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An improved mayfly algorithm based optimal power flow solution for regulated electric power network

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Abstract

This paper presents an improved mayfly algorithm (IMA) for identifying the optimum control settings of optimal power flow problem in regulated electric power networks. IMA is the improved version of the mayfly algorithm (MA) by implementing simulated binary crossover and polynomial mutation instead of arithmetic crossover and normal distribution mutation operators in MA. The attributes of genetic algorithm (GA), particle swarm optimization (PSO), and firefly algorithm (FA) are taken into account in IMA. Single objective functions such as total fuel cost, total active power losses, total voltage variation, and voltage stability index (VSI) are used to assess the performance of the algorithms. The optimal solution of each objective function is evaluated by representing the test systems in MATPOWER. The results of IMA are compared with GA, PSO, and MA. Investigations based on the optimal solution, convergence characteristics, and statistical measures of the solution ensure IMA's superiority over alternative algorithms. The performance of the algorithms is evaluated by simulation of the IEEE-30 bus system, 62-bus Indian utility system and the IEEE-118 bus system. For IEEE-30 bus system the optimal solutions of the objective functions are 802.1448 $/hr, 3.6487 MW, 0.5279 pu and 0.1247. In case of 62-bus utility system the optimal solutions of the objective functions are 13305.4267 $/hr, 73.8746 MW, 0.8049 pu and 0.0986. For IEEE-118 bus system the optimal solutions of the objective functions are 129611.5389 $/hr, 76.5261 MW, 0.8632 pu and 0.0611 are obtained by implementing IMA.

Keywords

Genetic algorithm, Improved mayfly algorithm, OPF, Polynomial mutation, Simulated binary crossover.

1.Introduction

The optimal power flow (OPF) problem is mathematically formulated by Carpentier [1]. The OPF is framed as the most important power system optimization problem. Power engineers can carry out the studies that are required for further planning and operation of the existing power systems with the integration of renewable energy sources. Mathematically, the OPF is represented by non-linear static equations. Solving the non-linear static equations gives a solution that describes the performance of power system networks. The solution of OPF problem is to obtain optimal values of design variables that optimize the objective function subjected to a set of constraints. The state variables describe the performance of the system at every step. The control variables control the systems to evolve from one step to the next step [2]. The objective functions are total fuel cost (TFC), total active power losses (TAPL), total voltage deviation (TVD), and voltage stability limit (VSI). TFC reduces the overall cost of generation. TAPL reduces transmission line losses, thereby increasing the power transfer capabilities of transmission lines. TVD minimises voltage variation in the load bus. VSI enhances stability by preventing the system from voltage collapse. The design variables are active power and voltage magnitudes at generators, transformer tap setting ratio and VAR compensators. The solution of optimization problems is achieved through the implementation of the following steps [3]: (i) Select the control and state variables, (ii) Frame the objective functions and constraints, (iii) Assign limits to the selected variables, (iv) Choose a suitable algorithm to optimize the problem, (v) Find the optimal solution to the problem.

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The OPF problem sets the goals as minimization of fuel cost, minimization of active power losses, minimization of voltage deviation and minimization of voltage stability limit. These goals are achieved by adapting improved mayfly algorithm (IMA) to OPF problem. The solution gives optimal values for the design variables. IMA is chosen to evaluate the results of OPF in the standard IEEE-30 bus system, IEEE-118 bus system and the practical 62-bus Indian utility system using MATPOWER with MATLAB. The results obtained by IMA illustrate the competition with MA, particle swarm optimization (PSO) and genetic algorithm (GA). The major contribution is implementing the simulated binary crossover operator and polynomial mutation operator in MA for OPF problem.

This paper is organized as: Section-1 is started with the origin and significance of OPF, section-2 with literature review of OPF, formulation of OPF problem with four single objective functions including constraints in section-3. It also describes about the attributes of IMA. The performances of various algorithms are reported in section-4. Section-5 discusses the analysis of results in discussions and section-6 concludes the research work through the findings.

