

Solving Optimal Power Flow Problem Using Improved Differential Evolution Algorithm

Layth AL-Bahrani¹, Murtadha AL-Kaabi², and Jaleel AL Hasheme³

¹Faculty of Engineering, Al-Mustansiriyah University, Baghdad, Iraq

²Ministry of Education/ Rusafa 3/ School Building Department, Baghdad, Iraq

³Faculty of Energy, University POLITEHNICA of Bucharest, Bucharest, Romania

Email: laith1973a@uomustansiriyah.edu.iq; {Mmsk.1986s; galeel.eng8080}@gmail.com

Abstract—The purpose of this article is to present a new improvement of the differential evolution algorithm for solving the Optimal Power Flow (OPF) problem with multiple and competing objective functions. The objective functions are fuel cost minimization of generating units, minimization of emission, reduction of real power losses in the transmission lines, voltage profile improvement, and voltage stability enhancement. These improvements include the random selection mechanism for a crossover, the trial operation modification, and finely introducing the mutation process calculations into the selection stage. To demonstrate the effectiveness of the proposed technique, the Improved Differential Evolution (IDE) has been performed on the IEEE 30-bus standard system. The optimization results reveal that the proposed approach has a high convergence speed with good variety. Lastly, the numerical results of the proposed approach are compared with other recent optimization methods. These comparisons demonstrate the effectiveness of the IDE technique for solving different OPF problems.

Index Terms—Improved differential evolution ide algorithm, Optimal Power Flow (OPF), fuel cost, emission, active power losses, voltage deviation, voltage stability index

I. INTRODUCTION

One of the most important problems in the electrical power systems is the economic operating conditions. It is based on select an optimum control variables and system quantities.[1]. J. Carpentier has been initially proposed the optimal power flow in 1962 [2]. Total fuel cost, emission, active power losses, voltage deviation, and voltage stability enhancement are the mainly objectives functions that used commonly [3]. The solutions of Optimal Power Flow (OPF) problem minimize a certain objective function by adjustment the parameters of power system elements such as generator active power output excepts the slack active power, generator bus voltage magnitude, transformer tap setting, reactive power injection of the shunt capacitor output, etc. with satisfying security constraints.

Several classical optimization techniques have been proposed to solve the OPF problem such as linear programming, gradient based method, newton methods,

dynamic programming, quadratic programming, and interior-point methods [4]. Also, several metaheuristics have been developed to overcome the weaknesses of these classical optimization techniques. Among these techniques are the Salp Swarm Algorithm (SSA) [5], genetic algorithm (GA) [6], enhanced genetic algorithm (EGA) [7], whale optimization algorithm (WOA) [8], Particle Swarm Optimization (PSO) [9], Moth Swarm Algorithm (MSA) [10], moth swarm algorithm with gravitational search algorithm (MSA-GSA) [11], Evolutionary Programming (EP) [12], biogeography-based optimization (BBO) [13], hybrid particle swarm optimization approach with small population (HPSO-SP) size [14], Chaotic Invasive Weed Optimization (CIWO) [15], novel Moth Swarm Algorithm (MSA) [10], Modified Bacteria Foraging Algorithm (MBFA) [16], Backtracking Search Algorithm (BSA) [17], modified Jaya algorithm (JAYA) [18], social spider optimization (SSO) [19], Cosine Optimization Algorithm (COA) [20], Hybrid Firefly Particle Swarm Optimization (HFPSO) algorithm [21], and enhanced Jaya optimization algorithm (EJOA) [22].

Despite achieving many satisfactory results, these methods still have some shortcomings to overcome the optimal solution of OPF problems. For example, through comparison the performance of Differential Evolution (DE) algorithm with the other recent methods, DE algorithm has convergence speed higher than GA [23]. The performance of DE is better than PSO according to the lowest fitness value, robust and the ability of introducing the same results with many trails, unlike PSO algorithm that depends on randomized initialization of the individuals [24]. Based on the results in the above literature, it is necessary to encourage more research to find the best results with new optimization methods.

Due to the diversity of the objectives, there is no specific algorithm has the best solutions to solve all OPF problems. Therefore, the developments of optimization techniques are continuous to find the best solutions of OPF problems.

Differential Evolution (DE) algorithm is one of the best algorithms using in optimal power flow solution to achieve an optimal solution by re-setting the control variables. It introduced by Storn and Price in 1997 [25]. DE algorithm uses few numbers of control parameters,

Manuscript received August 30, 2021; revised October 23, 2021; accepted November 6, 2021.

Corresponding author: Murtadha AL-KAABI (email: Mmsk.1986s@gmail.com).

and the convergence speed is significantly better than most heuristic techniques. In [26], the authors introduced DE for optimal settings of different objective functions, such as fuel cost, active power losses, and voltage deviation. Ref [27], the authors used an improved differential evolution to solve OPF in IEEE 57 bus power system. In [28], the Modified Differential Evolution (MDE) has been applied to solve optimal reactive power dispatch. In [29], the authors implemented DE algorithm for contingency analysis-based on optimal location of FACTS (flexible alternating current transmission systems) controllers in deregulated electricity market. In [30], the DE utilized for combined heat and power economic. Due to its advantages, DE got the desired results in benchmark problems compared with many heuristic techniques [31].

