



Article Multi-Objective Optimal Power Flow Solution Using a Non-Dominated Sorting Hybrid Fruit Fly-Based Artificial Bee Colony

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Abstract: A new optimization technique is proposed for solving optimization problems having single and multiple objectives, with objective functions such as generation cost, loss, and severity value. This algorithm was developed to satisfy the constraints, such as OPF constraints, and practical constraints, such as ram rate limits. Single and multi-objective optimization problems were implemented with the proposed hybrid fruit fly-based artificial bee colony (HFABC) algorithm and the non-dominated sorting hybrid fruit fly-based artificial bee colony (NSHFABC) algorithm. HFABC is a hybrid model of the fruit fly and ABC algorithms. Selecting the user choice-based solution from the Pareto set by the proposed NSHFABC algorithm is performed by a fuzzy decision-based mechanism. The proposed HFABC method for single-objective optimization was analyzed using the Himmelblau test function, Booth's test function, and IEEE 30 and IEEE 118 bus standard test systems. The proposed NSHFABC method for multi-objective optimization was analyzed using Schaffer1, Schaffer2, and Kursawe test functions, and the IEEE 30 bus test system. The obtained results of the proposed methods were compared with the existing literature.

Keywords: fruit fly-based ABC algorithm; multi-objective optimization; fruit fly algorithm; ABC algorithm; ramp rate limits; severity value; non-dominated sorting

1. Introduction

Recently, the operation, control, and management of power systems have become more complicated and difficult. The system severity value should be minimized to improve power system security and to avoid line overloading, bus voltage limit violations, and finally, line outage conditions. The transmission of bulk power and the difference in the loading pattern from the originally planned pattern affect the complexity of the power monitoring system. Hence, to secure and stabilize the operation of a power system, optimal power flow (OPF) performs a crucial role.

Optimization of the considered objective functions, such as generation cost, transmission loss, and severity value minimization, is the first target of the OPF problem. Recently, many heuristic optimization techniques have been proposed to solve the problems in power systems, such as the cost of power generation, transmission power loss, and severity value minimization. A hybrid fruit fly algorithm was previously utilized for solving multiobjective optimization in the presence of practical constraints, including the ramp rate limit and prohibited operating zone [1]. A hybrid cuckoo search algorithm was analyzed and used to converge the problem [2]. Using the firefly algorithm, the OPF solution was analyzed for cost, loss, and emission objective functions that were not optimized optimally [3]. To improve power system security, a multi-objective multi-population ant colony algorithm was used [4]. A dynamic population-based ABC algorithm was used for solving the OPF



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). problem. The results were compared to the NSGA-II and multi-objective ABC methods [5]. The linear OPF method was used to linearize AC load flow equations to optimize generator dispatch. This LOPF method is seven times faster than the existing methods [6]. To test the TLBO algorithm in this article, multi-objective OPF problems were solved. Standard 9-bus and 26-bus systems were used to test the performance of the proposed method. Cost, power loss, and voltage deviation minimization functions were used to optimize the power system problems. The results were compared with those of a mixed-integer PSO algorithm [7]. The fruit fly algorithm for solving the engineering optimization problem proves that the convergence of the optimal problem is less than that of the ABC algorithm [8]. For this purpose, a knowledge-guided MOFOA was proposed for simultaneously minimizing the cost and the makespan. This non-dominated sorting approach has been used to optimize multi-objective problems [9]. In this improved fruit fly method for solving engineering design problems, the results were compared with existing GA, PSO, and DSLC-FOA methods [10]. The basic MGWO was modified using a reproduction operator and by adding the two-archive concept. It was then used to solve the multi-objective reactive power dispatch problem [11]. This hybrid multi-objective genetic algorithm was used to reduce the computational cost of OPF calculations [12]. The artificial bee colony with firefly (ABC-FF) algorithm was used for solving the optimal reactive dispatch problem [13] and the novel quasi-oppositional modified Jaya (QOMJaya) algorithm was used for solving the multi-objective OPF problems [14]. The sine–cosine algorithm was used for solving the OPF problems [15] and the multi-objective spotted hyena optimizer was used for solving multi-objective optimization problems [16]. The firefly algorithm was proposed for solving optimization problems [17]. The moth swarm algorithm was used for solving the OPF problem [18]. Convexified multi-objective models for optimal power flow were used to minimize the objective functions [19]. The performance of the tree seed algorithm used to solve the OPF problem was tested using two standard test systems [20]. A heuristic Fuzzy Adaptive Heterogeneous Comprehensive-Learning Particle Swarm Optimization algorithm was used to derive optimal reactive power dispatch solutions [21] and the Shuffled Frog Leaping optimization technique was used to solve the OPF problem with the incorporation of FACTS controllers [22]. Authors have described different optimization techniques, such as PSO, ABC, and NSGA-II, to solve multi-objective optimization problems in different applications [23–28]. For solving the single-objective optimization problem, the social spider optimization algorithm was used [29]. The PSO algorithm was used for solving the OPF problems with and without FACTS controllers [30].