2.Literature review

OPF problem is solved by conventional methods such as gradient methods [4], NR method [5], sequential linear programming method [6], sequential quadratic programming [7], linear and non-linear interior point methods [8], semi-definite programming [9] and so on. The solution of OPF problem obtained by implementing conventional methods gives only one solution that may struck within the local space [10].

In order to obtain a solution in global search space, meta-heuristic techniques such as an improved heap optimization algorithm (IHOA) is proposed by Shaheen et al. (2022) to solve optimization problem [11]. Dash et al. (2022) proposed boundary assigned animal migration optimization algorithm (BAAMOA) [12] to solve OPF problem.

Kahraman et al. (2021) implemented manta ray foraging optimization (MRFO) [13], Phanden et al. (2021) implemented modified ant colony optimization (MACO) [14] are used to solve optimization problem in power system. Naderi et al. (2021) implemented fuzzy adaptive hybrid self-adaptive PSO and DE algorithm (FAHSA-PSODEA) to handle multiple objective functions and non-convex OPF problem [15]. Su et al. (2021) proposed deep learning algorithm that is being implemented through an unsupervised deep belief network (DBN) to obtain the optimal values of generators and transient stability index [16]. Meng et al. (2021) implemented crossover grey wolf optimizer (CS-GWO) by introducing horizontal crossover in the grey wolves' chasing mechanism to solve OPF problem for IEEE-30 bus and IEEE-118 bus [17] system. Li et al. (2021) presented adaptive constraint DE (ACDE) that reduces fuel cost by 3.76% when compared with modified pigeon inspired optimization through constraint objective sorting rule (MPIO-COSR) [18]. Rahman et al. (2021) developed a learning augmented approach (LAA) based on machine learning to solve AC OPF problem in 500 and 4918 bus test systems [19]. Karimulla et al. (2021) proposed enhanced sine cosine algorithm (ESCA) to reduce the objective functions such as total production cost and losses, to improve VSI and to reduce the emission level in the IEEE-30 bus system [20]. Aziz et al. (2021) implemented an artificial immune system (AIS) for reducing system losses and voltage deviation through optimal placement and sizing of static Var compensator [21].

Gungor et al. (2020) proposed tree seed algorithm (TSA) [22], Diab et al. (2020) implemented coyote optimization algorithm (COA) [23], Hussein et al. (2020) proposed cuttle fish algorithm (CFA) [24] and so on. are used to obtain the best solution of optimization problem. Chen et al. (2020) implemented MPIO to solve single and multi-objective functions as combination of fuel cost, active power loss, fuel cost combined with valve point [25]. Warid (2020) proposed an adaptive multiple team's perturbation guided jaya (AMTPG-Jaya) algorithm to solve OPF problem [26]. Srilakshmi et al. (2020) implemented most valued player algorithm (MVPA) to solve OPF problem in IEEE-30 and IEEE-57 bus systems [27].

Nguyen (2019) proposed novel improved social spider optimization algorithm (NISSOA) for optimizing fuel cost, losses, emission, bus voltage deviations, and L-index in IEEE-30 bus, IEEE-57 bus and IEEE-118 bus test systems [28]. Biswas et al. (2018) proposed DE algorithm integrated with constraint management techniques [29], Attia et al. (2018) presented novel sine cosine algorithm (NSCA) [30], Shaha et al. (2017) described water evaporation algorithm (WEA) [31], Mukherjee and Mukherjee (2016) proposed novel oppositional krill herd algorithm (NOKHA) to solve OPF problem

[32]. Each technique has own individual benefits and drawbacks to achieve the best solution for the particular problem. These artificial techniques are categorized based on the social behaviour of human, animals, birds, fishes and mammals.

3.Methods

The OPF problem can be represented mathematically as F(x,u), subjected to Equation 1 and Equation 2.

$$e\ (x,u) = 0 \qquad (1)$$

$$ne\ (x,u) \leq 0 \qquad (2)$$

F is the optimized objective function focuses on minimum or maximum, x is a state variable set, u is a control variable set, e is set of equality constraints, ne is set of inequality constraints.