In this article, Improved Differential Evolution (IDE) has been proposed to solve the optimal power flow problems. The contributions of this algorithm include three improvements:

- The parameters of Crossover Value (CR) and the scale factor F are variables and re-randomized randomly for each iteration between [0, 1]. This variety gives more diversity and efficiency.
- To increase the diversity and search for an optimal global solution with less iteration, the equation of trail has been modified, and the solutions of this modification will be added in the selection calculation for select the best solution. This addition is called trail new.
- To accelerate convergence, the mutation calculation will be taken into consideration the target and trail calculation to select the best control variable in the selection stage, this new mechanism in DE algorithm gives more ability to increase good genes to benefit from it in the next generation.

The proposed approach IDE enhances the convergence characteristics of DE. IDE aims to find the best solutions of OPF with various objectives functions such as the fuel cost minimization, active power losses minimization, reduction of generation emission, voltage profile improvement, and voltage stability enhancement. The system of IEEE 30-bus has been used to test and scrutinize the performance of the IDE.

The arrangement of the remaining of this article is as follows: mathematical representation of optimal power flow problems describes in Section II including state variables, control variables, objective function, and constraints. Section III briefly presents the main features of the DE algorithm. In Section IV, IDE algorithm has been presented to solve the OPF problem. Section V provides the results, discussions, and comparisons with different newly meta-heuristic algorithms. Finally, the conclusions according to on the performance of the IDE algorithm has been presented.

II. MATHEMATICAL REPRESENTATION OF OPTIMAL POWER FLOW PROBLEMS

The main aim of OPF is to minimize the objective functions by achieving an optimal control variable with

fulfilling the equality and inequality constraints. The OPF problem can be written in the following form [32]:

$$\text{Optimize } F_i(u, v), i = 1, 2, \dots, N \quad (1)$$

$$\text{subjected to } G_j(u, v) = 0, j = 1, 2, \dots, M \quad (2)$$

$$H_k(u, v) \leq 0, k = 1, 2, \dots, K \quad (3)$$

The state variables (u) represent as the following set:

$$u^T = [P_{G_1}, |V_{L_1}|, \dots, |V_{L_{NL}}|, Q_{G_1}, \dots, Q_{G_{NG}}] \quad (4)$$

The control variables (v) can be represented as follows:

$$v^T = [P_{G_2}, \dots, P_{G_{NG}}, |V_{G_1}|, \dots, |V_{G_{NG}}|, T_1, \dots, T_{N_T}, Q_{C_1}, \dots, Q_{C_{NC}}] \quad (5)$$

A. Objective Function of Optimal Power Flow

To achieve the optimal power system and prove the effectiveness of the proposed algorithm, many optimizations objective functions have been performed, including fuel cost minimization, emission minimization, active power losses minimization, voltage profile improvement, and voltage stability index minimization.

1) Total fuel cost objective

The total fuel costs are traditionally modelled as polynomial quadratic function and can be mathematically expressed as follows [33]:

$$F_{\text{cost}} = \sum_{i=1}^{N_G} a_i P_{G_i}^2 + b_i P_{G_i} + c_i \quad (6)$$

2) Total fuel emission objective

Nowadays, many countries strive to minimize the problem of air pollution caused by fossil-fueled thermal generation operation and environmental protection. The fossil-fueled thermal units emit harmful and greenhouse gases such as Sulphur Oxides SO_x , Nitrogen Oxides NO_x , and Carbon Dioxide CO_2 into the environment. The total emissions can be expressed as follows [34]:

$$F_{\text{emission}} = \sum_{i=1}^{N_G} 10^{-2} (\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2) + \zeta_i \exp(\lambda_i P_{G_i}) \quad (7)$$

3) Total active power losses objective

The minimization of active power losses F_{loss} in the transmission line can be formulated as below:

$$F_{\text{loss}} = \sum_{k=1}^{N_{TL}} g_{(i,j)} (V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{i,j}) \quad (8)$$

4) Improvement of voltage profile

This objective function improves the voltage profile via limiting the voltage magnitude deviation at the load buses from 1.0p.u and can be formulated as follow:

$$F_{V_d} = \Delta V = \sum_{i=1}^{N_B} |V_i - V_{\text{ref}}| \quad (9)$$

5) Enhancement of voltage stability Index (L-index)

The aim of this objective function is to enhance the voltage stability of the system. This indicator evaluates the voltage stability of the whole system. Its ranges between 0 (the no-load case) and 1 (voltage collapse). The voltage stability index (VSI) can be expressed as [35]:

$$F_{L_{\text{index}}} = \min(\text{VSI}) = \min(\max(L_j)) \quad (10)$$

$$L_j = \left| 1 - \sum_{i=1}^{N_G} \left[[M_2] \times \frac{V_i}{V_j} \angle(\theta_{i,j} + (\delta_i - \delta_j)) \right] \right| \quad (11)$$

for $j = 1, 2, \dots, N_L$

$$[M_2] = -[Y_{LL}]^{-1} [Y_{LG}] \quad (12)$$

$$[I_B] = [Y_B][V_B] \quad (13)$$

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \quad (14)$$

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} M_1 & M_2 \\ M_3 & M_4 \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (15)$$

B. The Constraints of Optimal Power Flow

The constraints of optimal power flow include two types of constraints which are: equality and inequality constraints. The physics of the power systems are considered as the equality constraint such as the balance between the input and output power. Equality constraints are can be formulated as [36]:

$$\sum_{i=1}^{N_B} P_i = P_{g_i} - P_{d_i} = V_i \sum_{j=1}^{N_B} V_j [G_{i,j} \cos \theta_{i,j} + B_{i,j} \sin \theta_{i,j}] \quad (16)$$

$$\sum_{i=1}^{N_L} Q_i = Q_{g_i} - Q_{d_i} = V_i \sum_{j=1}^{N_L} V_j [G_{i,j} \sin \theta_{i,j} - B_{i,j} \cos \theta_{i,j}] \quad (17)$$