In the above literature, several single and multi-objective optimization algorithms have been described. In the current study, the authors did not consider practical constraints, or the severity of the function under abnormal conditions, such as line outage conditions. We hybridized the considered algorithms to enhance the potential of the proposed algorithm. In this paper, we propose a novel hybrid fruit fly-based artificial bee colony (HFABC) algorithm to optimize the objective parameters. In the past, multi-objective optimization problems were solved using the weighted sum and the constraint method. In this study, a non-dominated sorting hybrid fruit fly-based artificial bee colony (NSHFABC) algorithm is proposed. The proposed algorithm was used for solving different standard test functions, in addition to the standard electrical IEEE 30 bus system. The optimal result obtained from the proposed method was compared with the existing literature results.

In this paper, Sections 2 and 3 describe the problem formulation and objective functions, respectively. Section 4 describes the proposed HFABC algorithm, Section 5 describes the multi-objective control strategy, and Section 6 presents results and analysis for single and multi-objective optimization problem solutions.

2. Problem Formulation

The problem formulation of a multi-objective OPF consists of two components, namely, the objective function and the constraints, such as equality, inequality, and the ramp rate limit [1].

Ramp Rate Limit

Here, generator ramp rate limits are considered because, in a thermal power plant, the generator power output cannot change by more than a certain amount:

$$\max\left(P_{gi}^{\min}, P_i^0 - DR_i\right) \le P_{gi} \le \min\left(P_{gi}^{\max}, P_i^0 + UR_i\right)$$

where P_i^0 is the power generation of the *i*th unit in the previous hour. DR_i and UR_i are the down and up ramp rate limits of the *i*th unit, respectively.

3. Objective Functions

In this paper, the main aim is to individually and simultaneously minimize the objectives. We consider the three objective functions to be generation fuel cost, transmission power loss, and severity value minimization. The considered objective functions are described as follows.

3.1. Generation Fuel Cost Minimization

The generation fuel cost quadratic expression is $F_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \ /h$. The total fuel cost of generation for all generator units can be mathematically expressed as:

$$F_1 = \min(F_T) = \sum_{i=1}^{N_G} F_i(P_{G_i}) \quad \$/h \tag{1}$$

where a_i , b_i , and c_i are the coefficients of cost for the *i*th unit.

3.2. Transmission Loss Minimization

This objective can be written as:

$$F_2 = \min(TPL) = \sum_{i=1}^{N_{line}} P_{Loss,i}$$

$$MWP_{Loss} = \sum_{m,n} g_{mn} \left[V_m^2 + V_n^2 - 2V_m V_n \cos(b_m - b_n) \right]$$
(2)

where $P_{Loss_{i}}$ is the real power loss in the *i*th line. g_{mn} is the conduction of the line between buses *m* and *n*; and V_m , V_n , δ_m , and δ_n are the magnitude and angle of voltage of the *m*th and *n*th buses, respectively.