The state variables are real power at reference bus, voltage magnitude at load bus, reactive power(PV) at generator bus and apparent power through power lines. The control variables are real power at generator bus except reference bus, voltage magnitudes at generator bus, VAR compensators and transformer tap settings. The constraints are equality constraints and inequality constraints. The real and reactive power balance between generator and load bus are treated as equality constraints. The limits of real at generator bus, limits of voltage magnitudes at generator bus, limits of VAR compensators and limits of transformer tap settings are picked as inequality constraints in OPF problem.

State vector is modelled as shown in Equation 3.

$$x = [\mathrm{P_S}, \mathrm{V_{NPQ}^T}, \mathrm{Q_{NPV}^T}, \mathrm{S_{NTL}^T}] \qquad (3)$$

$\mathrm{P_S}$ is the real power at reference bus, $\mathrm{V_{NPQ}}$ is the load bus voltage, $\mathrm{Q_{NPV}}$ is the reactive power at generator bus, $\mathrm{S_{NTL}}$ is the apparent power in line, NPQ is the number of load bus, NPV is the number of generator bus, NTL is the total number of lines

Control vector is modelled as shown in Equation 4.

$$u = [\mathrm{P_{NPV}^T}, \mathrm{V_{NPV}^T}, \mathrm{Q_{NC}^T}, \mathrm{T_{NT}^T}] \qquad (4)$$

$\mathrm{P_{NPV}}$ is the real power at generator buses, $\mathrm{V_{NPV}}$ is voltage at generator bus, $\mathrm{Q_{NC}}$ is the shunt reactive power, T is the transformer tap settings, NC is the number of shunt compensators, NT is number of transformers.

3.1Objective functions

3.1.1TFC

$$OF1 = \sum_{k=1}^{NPV}(a_k P_{\mathrm{PV\,k}}^2 + b_k P_{PV\,k} + c_k) \qquad (5)$$

a_k, b_k, c_k are cost coefficients at generator k, $P_{PV\ k}$ is real power at kth PV bus (Equation 5).

3.1.2TAPL

$$OF2 = \sum_{\mathrm{k=1}}^{\mathrm{NTL}} \sum_{j=1}^{NTL} G_{jk}(V_j^2 + V_k^2 - 2V_jV_k cos\delta_{jk}) \qquad (6)$$

G_{jk} is the conductance of line connected between jth bus and kth bus, δ_{jk} is the voltage phase angle of line between bus j and bus k (Equation 6).

3.1.3TVD

$$OF3 = \sum_{k=1}^{NPQ}\left|(V_{PQ\,k} - 1)\right| \qquad (7)$$

$V_{PQ\,k}$is voltage magnitude at kth PQ bus (Equation 7)

3.1.4VSI

$$OF4 = \min(\max(L_n))\,; n = 1,2,.,NPQ \qquad (8)$$

$$L_n = \left|1 - \sum_k^{NPV} H_{jk}\frac{V_j}{V_k}\right| \quad j = 1,2,\dots,NPQ \qquad (9)$$

H_{jk} is matrix obtained by partition inversion of Y_{BUS} between jth PQ bus and kth PV bus (Equation 8 and 9).

3.2Constraints

3.2.1Equality constraints

$$P_{PV\,k} - P_{PQ\,k} = |V_{\mathrm{k}}| \sum_{j=1}^{NB} |V_j| (G_{kj} cos\delta_{kj} + \mathrm{B_{kj}} sin\delta_{kj}) \qquad (10)$$

$$Q_{PV\,k} - Q_{PQ\,k} = |V_{\mathrm{k}}| \sum_{j=1}^{BN} |V_j| (G_{kj} sin\delta_{kj} - \mathrm{B_{kj}} cos\delta_{\mathrm{kj}}) \qquad (11)$$

($P_{PV\ k}$- $P_{PQ\ k}$) is the net real power at kth bus,($Q_{PV\ k}$-$Q_{PQ\ k}$) is the net reactive power at kth bus,V_k and V_j are voltage magnitudes at kth and jth bus, G_{kj} is conductance between kth and jth bus, B_{kj} is the susceptance between kth bus and jth bus, δ_{kj} is the voltage phase difference between kth bus and jth bus (Equation 10 and 11).