The inequality constraints reflect the operating limits in power systems such as the limits on physical devices that created to ensure the system security. The inequality constraints on power system include four categories: The generation constraints, reactive power constraints, and transformer and security constraints. The mathematical expression of these constraints can be expressed as follows:

1) The limit of generators:

$$V_{G_i}^{\min} \leq V_{G_i} \leq V_{G_i}^{\max} \quad i = 2, 3, \dots, N_G \quad (18)$$

$$P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max} \quad i = 2, 3, \dots, N_G \quad (19)$$

$$Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max} \quad i = 2, 3, \dots, N_G \quad (20)$$

2) The limit of transformer:

$$T_j^{\min} \leq T_j \leq T_j^{\max} \quad j = 1, 2, \dots, N_T \quad (21)$$

3) The limit of shunt compensator:

$$Q_{C_k}^{\min} \leq Q_{C_k} \leq Q_{C_k}^{\max} \quad k = 1, 2, \dots, N_C \quad (22)$$

4) The limit of security:

$$V_{L_q}^{\min} \leq V_{L_q} \leq V_{L_q}^{\max} \quad q = 1, 2, \dots, N_L \quad (23)$$

$$S_{L_m} \leq S_{L_m}^{\max} \quad m = 1, 2, \dots, N_{TL} \quad (24)$$

III. DIFFERENTIAL EVOLUTION ALGORITHM (DE)

Differential Evolution algorithm is a heuristic optimization method based on the natural evolution principles. It was initially introduced by Storn and Price in 1997 [25]. The technique of DE includes four operations. These operations are initialization, mutation, crossover, and selection. DE uses several optimization parameters to reach an optimal solution such as number of populations N_p , D-dimensional variable vectors, mutation constant F , crossover constant CR, number of iterations GEN, low boundary constraints and high boundary constraints. Fig. 1 illustrates the stages of DE. These stages can be described in detail as follow.

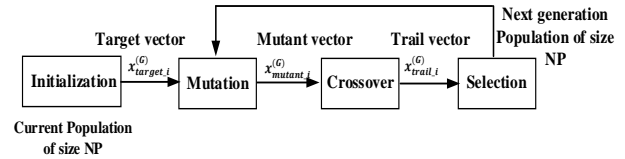


Fig. 1. Stages of differential evolution.

A. Initialization

At this stage, DE generates a population randomly within the decision space. The initial individuals can be initialized as follow:

$$x_{i,j}(\text{init}) = x_j^{\text{lower}} + \text{rand}(x_j^{\text{upper}} - x_j^{\text{lower}}) \quad (25)$$

B. Mutation

Several strategies of DE have been discussed. Reference [26] proved the best strategy of mutation in DE to solve the OPF problems is technique of mutation equation (26) for the j th component which generate a mutant vector $(v_{i,j}) = (v_{i,1}, v_{i,2}, v_{i,n})$ at every generation. This strategy can be expressed as:

$$v_{i,j}(t+1) = y_{\text{best},j}(t) + F(y_{r1,i}(t) - y_{r2,j}(t)) \quad (26)$$

In this article, (26) replace to (27) if the mutant vector component violates the boundary constraint, a mutant vector component is reset as:

$$y_j(t) = \begin{cases} y_j(t), & \text{if } (x_j^{\text{lower}} \leq y_j(t) \leq x_j^{\text{upper}}) \\ x_j(t), & \text{else} \end{cases} \quad (27)$$

C. Crossover

Crossover is the process which aims to increase the diversity of the population and reinforcing prior successes by combining both for target vector $x_{i,j}$ and mutant vector $y_{i,j}$. This process produces a trail vector $z_{i,j}$ and can be expressed as follow:

$$z_{i,j}(t) = \begin{cases} y_{i,j}(t), & \text{if } (\text{rand} \leq C_R) \text{ or } (j = j_{\text{rand}}) \\ x_{i,j}(t), & \text{otherwise} \end{cases} \quad (28)$$

D. Selection

The selection process based on a greedy strategy and performed after the crossover operation to make a comparison between the fitness of the trial vector and the fitness of the target vector then choose the better case between them to keep the continue in the next generation. This process can be expressed as follow:

$$x_i(t+1) = \begin{cases} z_i(t), & \text{if } f(z_i(t)) \leq f(x_i(t)) \\ x_i(t), & \text{otherwise} \end{cases} \quad (29)$$

From (29), if the fitness value of the trail vector is less or equal than the fitness value of the target vector, the target vector of next-generation replaces to trail vector, else the vector of next-generation replaces target vector.

IV. IMPROVED DIFFERENTIAL EVOLUTION

In this section, the differential evolution (DE) algorithm has been developed to improved differential evolution (IDE) algorithm. The improvements including three parts, the first one is the reorganization mechanism for crossover rate C_R and scale factor F , the second improvement is adding a new modification into the trail stage and the third improvement is introducing the mutation calculations into consideration. These improvements can be described as follow.

A. Random Selection Mechanism for (C_R)

The diversity of the population and the efficiency are the most important tasks carried out by crossover in the differential evolution algorithm that previously mentioned in Section III C. The crossover rate C_R is fixed and often greater than 0.5. This factor was not taken into consideration in the fitness values for everyone. Therefore, to achieve the maximum diversity and efficiency, the Crossover Rate is distributed randomly for each generation. This mechanism is proposed as follows:

$$C_R = \text{rand}(N_p, D) \quad (30)$$

where N_p and D are the numbers of population and D -dimensional variable vectors respectively.

