss is more for Case-I, the cost is less and VSI is more for Case-II and the total power loss is less and VSI is more for Case-III with respect to the weights $W_1 = 0.9$ and $W_2 = 0.1$ compared to other weight combinations. Similarly, the fuel cost is high and loss is low for Case-I, the fuel cost is high and VSI is low for Case-II and the total power loss is high and VSI is low for Case-III with respect to the weights $W_1 = 0.1$ and $W_2 = 0.9$ compared to other weight combinations. It is also observed that the objective function value depends upon the weights assigned to the respective objectives. The optimal function values are fuel cost is 802.2387 \$/h and loss is 3.7974 MW for Case-I, fuel cost is 803.120 \$/h and voltage stability index is 0.126 for Case-II, power loss is 4.487 MW and voltage stability index is 0.124 for Case-III and for weights assigned to objects is 0.9.

Further the analysis has been extended for three objectives optimization to show the effectiveness of the proposed NSHFFA. The three dimensional Pareto front for the three objectives optimization is shown in Fig. 9. It is observed that these Pareto front are well distributed over the entire region. There are 34 possible sets as per the weights distribution among the three objectives. Some of the important sets are given in Table 7. From Table 7 the optimal function values are fuel cost is 804.0934 \$/h, power loss is 5.1369 MW and voltage stability index is 0.1295 and for weights assigned to objects is 0.8.

7. Conclusions

A novel hybrid optimization algorithm that is HFFA has been proposed to solve OPF problem with generation fuel cost, total power loss and voltage stability index as objectives while satisfying system equality, in-equality and ramp-rate limits constraints to analyze the effect of ramp-rate limits on OPF problem. The proposed algorithm was tested in terms of convergence rate and the number of iterations taken for final convergence. The proposed method is tested on standard Booth's function, Schaffer 2 function and IEEE-30 bus test systems with supporting numerical results. The result shows the proposed method is giving final optimal value with less number of iterations and less time. And it is also observed that it starts with good initial value and reaches best final value with less time. The proposed method enhances the performance and applicability of the convergence and produces a superior solution compared to existing methods.

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