3.2.2Inequality constraints

PV bus constraints, *Real power*, $P_{PV\,k}^{min} \leq P_{PV\,k} \leq P_{PV\,k}^{max} \quad k \in NPV$ (12)

Voltage magnitude, $V_{PV\,k}^{min} \leq V_{PV\,k} \leq V_{PV\,k}^{max} \quad k \in NPV$ (13)

Reactive power, $Q_{PV\,k}^{min} \leq Q_{PV\,k} \leq Q_{PV\,k}^{max} \quad k \in NPV$ (14)

PQ bus constraints *Voltage magnitude*, $V_{PQ\,k}^{min} \leq V_{PQ\,k} \leq V_{PQ\,k}^{max}\ k \in NPQ$ (15)

Transmission lines constraints *Transformer ratio*, $T_k^{min} \leq T_k \leq T_k^{max} k \in NT$ (16)

VAR compensator, $Q_{Ck}^{min} \leq Q_{Ck} \leq Q_{Ck}^{max} k \in NC$ (17)

Apparent power,$S_{Lk} \leq S_{Lk}^{max} k \in NTL$ (18)

$\mathrm{P_{PV\,k}^{min}}$ *and* $\mathrm{P_{PV\,k}^{max}}$is the lower and higher values of generators' real power at kth bus, $\mathrm{Q_{PV\,k}^{min}}$*and* $\mathrm{Q_{PV\,k}^{max}}$is the lower and higher values of generators' reactive power at kth bus, $V_{PV\,k}^{min}$ and $V_{PV\,k}^{max}$ is the lower and higher values of generators' voltage magnitudes at kth bus, $V_{PQ\,k}^{min}$ *and* $V_{PQ\,k}^{max}$ is the lower and higher values of loads' voltage magnitude at kth bus, T_k^{min} and T_k^{max} is the lower and higher values of transformer tap setting ratio at kth bus, $Q_{C\,k}^{min}$ and $Q_{C\,k}^{max}$ is the lower and higher values of VAR compensation at kth bus, $S_{L\,k}^{max}$ is maximum apparent power to be transmitted through kth transmission line.

3.3Improved mayfly algorithm (IMA)

Mayfly algorithm (MA) is proposed by Zervoudakis and Tsafarakis in 2020 [33] inspired through social behavior of mayflies. They derived the named as, the Mayflies appears only in the month of May in United Kingdom. MA is developed as hybrid algorithm with combination of PSO, FA and GA.GA is population based evolutionary method based on the Survival of Fittest concept of Darwin's theory introduced by Holland in 1960 and further analyzed by Goldberg in 1989 [34]. The solutions of GA are in the form of chromosomes. The chromosomes are updated by using genetic operators like crossover and mutation. The best solutions are obtained by replacing the worst solutions in the stages of selection, crossover and mutation. PSO is a population-based swarm intelligent method that is based on swarm behavior of fishes or birds introduced by Kennedy and Ebehart in 1995 [35] to solve the continuous optimization problem. The position of the particles in swarm represents the solution obtained by PSO in solution space. The current position of the particles is updated by adding velocity to the particle. The particle's velocity depends on the previous position of local and global. FA is also population-based swarm intelligent method that is based on the behavior of fireflies proposed by Yang in 2008 [36] to solve problems having continuous and discontinuous variables. The solution of FA depends on the variation in intensity of light and attractiveness. The fitness value of each firefly is related according to it stability to ejaculate brightness. The firefly with less intensity is attracted towards high intensity. The fireflies with same light intensity moves randomly. The best solution is obtained by updating the current position, attractiveness and random terms.

The proposed IMA is a nature inspired algorithm that has the advantages of evolutionary algorithm (GA) [37, 38], swarm intelligence algorithm (PSO) [39] and population-based algorithm (FA) [40−42]. The important steps involved in IMA are (i) Initialization, (ii) Updating of male mayflies, (iii) Updating of female mayflies, (iv) Mating of male mayflies with female mayflies.