3.3. Severity Value Minimization

Minimization of the bus voltages limits the violations under contingency conditions and enhances system security. Here, to increase the protection of the electrical power system, the value of the system severity function must be minimized.

The severity function can be written as:

$$F_{Severity} = \sum_{i=1}^{N_L} \left(\frac{S_i}{S_i^{\max}}\right)^{2q} + \sum_{j=1}^{N_B} \left(\frac{V_{j,ref} - V_j}{V_{j,ref}}\right)^{2r}$$
(3)

where N_L , N_B , N_{line} , N_{bus} are the lines and buses, respectively. S_i and S_i^{max} are the apparent powers of the *i*th line. $V_{j,ref}$ and V_j are the nominal and present voltage values, respectively. q and r are two coefficients.

4. Hybrid Fruit Fly-Based Artificial Bee Colony (HFABC)

By combining the ABC and fruit fly algorithms, the advantages of the ABC and fruit fly techniques can be inherited. The main drawback of the ABC algorithm is the untimely convergence in the search period. As a result, the desired accuracy of the optimal value may not be achieved. By hybridizing with the fruit fly algorithm, this problem can be overcome and the accuracy of the optimal value can be improved. Both the artificial bee colony and fruit fly algorithms are worth discovering in the search space. HFABC was developed to take advantage of the benefits of both the ABC and fruit fly algorithms. HFABC begins with the initial population and updates the solution by employing bees in the ABC, and then follows the mechanism of fruit fly optimization.

The proposed HFABC algorithm has five phases; initialization, the employed bee phase, the Osphersis foraging phase, the vision foraging phase, and stopping criteria.

Step-1: Initialization

Start with a random selection using the following equation:

$$x_{pq} = x_q^{\min} + \lambda \left(x_q^{\max} - x_q^{\min} \right), \qquad p = 1, 2, \dots, N, \quad q = 1, 2, \dots, D$$
(4)

where λ is [0, 1], N represents the food sources, and D is the dimensionality.

Step-2: Employed bee phase

Initially, the solution of the employed bee is copied to the new candidate solution $(v_p = x_p)$. The solution is updated using Equation (5):

$$v_{p,q} = \psi x_{p,q} + \varphi (x_{p,q} - x_{r,q}), \quad p,r \in \{1, 2, \dots, N\}, q \in \{1, 2, D\} \text{ and } p \neq r$$
 (5)

where \emptyset is a random number between [-1, 1], and Ψ is taken as unity.

Step-3: Osphersis foraging phase

Around the current fruit fly location, the population of food sources is generated randomly as Δ (randomly initialized swarm location), where the generated food sources are given by:

$$x_{p,q} = \delta_q \pm \mu.rand(), \ q = 1, 2, ..., n$$

These food sources are within a radius of 1. The dynamically searched radius can be altered for the optimal solution with the iteration number, which is given by:

$$\lambda = \lambda_{\max} \cdot \exp\left[\log\left(\frac{\lambda_{\min}}{\lambda_{\max}}\right) \frac{iteration}{iteration_{\max}}\right]$$
(6)

Step-4: Vision foraging phase

The fruit fly follows a greedy selection procedure in which discovery of the best food source having a low value of fitness is given by:

$$x_{best} = \arg(\min f(x_p)), \quad p = 1, 2, ..., N$$
 (7)

where x_{best} is superior to the current location. If it is the best position, then the new position location is updated; otherwise, there will be no change.

Step-5: Stop Off Criteria

Stop the process when the number of generations equals the set iteration count; else, go to Step-2 and repeat until the set iteration count is reached.

5. Multi-Objective Control Strategy

To solve the multi-objective problem, the proposed non-dominated sorting hybrid fruit fly-based artificial bee colony (NSHFABC) algorithm was implemented. The steps for the proposed NSHFABC are detailed in the flow chart depicted in Figure 1. The non-dominated sorting and fuzzy decision-making process is given in [2].



Figure 1. Flow chart of the proposed strategy.