B. Trial Operation Modification

As previously stated in the Section III C, the crossover process aims to increase the diversity of the population. The increasing population size N_p in the selection stage will be led to increase the probability of the exploration for the search space and improving the relationship between the C_R values and the fitness values. This process produces a new gene in the selection stage called a trail new vector ($z_{i,j}^*(t)$) and expressed as follows:

$$z_{i,j}^*(t) = \begin{cases} y_{i,j}(t), & \text{if } (\text{rand} \geq C_R) \text{ or } (j \neq j_{\text{rand}}) \\ x_{i,j}(t), & \text{otherwise} \end{cases} \quad (31)$$

Equation (31) increase the probability to select the best vector that will be added to the selection stage.

C. Introduce Mutational Process Calculations Into the Selection Stage

The third improvement is a comparison among target, trail, mutation, and new trail vectors in the selection stage

to choose the best control variable. The convergence speed of Improved Differential Evolution will be increased, therefore achieving good genes in the next generation. This improvement can be express as follows:

$$x_i(t+1) = \begin{cases} z_i(t) \rightarrow f(z_i(t)) \leq (f(z_i^*(t)) \& f(x_i(t)) \& f(m_i(t))) \\ z_i^*(t) \rightarrow f(z_i^*(t)) \leq (f(x_i(t)) \& f(m_i(t))) \\ z_i(t) \rightarrow f(x_i(t)) \leq f(m_i(t)) \\ m_i(t) \rightarrow \text{otherwise} \end{cases} \quad (32)$$

From (32), it can be noted that the lowest fitness values will be chosen from the current population after a competition among the target, mutant, trail, and the new trail vectors. Implementation of IDE is shown in Fig. 2.

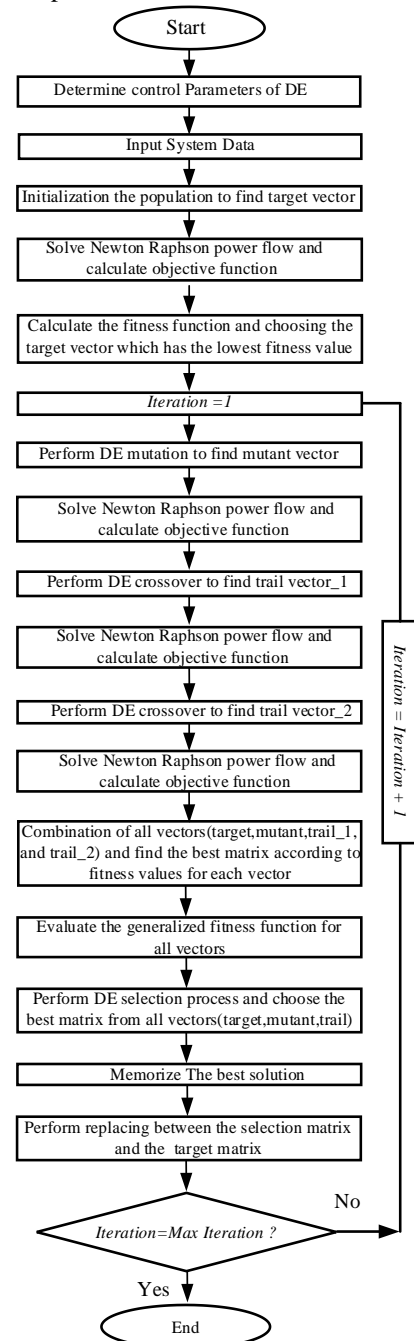


Fig. 2. Flowchart of Improved differential evolution algorithm.

The main steps of improved differential evolution algorithm as follows:

Step 1: Determine control parameters of DE.

Step 2: Generate the initial population to find target vector as defined in (25).

Step 3: Calculate the fitness function and choosing the target vector which has the lowest fitness value.

Step 4: Perform DE mutation to find mutant vector described in (26) & (27).

Step 5: Perform DE crossover to find trail vector_1 as given in (28).

Step 6: Perform DE crossover to find trail vector_2 as given in (31).

Step 7: Evaluate the generalized fitness function for all vectors.

Step 8: Perform DE selection process to choose the best solution described in (32).

Step 9: Run until "the number of iterations= number of maximum iterations".

V. NUMERICAL RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed approach improved differential evolution IDE algorithm, IEEE 30-bus test system have been considered. In this article, five objective functions have been used. These objectives are the fuel cost of the generation units, the fuel emission of the generation units, active power losses in the transmission lines, voltage deviation at the load buses, and the voltage stability index. The parameters used in the proposed approach are $N_p=100$, $F_{scaling}=0.8$, $C_R=rand$ [0, 1], and the number of iterations =100. The IEEE 30-bus test system has 6 generators, 41 transmission lines, 4 transformers, and 9 shunt capacitive sources [37]. The control variables parameters include the active power of the generation unit except the slack generator, voltage magnitude of the generators, transformer tap settings, and the VAR power of the shunt capacitances. The total active and reactive power demand are 2.834 p.u. and 1.262 p.u., respectively at apparent power of 100 MVA

base power. The limits of bus voltages are 0.95-1.1 p.u. The maximum and minimum tap setting of transformers are 0.9 p.u. and 1.1 p.u., respectively, while the VAR injections are in the range [0–5] MVar. Table I illustrates the generation cost and emission coefficients [17].