3.3.1Initialization

Initialize the positions and velocities of mayflies as given in Equation 19 to Equation 22.

$$x_i^m = [x_1^m, x_2^m, x_3^m, \dots \dots, x_n^m] \qquad (19)$$

$$v_i^m = [v_1^m, v_2^m, v_3^m, \dots \dots, v_n^m] \qquad (20)$$

$$x_i^f = [x_1^f, x_2^f, x_3^f, \dots \dots, x_n^f] \qquad (21)$$

$$v_i^f = [v_1^f, v_2^f, v_3^f, \dots \dots, v_n^f] \qquad (22)$$

x_i^m is the positions of ith male mayfly, x_i^f is the positions of ith female mayfly, v_i^m is the velocities (change of positions) of ith male mayfly, v_f^m is the velocities of ith female mayfly.

3.3.2Updating of male mayfly

The updated velocity of male mayfly given by

$$iff\left(x_{ij}^m(t)\right) \geq best(p_{ij}^m),\ \ \mathrm{v_{ij}^m(t+1) = g * v_{ij}^m(t) + a_1 e^{-\beta r_p^2}\left(p_{ij}^{best} - x_{ij}^m(t)\right) + a_2 e^{-\beta r_g^2}\left(g_j^{best} - x_{ij}^m(t)\right)} \qquad (23)$$

otherwise

$$v_{ij}^m(t+1) = v_{ij}^m(t) + d * r \qquad (24)$$

$v_{ij}^m(t+1)$-ith male mayfly velocity in jth dimension during (t+1)th iteration, $v_{ij}^m(t)$- ith male mayfly velocity in jth dimension during tth iteration, $x_{ij}^m(t+1)$- ith male mayfly position in jth dimension during(t+1)th iteration, $x_{ij}^m(t)$-ith male mayfly position in jth dimension during tth iteration, p_{ij}^{best} is the individual best position during(t+1)th iteration, g_j^{best} is the global best position during tth iteration, r_p is the Cartesian distance between individual and personal best, r_g is the Cartesian distance between individual and global best, g is the gravitational co-efficient, a_1 and a_2 are the positive attractive co-efficient, β is the fixed visible co-efficient, *d* is the nuptial co-efficient, *r* is the random number.

The personal best solution of male mayfly is given as,

$$p_{ij}^{best} = \begin{cases} x_{ij}^m(t+1), iff(x_{ij}^m(t+1)) \leq f(p_{ij}^{best}) \\ x_{ij}^m(t), \qquad otherwise \end{cases} \qquad (25)$$

The global best position is given by

$$g_j^{best} = \min\{f(p_1^{best}), f(p_2^{best}), \dots \dots, f\left(p_j^{best}\right)\} \qquad (26)$$

3.3.3Updating the female mayfly

The updated velocity of female mayfly given by

$$iff\left(x_{ij}^f(t)\right) \geq f\left(x_{ij}^m(t)\right)$$

$$v_{ij}^f(t+1) = g * v_{ij}^f(t) + a_2 e^{-\beta r_{mf}^2}(x_{ij}^m(t) - x_{ij}^f(t)) \qquad (27)$$

otherwise

$$v_{ij}^f(t+1) = g * v_{ij}^f(t) + fl * r \qquad (28)$$

$v_{ij}^{f}(t+1)$-i^th female mayfly velocity in j^th dimension during(t+1)^th iteration,$v_{ij}^{f}(t)$- i^th female mayfly velocity in j^th dimension during t^th iteration,$x_{ij}^{f}(t+1)$- i^th female mayfly position in j^th dimension during(t+1)^th iteration,$x_{ij}^{f}(t)$-i^th female mayfly position in j^th dimension during t^th iteration,$p_{ij}^{best}$is the individual best position during(t+1)^th iteration, r_{mf} is the distance in cartesian space between the male and female mayflies, fl is random walk co-efficient.

3.3.4Mating of male mayflies with female mayflies

Mating process is done through crossover and mutation. Simulated binary crossover and polynomial mutation is used to obtain better new solutions.