Decision Variables

The IEEE 30 bus test system was contemplated for testing the potency of the proposed algorithms. The considered system has 41 transmission lines and 18 control variables, namely 6 active power generators, 6 generator voltage magnitudes, 2 shunt compensators, and 4 tap setting transformers.

6. Results and Analysis

The obtained results of the Himmelblau function, Booth's function, and the power system standard IEEE 30 bus and IEEE 118 bus test systems for single-objective optimization, and SCH1, SCH2, and IEEE 30 bus systems for multi-objective optimization, were used to

validate the proposed methods. For the test system, individual single objectives were used for optimization by implementing the proposed HFABC, and multi-objective optimization was simultaneously implemented using the proposed NSHFABC algorithms. The input parameters for the test examples are tabulated in Table 1.

Parameters	Value
Swarm size	50
Employed bees	25
Food sources	25
Λ	[0, 1]
Ø	[-1, 1]

Table 1. Input parameters for test examples.

6.1. Single-Objective Optimization

6.1.1. Himmelblau Test Function

Initially, the proposed HFABC algorithm was applied to the Himmelblau test function, and then applied to Booth's function, as described in Section 6.1.2, to test the effectiveness of the proposed method.

The Himmelblau function equation is expressed as:

$$f(x_1, x_2) = \left(x_1^2 + x_2 - 11\right)^2 + \left(x_1 + x_2^2 - 7\right)^2 \tag{8}$$

For the Himmelblau function, solutions are obtained using the existing genetic algorithm (GA), particle swarm optimization (PSO), artificial bee colony (ABC), and the proposed hybrid fruit fly-based artificial bee colony (HFABC) techniques. A comparison of the optimal solution for the Himmelblau function is shown in Table 2. Table 2 shows that the proposed method results in a superior solution in comparison to that of the existing methods, and the values of parameters (x_1, x_2) obtained using the proposed HFABC method are improved compared to those of the existing GA, PSO, and ABC methods. The function value is also lower. The computing time in the proposed HFABC method is 0.4326 s, whereas that in the existing PSO and ABC algorithms is 4.1726 and 2.5948 s, respectively; these values are greater than those of the proposed method. From Table 2, the function values for GA, PSO, ABC, and HFABC are 1.000×10^{-3} , 0.004287118, 8.2451×10^{-4} , and 2.0229×10^{-6} , respectively. It is evident that the proposed method function value is minimized effectively. The standard deviation is 1.7288, and 0.788 for the ABC and the proposed HFABC methods, respectively. For the Himmelblau function, the x_1 and x_2 values are 3.0 and 2.0, respectively. The proposed method variable values are exactly the same as those of the standard test function values. From the above statistical analysis, it is concluded that the proposed method is better than those of the existing literature.

Table 2. Comparison of the optimal solution for the Himmelblau function.

Parameters	Existing GA [31]	Existing PSO [31]	Existing ABC	Proposed HFABC
<i>x</i> ₁	3.003	2.9960	3.002734964	3.000095287
x ₂	1.994	2.0172	2.0042859276	2.000263891
Function value	1.000×10^{-3}	0.004287118	8.2451×10^{-4}	2.0229×10^{-6}
Standard deviation			1.7288	0.788
Time (s)	_	4.6052	3.0274	0.4326

The convergence characteristic of the Himmelblau test function is depicted in Figure 2, which shows its iteration starts at a good function value and the rate of convergence is

faster for the proposed method than that of the existing literature. This indicates that the proposed HFABC is superior to the existing method.



Figure 2. Convergence characteristic of the Himmelblau function.

6.1.2. Booth's Test Function

The second example considered is Booth's function. The Booth function equation is given by:

$$f(x,y) = (x+2y-7)^2 + (2x+y-5)^2$$
(9)

The solution for the function was obtained by the existing PSO, CSA, and ABC methods, and the proposed HFABC method. The optimal solutions obtained by the various methods for Booth's function are depicted in Table 3.