TABLE I: COST AND EMISSION COEFFICIENTS OF GENERATORS FOR IEEE 30-BUS POWER SYSTEM

Coefficient generating unit						
	G1	G2	G5	G8	G11	G13
Fuel cost coefficient						
a	0	0	00	0	0	0
b	2	1.75	1	3.25	3	3
c	0.00375	0.0175	0.0625	0.00834	0.025	0.025
Emission coefficient						
α	4.091	2.543	4.258	5.326	4.258	6.131
β	-5.554	-6.047	-5.094	-3.55	-5.094	-5.555
γ	6.49	5.638	4.586	3.38	4.586	5.151
ζ	2.00E-04	5.00E-04	1.00E-06	2.00E-03	1.00E-06	1.00E-05
λ	2.857	3.33	8	2	8	6.67

Five cases of different objective functions have been considered to demonstrate the effectiveness of the proposed approach IDE over the original DE. These cases are as follows.

Case 1: In this case, the minimization of quadratic fuel cost objective function has been considered to evaluate the performance of the proposed approach. It can be observed that the value of fuel cost is decreased from the initial case of 901.6391\$/h to optimal case of 799.2642 \$/h using IDE algorithm with a reduction of 11.35% as shown in Table II. Fig. 3 shows the convergence characteristics obtained by IDE and DE for the minimum fuel cost function. This figure shows the ability of the proposed algorithm to reach the minimum fuel costs with a fewer iteration. Table II compares the results of the total fuel cost according to the proposed approach with the other evolutionary algorithms to prove the performance and efficiency of the proposed algorithm.

TABLE II: COMPARISON OF THE VALUE OF FUEL COST, EMISSION, LOSSES, VOLTAGE DEVIATION, AND VOLTAGE STABILITY INDEX FOR DIFFERENT TECHNIQUES

Case 1		Case 2		Case 3		Case 4		Case 5	
Algorithm	Fuel Cost (\$/h)	Algorithm	Emission (ton/h)	Algorithm	Losses (MW)	Algorithm	Voltage Deviation (p.u.)	Algorithm	Voltage Stability Index
Initial	901.6391	Initial	0.3661	Initial	5.830	Initial	1.1747	Initial	0.1727
AMTPG-Jaya [38]	800.1946	MSLFA [39]	0.2056	MSA-GSA [11]	3.09	HFPSO [21]	0.1467	HFPSO [21]	0.1170
MABC [40]	799.3862	BSA [17]	0.2425	AMTPG-Jaya [38]	3.0802	EJADE-SP [41]	0.3752	AMTPG-Jaya [38]	0.1243
MSCA[20]	799.31	SLFA [39]	0.2063	MSCA[20]	2.9334	MSCA[20]	0.1030	JAYA [42]	0.1243
SCA [20]	800.1018	MABC [40]	0.2048	SCA [20]	2.9425	SCA [20]	0.1082	TLBO [38]	0.12444
DSA [43]	800.3887	GA [39]	0.21170	DSA [43]	3.09450	DE [26]	0.1017	ARCBBO [44]	0.1369
JAYA [42]	800.479	ABC [45]	0.204826	MSA [10]	3.1005	BSA [17]	0.1147	SSO [19]	0.1267
MSA [10]	800.5099	MFO [46]	0.205641	DE [26]	2.9748	DE	0.1245	DE	0.1090
SP-DE [47]	800.4131	DE	0.204888	SP-DE [47]	3.0844	IDE	0.0945	IDE	0.1078
MGOA[48]	800.4744	IDE	0.204759	MGOA[48]	3.0039				
DE [26]	799.365			MABC [40]	2.8864				
TLBO [38]	800.4604			TLBO [38]	3.11389				
ABC [49]	800.6850			MFO [46]	2.86114				
IABC [49]	800.4215			SSO [19]	3.8239				
DE	799.3426			DE	2.8985				
IDE	799.2642			IDE	2.8828				