The simulated binary crossover [43] is implemented as

$$mf_{new}^{1} = 0.5[(1+\varepsilon) * v_{ij}^{m}(t) + (1-\varepsilon) * v_{ij}^{f}(t)] \tag{29}$$

$$mf_{new}^{2} = 0.5[(1-\varepsilon) * v_{ij}^{f}(t) + (1+\varepsilon) * v_{ij}^{m}(t)] \tag{30}$$

$$\varepsilon = \begin{cases} 2r^{d} if r \leq 0.5 \\ \left[\frac{1}{2(1-r)}\right]^{d} if r > 0.5 \end{cases} \tag{31}$$

$$d = \frac{1}{(d_i+1)} \tag{32}$$

The polynomial mutation is implemented through

$$mf_{new}(t+1) = mf_{new}(t) + \{mf_{new}^{max}(t) - mf_{new}^{min}(t)\}\sigma_m \tag{33}$$

$$\sigma_m = \begin{cases} 2r^{\frac{1}{m_i-1}} - 1 & if r \leq 0.5 \\ 1 - 2(1-r)^{\frac{1}{m_i+1}} if r > 0.5 \end{cases} \tag{33}$$

$m_i$is the mutation index, d_i is the crossover index

The process of IMA is as follows: Initially, the positions and velocities of mayflies are assigned randomly. The objective function value of each mayfly is computed. After evaluating mayfly's fitness value, the stopping criteria need to be verified. If the stopping criteria is not met, then update the velocities of both mayflies i.e., male and female. Calculate the fitness of updated mayflies and sort the mayflies with high fitness value to low fitness value. Randomly separate the mayflies into male and female mayflies. Replace the worst mayfly with best mayfly and update individual best and global best value of fitness function. The process is repeated until the stopping criterion is achieved to obtain the optimal solutions. The flow chart of IMA is drawn in *Figure 1*.

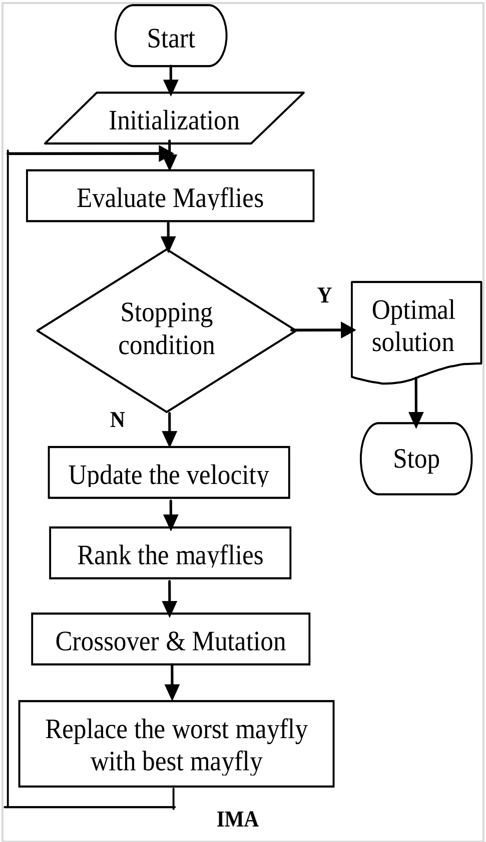


Figure 1 Flowchart related to improved mayfly algorithm (IMA)

The pseudo-code of IMA is given below:

```
Start
Set the positions and velocities of male mayflies
Set the positions and velocities of female mayflies
Configure the objective functions
Measure the solutions
While do stopping condition is not satisfied
    Upgrade the velocities of mayflies
    Upgrade the fitness values of mayflies
    Measure the new solutions
    Sort the mayflies in order
    Apply crossover and mutation
    Calculate the fitness of off-springs
    Randomly partition the mayflies into two
    Substitute the worst with best mayflies
    Upgrade the pbest and gbest
End while
Obtain the optimal solution
End
```