Parameters	Existing PSO [1]	Existing CSA [1]	Existing ABC	Proposed HFABC
x	1.012698	1.00224	1.000	1.000
y	2.98924	2.99197	3.000	3.000
Minimum function value	0.00029	0.00020	2.9285×10^{-7}	$1.6234 imes 10^{-12}$
Standard deviation			0.086	0.035
Time (s)	8.23299	6.9547	2.12912	0.5297

Table 3. Comparison of the optimal solution for Booth's function.

From Table 3, it is observed that the function values are 0.00029, 0.00020, 2.9285×10^{-7} , and 1.6234×10^{-12} , for PSO, CSA, ABC, and HFABC, respectively. The standard deviation is 0.086 and 0.035 for the ABC and proposed HFABC methods, respectively. The computation times are 8.23299, 6.9547, 2.12912, and 0.5297 s, respectively, for PSO, CSA, ABC, and HFABC. From these statistical analyses, the proposed method yields a better value compared to that of the existing methods.

From Figure 3, it is noticed that the proposed HFABC provides a better value and convergence occurs in fewer iterations in comparison to the existing ABC method.



Figure 3. Convergence characteristic of Booth's function.

6.1.3. Electrical IEEE 30 Bus Test System

This system was contemplated for validating the proposed HFABC technique. The system data were taken from [32–34].

In this analysis, the considered objectives were solved using the proposed method with two cases: Case-A, without consideration of the ramp rate limit; and Case-B, with consideration of the ramp rate limit.

The summary of the test results is tabulated in Table 4. It is seen that, for the generation fuel cost minimization, Case-A yields lower values compared to Case-B; this is because of the ramp rate limit. Similarly, transmission loss and severity values are also increased with the ramp rate limit. The restriction of ramp rate limits on power generation leads to the rescheduling of the generators by changing their generation values. Hence, the total generation, power loss, and severity of the system is varied.

Table 4. Comparison of the OPF solution for the IEEE 30 bus system.

Control Variable	Generation Fuel Cost (USD/h) Case-1		Transmission Loss (MW) Case-2		Severity Value Case-3	
	Case-A	Case-B	Case-A	Case-B	Case-A	Case-B
PG1 (MW)	174.297	179.337	51.524	51.731	126.569	121.997
PG2 (MW)	48.123	44.109	80.000	80.000	39.026	43.171
PG5 (MW)	22.026	19.893	50.000	50.000	48.258	41.608
PG8 (MW)	20.833	22.584	35.000	35.000	35.000	30.000
PG11 (MW)	12.741	13.000	30.000	30.000	18.774	24.626
PG13(MW)	14.027	14.000	40.000	40.000	22.684	30.253
VG1 (p.u.)	1.099	1.100	1.100	1.100	1.053	0.913
VG2 (p.u.)	1.082	0.968	1.096	1.064	0.979	0.900
VG5 (p.u.)	1.055	1.042	1.093	1.100	0.937	1.033
VG8 (p.u.)	1.054	1.091	1.100	1.099	0.998	0.999
VG11 (p.u.)	1.069	1.100	0.943	1.0533	0.989	0.977

Control Variable	Generation Fuel Cost (USD/h) Case-1		Transmission Loss (MW) Case-2		Severity Value Case-3	
	Case-A	Case-B	Case-A	Case-B	Case-A	Case-B
VG13 (p.u.)	1.091	1.100	1.100	1.0979	1.029	0.953
TAP,6–9 (p.u.)	0.948	1.089	1.001	0.900	1.042	0.936
TAP,6–10 (p.u.)	1.009	0.984	1.079	1.100	1.051	0.927
TAP,4–12 (p.u.)	0.987	1.040	1.100	0.900	0.955	0.900
TAP,28–27 (p.u.)	0.996	1.100	1.002	0.9522	1.036	0.900
QC10 (MVAr)	22.848	5.000	30.000	29.998	21.378	6.179
QC24 (MVAr)	10.427	14.632	10.218	5.0160	9.065	5.763
COST (USD/h)	800.212	802.922	967.7189	968.2135	871.9846	865.4640
Standard deviation	4.238	4.234				
P LOSS (MW)	8.6462	9.5228	3.124	3.4527	6.9107	8.2548
Severity value					1.304	1.534

Table 4. Cont.