TABLE III: CONTROL VARIABLES AND RESULT SIMULATION FOR DA AND IDA (PREPARED BY AUTHORS) FOR CASE 1 TO CASE 5

Control variables	Initial	Case 1		Case 2		Case 3		Case 4		Case 5	
		DE	IDE	DE	IDE	DE	IDE	DE	IDE	DE	IDE
P_1	99.23	177.0716	177.1456	64.7847	63.9573	51.5205	51.3053	168.6795	123.1917	128.3194	81.7450
P_2	80	48.0816	48.6773	67.0123	67.4747	79.9751	79.9983	49.1614	64.5039	56.7316	78.6847
P_5	50	21.1805	21.2836	49.9918	50.0000	49.9636	49.9999	37.6462	39.6237	33.3498	49.9522
P_8	20	21.4129	21.1198	34.9606	35.0000	34.9314	34.9996	15.7346	20.0135	27.6379	34.9803
P_{11}	20	12.1852	11.8579	29.9826	30.0000	29.9665	29.9999	11.1429	29.5631	28.6993	29.9739
P_{13}	20	12.1439	12.0003	39.9673	40.0000	39.9613	39.9998	12.6314	15.5509	14.8818	12.0249
V_1	1.05	1.0999	1.1000	1.0851	1.1000	1.0997	1.1000	1.0044	1.0027	1.0877	1.1000
V_2	1.04	1.0868	1.0878	1.0758	1.0959	1.0975	1.0976	0.9702	0.9680	1.0994	1.1000
V_5	1.01	1.0626	1.0614	1.0474	1.0783	1.0789	1.0798	1.0254	1.0211	1.0910	1.1000
V_8	1.01	1.0680	1.0692	1.0606	1.0856	1.0866	1.0869	1.0139	1.0219	1.0986	1.1000
V_{11}	1.05	1.0972	1.1000	1.0734	1.1000	1.0993	1.1000	1.0770	0.9843	1.0964	1.1000
V_{13}	1.05	1.0997	1.1000	1.0675	1.1000	1.0993	1.1000	1.0591	1.0681	1.0995	1.1000
T_{11}	1.078	1.0169	1.0127	1.0552	0.9995	1.0012	1.0014	1.0618	1.0863	0.9724	0.9500
T_{12}	1.069	1.0273	1.0318	1.0476	1.0311	1.0219	1.0327	1.0488	0.9653	0.9608	0.9500
T_{15}	1.032	0.9563	0.9504	1.0002	0.9503	0.9603	0.9500	0.9556	0.9503	0.9505	0.9500
T_{36}	1.068	0.9703	0.9761	0.9851	0.9788	0.9780	0.9799	0.9672	0.9677	0.9501	0.9500
Q_{e10}	0	4.8011	4.9857	0.8365	4.9992	4.9416	4.9888	4.8776	4.9451	4.9425	4.9998
Q_{e12}	0	3.2419	4.9841	1.7302	4.9959	4.2978	4.9968	2.2287	1.3685	4.1492	4.9996
Q_{e15}	0	4.1747	4.9880	0.9886	4.9903	4.0910	4.9312	3.3834	4.9916	4.6572	4.9997
Q_{e17}	0	4.3412	4.9940	1.6167	4.9910	4.8827	4.9978	4.8617	1.0082	4.8604	4.9999
Q_{e20}	0	4.4427	4.9830	4.6375	4.9522	4.2520	4.9932	4.3352	4.9920	4.7128	4.9999
Q_{e21}	0	4.7021	4.9993	4.9745	4.9917	4.6985	4.9989	4.5546	4.9201	4.8500	4.9997
Q_{e23}	0	4.7881	3.9607	4.3253	4.1022	3.6464	3.9946	4.5827	4.9752	4.8842	5.0000
Q_{e24}	0	4.9558	4.9947	2.7598	4.9981	4.9715	4.9970	2.3086	4.9834	4.8290	4.9999
Q_{e29}	0	3.4207	3.0853	3.4788	2.9431	2.9660	2.9316	2.9601	2.4830	4.8446	4.9999
FC (\$/h)	901.6	799.3426	799.2642	943.4304	943.7258	966.7273	967.1869	830.23	858.362	829.917	916.4612
Em (ton/h)	0.239	0.3659	0.3664	0.204888	0.204759	0.2073	0.2072	0.3423	0.2575	0.2631	0.2251
loss (MW)	5.689	8.6557	8.6645	3.2793	3.0120	2.8985	2.8828	11.576	9.0269	6.1997	3.9411
V.D (p.u.)	1.175	1.6068	1.6386	0.7698	1.8869	1.8574	1.8921	0.1245	0.0945	2.3891	2.5648
L_{max}	0.172	0.1182	0.1185	0.1284	0.1163	0.1168	0.1163	0.1359	0.1363	0.1090	0.10776
Reduction ratio	-	11.346%	11.354%	14.27%	14.33%	49.05%	49.33%	89.40%	91.96%	36.88%	37.60%

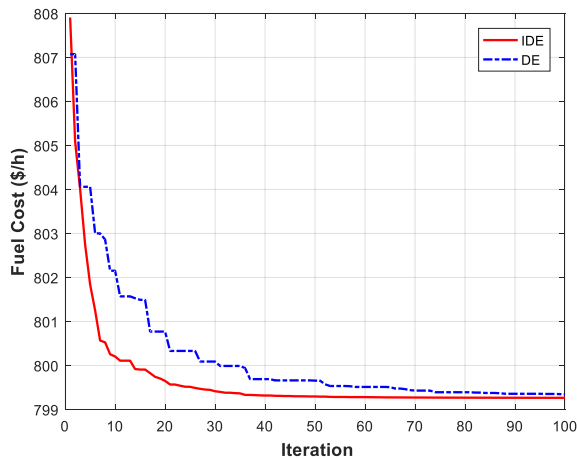


Fig. 3. Convergence slop for fuel cost function based on IDE and DE.

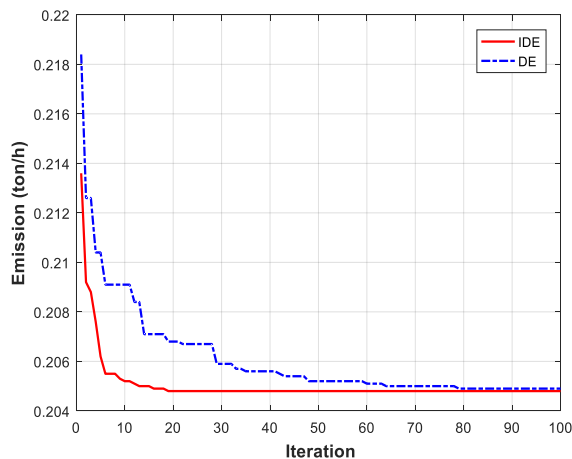


Fig. 4. Convergence slop for emission function based on IDE and DE.

Case 2: The fuel emission of the generation units is given by (7). The total minimum generation fuel emission found by the proposed approach IDE is 0.204759 ton/h. The emission has been decreased from 0.239 ton/h (initial state) to 0.204759 ton/h (optimal state) with a reduction of 14.33% as shown in Table III. According to Table II, the results of the fuel emission calculated by the proposed approach is much less with other algorithms. Fig. 4 illustrate the convergence characteristics obtained by the IDE and DE for the minimum fuel emission function.

Case 3: Active power losses as illustrated in (8) has been minimized in this case. The obtained results by IDE algorithm have been compared with other algorithms as tabulated in Table II. This comparison gives the effectiveness of the proposed algorithm. According to the proposed algorithm IDE, the active power losses is reduced from the initial state of 5.6891 MW to the optimal state of 2.8828 MW with a reduction of 49.33% as shown in Table III. Fig. 5 illustrates the comparison of convergence characteristics between IDE and DE algorithms.

Case 4: The safety and voltage quality are mainly dependent on voltage deviation in the power network. The objective of this section is to give better objective values and improve the voltage profile by minimizing the voltage deviation from the reference of 1.0 per unit (for the load buses (PQ buses)). The voltage deviation can be expressed in (9). Fig. 6 compares the convergence characteristic curve of minimization of the voltage deviation between the differential evolution algorithm and improved differential evolution algorithm. Table III

shows that the voltage deviation VD decreases from 1.1747 p.u. (initial state) to 0.0945 p.u. (optimal state) with reduction of 91.96% based on the proposed technique. To verify the effectiveness of the proposed approach, Table II compared the results obtained of IDE and DE algorithm with other heuristic methods.

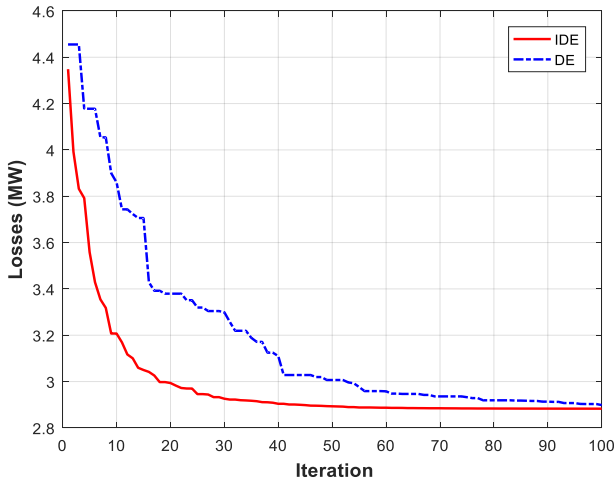


Fig. 5. Convergence slop of active power losses function based on IDE and DE.

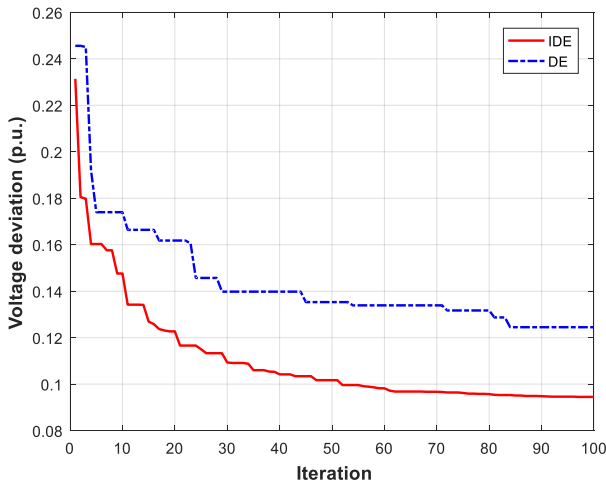


Fig. 6. Convergence slop of voltage deviation function based on IDE and DE.

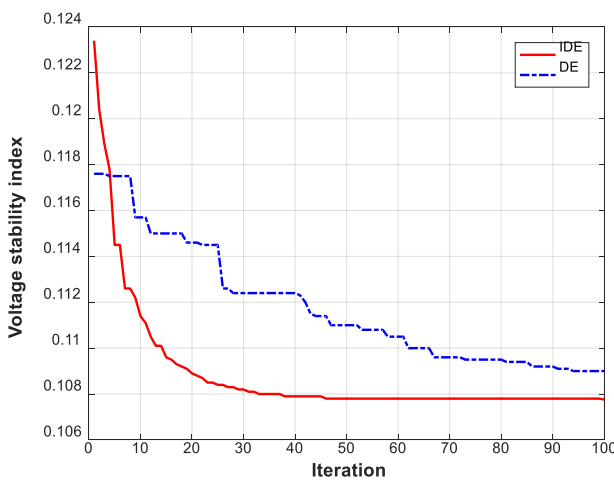


Fig. 7. Convergence slop of voltage stability index function based on IDE and DE.

Case 5: Voltage stability index L_{max} is one of the most important issues in power system. This indicator L_{max} has been expressed in (11). The aim of this objective function is to minimize the voltage stability index for more system stable. In this case the proposed algorithm IDE has been used to enhance the voltage stability index. The convergence rate of voltage stability index based on the proposed approach algorithm and the DE algorithm are illustrated in Fig 7. The obtained results of this method are given in Table III. The voltage stability index L_{max} of improved differential evolution has been decreased from the initial state of 0.1727 to optimal state of 0.10776 with reduction rate up to 37.60%.

To prove the effectiveness the approach proposed, Table II illustrates the comparison between the obtained results of this technique with other previous methods. Table III presents the initial and optimal control variables based on both DE and IDE with the five cases of objective function of generation fuel cost, generation fuel emission, active power losses, voltage deviation, and the voltage stability index. The control variables in this article are the active power of the generators except the slack generator, the magnitude voltage of the generators, tap changer of the transformers, and the compensator VAR of the shunt injection capacitors at the load buses.