The proposed method results are corroborated with the current literature methods and presented in Table 5. The proposed HFABC technique is superior compared to the existing methods.

Table 5. Variations in OPF results for generation fuel cost, transmission power loss, and severityobjectives for Case-A.

Existing Methods	Generation Fuel Cost (\$/h)	Transmission Power Loss (MW)
MSFLA [2]	802.287	_
SFLA [2]	802.5092	
PSO [2]	802.190	
MDE [2]	802.376	
IEP [2]	802.465	
IPSO [2]	_	5.0732
RGA [2]	_	4.57401
CLPSO [2]	_	4.6282
DE [2]	_	5.011
CMAES [2]	_	4.945
HAS [2]	_	4.9059
HCSA [2]	802.0347	3.208022
EP [35]	802.62	
TS [35]	802.29	
SGA [35]	803.699	
EGA [35]	802.06	
ACO [35]	802.578	
FGA [35]	802	
IPSO [35]	801.978	
Proposed HFABC	800.212	3.124

6.1.4. Electrical IEEE 118 Bus Test System

To validate the proposed method, the IEEE 118 bus system was taken into consideration. This system has 77 control variables and comprises 54 generators, 9 tap changing transformers, 186 transmission lines, and 14 VAR compensators. A comparison of the generation cost and total power loss obtained by the proposed method and different existing optimization methods is tabulated in Table 6. The proposed method is superior in comparison to existing methods. As per the simulation results, the computational time of the proposed method is 50 s, and the number of iterations to converge the control parameters is 30. Generator voltage profiles are better compared to those of the existing literature.

Existing Methods	Generation Fuel Cost (USD/h)	Transmission Power Loss (MW)
BSA [36]	135,333.4743	—
MPSO [18]	132,039.2120	—
PSO [37]	_	137.2831
HPSO [37]	_	133.1005
RGA [38]	_	71.89
BBO [38]	_	51.43
Proposed HFABC	131,400.6342	50.153

Table 6. Validation of the proposed method with the literature for the IEEE 118 bus system.

6.2. Multi-Objective Optimization

The proposed non-dominated sorting hybrid fruit fly artificial bee colony (NSHFABC) method was utilized for the multi-objective optimization problem solutions. To validate the implementation of the proposed NSHFABC method, standard test functions, such as the Schaffer1, Schaffer2, and Kursawe functions, and the IEEE 30 bus system, were considered. In this problem, weights were taken equally for each objective function. In this research, for the multi-objective function minimization, and weights of all the considered functions were taken equally, at 50%, for the adapted setting for the proposed NSHFABC.

6.2.1. Schaffer1 (SCH1) function

The first multi-objective test function considered was the Schaffer function (SCH1). This is given by:

$$Minimize = \begin{cases} f_1(x) = x^2 \\ f_2(x) = (x-2)^2 \end{cases}$$
(10)

The multi-objective total generated Pareto front, best Pareto front, and selected Pareto fronts are shown in Figure 4 for the SCH1 function.



Figure 4. Multi-objective Pareto front solutions for the SCH1 function.

From Figure 4, the best solution for the given objective functions by implementing the fuzzy decision tool for the first function is 1.005 and for the second function is 0.995.

Similar to the SCH1 analysis, the proposed method was analyzed for the Schaffer2 function (SCH2). The SCH2 function is given by:

$$Minimize = \begin{cases} f_1(x) = \begin{cases} -x, & \text{if } x \le 1\\ x - 2, & \text{if } 1 < x < 2\\ 4 - x, & \text{if } 3 < x \le 4\\ x - 4, & \text{if } x > 4 \end{cases}$$
(11)

The proposed method was analyzed with the SCH2 function, considering equal weights for the objectives. The total generated Pareto front, best Pareto front, and selected Pareto fronts are shown in Figure 5. From this figure, the best solution for the SCH2 function is 0, 1.