VI. CONCLUSION

The aim of this article is to solve the optimal power flow problem by proposing an enhanced and effective version of differential evolution algorithm, namely improved differential evolution algorithm. Three improvements had been presented to enhance the performance of the original DE algorithm. These improvements are the random selection mechanism for a crossover, trial operation modification, and introduce mutational process calculations into the selection stage. To demonstrate the effectiveness and superiority of the IDE algorithm above the DE algorithm, five objective functions have been solved on power systems of IEEE 30 bus. The results obtained by IDE shows the efficiency and superiority compared with DE and other recent approaches mentioned in the literature. Comparative results show that the IDE has an outstanding competitive performance: the rate of reduction of the fuel cost, emission, real power losses, voltage deviation, and voltage stability index are 11.354%, 14.33%, 49.33%, 91.96%, and 37.60%.

As future work, the proposed approach (IDE) algorithm can be used to solve large scale power systems with more control variables, such as IEEE 57 bus system and IEEE 118 bus systems, also to solve the multi-objective functions problems using Pareto front method.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTIONS

Layth AL-BAHRANI edited the paper and the experimental validation of the work. Murtadha AL-KAABI prepared the program code to get the numerical results. Jaleel AL HASHEME wrote the paper.

ACKNOWLEDGMENT

The authors would like to thank the Ministry of Education/ Iraq and the Mustansiriyah University-College of Engineering/Iraq for their encouragement and support.

NOMENCLATURE

Symbol	Description
$F_i(u, v)$	The objective function
$G_j(u, v)$, $H_k(u, v)$	The equality and inequality constraints
u and v	The state and control variable.
P_{G_i}	Active power output for slack generator
N_G, N_T , N_C	Number of generators, transformers and shunt VAR compensation
F_{cost}	The total generation cost function
F_{emission}	The total emission function
F_{loss}	The total real power losses function
F_{V_d}	The total voltage deviation function
$F_{L_{\text{index}}}$	The voltage stability enhancement function
P_G, Q_G	Active and reactive power output
$g(i, j)$	Transmission conductance
$\delta(i, j)$	The difference of phase angles between bus i and j ;
V_i, V_j	The voltage magnitude for each bus i and j .
V_{ref}	Voltage reference and equal to 1.0 is per unit.
Y_B	Total bus admittance of the system
Y_{LL}, Y_{LG} , Y_{GL}, Y_{GG}	Sub matrix obtain from the original admittance Y_B
P_i, Q_i	The i th bus injection active and reactive power
P_{d_i}, Q_{d_i}	The demand active and reactive power at the load bus i
$G_{i,j}, B_{i,j}$	The transfer conductance and susceptance between bus i and bus j
$\theta_{i,j}$	The voltage angle difference between bus i and bus j
N_{TL}, N_L , N_B	Number of transmission lines, load and total buses
T_j	Tap changer of a transformer j
Q_c	Reactive power output of the VAR source
S_L	Apparent power flow in each transmission line
a_i, b_i, c_i	Cost coefficients of the i th generator
$\alpha_i, \beta_i, \gamma_i$, ζ_i, λ_i	Emission coefficients
x_j^{lower} , x_j^{upper}	The lower and upper limit of the control variable j
rand	Random number between the limit 0 and 1
$y_{\text{best},j}, Y_{\text{best},j}$	The population with the best fitness value
r_1, r_2	Integers taken randomly between 1 to N_p
F	Scaling factor which ranges between 0 and 1
$z_{i,j}$	Trail that competes with the target vector $x_{i,j}$
C_R	Crossover rate which specified as a constant in the ranges [0, 1]

j_{rand}	Integer number chosen randomly in the range [1, D]
$w_{i,j}$	Mutant vector that competes with the target vector $x_{i,j}$, the trail vector $z_{i,j}$ and the trail new vector $z_{i,j}^*$

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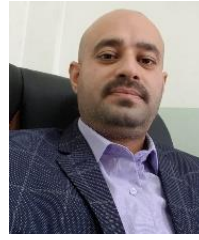


Layth Al-Bahrani was born in Baghdad, Iraq in 1973. He received the B.Sc. degree from University of Baghdad, Faculty of Engineering, in 1995 (Iraq-Baghdad) in the field of electrical engineering. He received the M.Sc. degree from University of Baghdad, Faculty of Engineering, in 1998 (Iraq-Baghdad) in the field of electrical power and machine engineering. He received the Ph.D. degree from University POLITEHNICA of Bucharest, Romania (UPB), Faculty of power engineering in 2015 in the field of power system engineering. He is currently teaching at the Mustansiriyah University- College of Engineering Electrical Department (Iraq-Baghdad). The field of his research concern in the power system operation and control, reliability evaluation of power system, optimal power flow, artificial Intelligence, optimization techniques, renewable Energy, power system generation, protection system.



Murtadha Al-Kaabi was born in Baghdad, Iraq in 1986. He received the B.Sc. degree in 2008 from College of Engineering Electrical Department, Mustansiriyah University, Baghdad, Iraq and M.Sc. degree in the field of power system engineering in 2017 from Faculty of Power Engineering, University POLITEHNICA of Bucharest, Romania (UPB). He is currently an assist lecturer and engineer at the School Building Department

for Ministry of Education in Iraq. His research interests cover power flow optimization for power systems. He has published over 6 papers in refereed international journals.



Jaleel Al Hasheme was born in Babylon, Iraq in 1980. He received the B.Sc. degree from the University of Baghdad, Faculty of Engineering, in 2007 (Iraq-Baghdad) in the field of electrical engineering. He received the M.Sc. degree from the University POLITEHNICA of Bucharest, Romania (UPB), Faculty of power engineering in 2017 in the field of power system engineering. He has been working for the Iraqi Ministry of

Electricity since 2008 in the distribution sector (maintenance and operation of the electrical network). The field of his research concern with the power system operation and control, renewable energy, power system generation.