Figure 5. Multi-objective Pareto front solutions for the SCH2 function.

6.2.3. Kursawe Function

The third example considered was the Kursawe function. The Kursawe function is given by:

$$Minimize = \begin{cases} f_1(x) = \sum_{i=1}^{2} \left[-10 \exp\left(-0.2\sqrt{x_i^2 + x_{i+1}^2}\right) \right] & -5 \le x \le 5\\ f_2(x) = \sum_{i=1}^{3} \left[|x_i|^{0.8} + 5 \sin\left(x_i^3\right) \right] & 1 \le i \le 3 \end{cases}$$
(12)

The proposed method was applied to the Kursawe function, considering equal weights for the objectives. The total Pareto front, best Pareto front, and marked selected Pareto fronts are shown in Figure 6. From this figure, the best solution for the Kursawe function is -14.644, -11.379.



Figure 6. Pareto front solutions for the Kursawe function.

6.2.4. IEEE 30 Bus Test Systems

To extend the effectiveness of the proposed NSHFABC method, the IEEE 30 bus test system was considered, with and without ramp rate limits, for different objective function combinations, as follows:

Case-4: Cost-Loss combination

Case-5: Cost-Severity combination

Case-6: Loss-Severity combination

Case-7: Cost-Loss-Severity combination

Optimal decision variables using multi-objective optimization for the IEEE 30 bus system are given in Table 7. It is shown that the combination of objective function values is increased by considering the ramp rate limit, compared to without the ramp rate limit. Validations of the proposed NSHFABC OPF results are given in Table 8. These data show that the cost and losses are lower in the proposed method compared with those of the existing methods.

Constant Veriable	Cas	se 4	Cas	se 5	Cas	se 6	Cas	se 7
Control variable	Case A	Case B						
PG1(MW)	133.9825	144.1367	138.3332	140.3535	58.22553	82.56956	138.1317	134.6141
PG2 (MW)	61.64107	49.41045	57.50178	63	80	63	49.28703	63
PG5 (MW)	26.58247	33.49581	25.38848	24.45096	50	49	25.16808	21.65767
PG8 (MW)	35	30	35	30	35	30	35	29.24235
PG11 (MW)	14.82879	19.14705	15.28843	15.74895	30	28	22.61887	28
PG13 (MW)	17.97686	14	18.96543	18.31494	33.29999	35	20.31096	14
VG 1 (p.u.)	1.1	1.084887	1.059755	1.0449	1.1	1.041552	1.076465	1.076605
VG 2 (p.u.)	1.1	1.037541	1.049932	0.959809	1.094372	1.031484	0.985134	1.052951
VG 5 (p.u.)	1.06103	1.038822	1.017991	1.045268	1.076186	1.030485	1.01856	1.031196
VG 8 (p.u.)	1.085257	1.029494	1.022296	1.014201	1.082601	1.021	1.015163	1.020506
VG 11 (p.u.)	0.916737	1.080233	1.095377	1.011141	1.061172	1.1	0.991042	1.003952
VG 13 (p.u.)	1.1	1.1	1.044095	0.985591	1.076334	1.1	1.039085	1.081282
TAP,6–9 (p.u.)	1.019361	1.081856	0.934663	1.059802	1.042781	0.973826	0.997074	0.956768
TAP,6–10 (p.u.)	0.956273	0.9	0.983163	1.07789	1.052493	0.92203	1.046692	0.963351
TAP,4–12 (p.u.)	1.1	0.942512	0.940031	1.1	1.006434	0.926004	1.08331	0.905993
TAP,28–27 (p.u.)	0.954972	0.932137	0.952542	1.05998	0.997475	0.986524	0.986524	0.946003
QC10 (MVAr)	13.31924	29.13522	5	12.12297	30	5	11.49146	23.46145
QC24 (MVAr)	7.605346	11.93253	9.521084	15.95451	11.34165	20.20976	5.732153	12.01105
COST (USD/h)	816.3544	817.5049	814.1558	817.887	_	_	817.1957	820.532
P LOSS (MW)	6.611724	6.789968	—	_	3.125514	4.169562	7.116676	7.114076
Severity value	_	_	1.18808	1.322637	0.752894	1.021353	1.04962	1.210963

Table 7. Multi-objective OPF results for all the considered cases.

Sno	Methods	Cost (USD/h)	Loss (MW)
1	NSHCSA [2]	819.5982	5.480605
2	SPEA using EGA-DQLF [39]	822.9	5.613
3	PSO–Fuzzy [39]	847.01	5.666
4	MO-IPSO [35]	850.916	7.893
5	Proposed NSHFABC	816.3544	6.611724

Table 8. Comparison of the existing and proposed methods for Case-4.

The total Pareto generated front, best Pareto front, and preferred Pareto front are based on the user requirements obtained from the fuzzy decision approach for different combinations of the objective functions without consideration of ramp rate limits (Case-A) and with consideration of ramp rate limits (Case-B), as shown in Figures 7–12. To show the effects of ramp rate limits on the total generated solutions, the best Pareto and preferred Pareto fronts for equal weights of the objective functions are shown in separate figures. From these figures, it can be noted that the function values are increased by considering ramp rate limits, compared to without consideration of ramp rate limits.



Figure 7. Best Pareto optimal solution for Case-4 combined with Case-A.



Figure 8. Best Pareto optimal solution for Case-4 combined with Case-B.



Figure 9. Best Pareto optimal solution for Case-5 combined with Case-A.



Figure 10. Best Pareto optimal solution for Case-5 combined with Case-B.



Figure 11. Best Pareto optimal solution for Case-6 combined with Case-A.



Figure 12. Best Pareto optimal solution for Case-6 combined with Case-B.

7. Conclusions

In this study, a novel non-dominated sorting hybrid fruit fly-based artificial bee colony (NSHFABC) algorithm was designed for solving multi-objective optimization problems considering equality, inequality, ramp rate limits, and power system security constraints. To validate the proposed methods, standard test functions, such as the Himmelblau test function, Booth's test function, the Schaffer1 (SCH1) function, the Schaffer2 (SCH2) function, the Kursawe function, and the standard IEEE 30 bus system, were tested. The Himmelblau function value using the proposed method was 2.0229×10^{-6} , and the time taken to reach the optimal value was 0.4326 s; this compares to the time of the existing method of 4.6052 s. The Booth function value was 1.6234×10^{-12} and the time to reach the optimal value was 0.5297 s. The IEEE 30 bus system generation cost was 800.212 USD/h and 802.922 USD/h without and with ramp limits, respectively. Similarly, the severity values were 1.304 and 1.534 without and with ramp rate limit constraints, respectively. The multi-objective optimal power flow problem was solved as a multi-objective and multi-constrained optimization problem, where the cost, loss, and severity value were minimized. The obtained results show the Pareto optimal front obtained by NSHFABC was better than that of the existing literature. It was also observed that the proposed method can handle ramp rate limit constraints. The result shows that the proposed method is superior to the those presented in the existing literature.

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Nomenclature

OPF	Optimal power flow
ABC	Artificial bee colony
HFABC	Hybrid fruit fly-based artificial bee colony
NSHFAB	Non-dominated sorting hybrid fruit fly-based artificial bee colony
TLBO	Teaching learning-based optimization
DG	Distributed generation
ABC-FF	Artificial bee colony with firefly
QOMJaya	Quasi-oppositional modified Jaya
TSA	Tree seed algorithm
PSO	Particle swarm optimization
FACTS	Flexible alternating current transmission system
CSA	Cuckoo search algorithm
DSLC-FOA	Diminishing step and logistic chaos- fruit fly optimization algorithm

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