4.Results

The effectiveness of different algorithms such as IMA, GA, PSO and MA was tested on IEEE-30 bus system, 62-bus Indian utility system, IEEE-118 bus system. The performance of the EAs is investigated by considering optimal values and convergence rate. Performance metrics are taken into account for the evaluation of EAs. The OPF problem is modelled and simulated in Laptop build with 8 GB RAM, AMD Ryzen V generation processor installed with 64-bit Windows 10 OS. The results are simulated in MATPOWER 7.0b with MATLAB 2016. The details of test systems are displayed in *Table 1*. The parameters of different EAs are given in *Table 2.*

Table 1 Details of test system

Parameters	Test System-1	Test System-2	Test System-3
No. of bus	30	62	118
No. of branches	41	89	186
Total Generation Capacity	287.22 MW 78.16 MVAR	2985.82 MW 680.09 MVAR	4319.4 MW 388.26 MVAR
Total Connected Load	283.40 MW 126.20 MVAR	2908 MW 1270MVAR	4242 MW 1438 MVAR
Location of variables for Test System-1			
Generators 6: Bus-1,2,5,8,11,13 Transformers 4: Branch-11,12,15,36 Shunt Compensators 9: Bus-10,12,15,17,20,21, 23, 24, 29			
Location of variables for Test System-2			
Generators 19: Bus- 1, 2, 3, 5, 9, 14, 23, 25, 32, 33, 34, 37, 49, 50, 51, 52, 54, 57, 58 Transformers 11: Branch – 3, 11, 12, 13, 14, 37, 38, 39, 82, 83, 85			
Location of variables for Test System-3			
Generators 54: Bus – 1, 4, 6, 8, 10, 12, 15, 18, 19, 24, 26, 27, 31, 32, 34, 36, 40, 42, 46, 49, 54, 55, 56, 59, 61, 62, 65, 66, 69, 70, 72, 73, 74, 76, 77, 80, 85, 87, 89, 90, 91, 92, 99, 100, 103, 104, 105, 107, 110, 111, 112, 113, 116 Transformers 9 : Branch – 8, 32, 36, 51, 93, 95, 102, 107, 127 Shunt Compensators 12 : Bus – 34, 44, 45, 46, 48, 74, 79, 82, 83, 105, 107, 110			

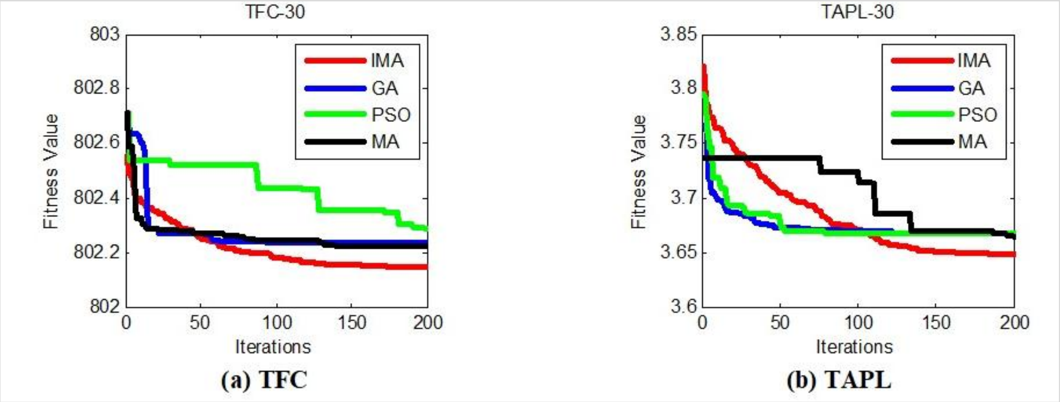
Table 2 Parameters of IMA, GA, PSO, FA

EAs	**Parameters**	**Values**	**EAs**	**Parameters**	**Values**
IMA	Iterations	200	GA	Iterations	200
	Mayflies	50		Chromosomes	50
	Male mayflies	30		Mutation percentage	4%
	Female mayflies	20		Crossover percentage	80%
	Inertia weight	0.8	PSO	Iterations	200
	Inertia weight damping ratio	1		Particles	50
	Individual learning co-efficient (a1 and a2)	1 and 1.3		Inertia weights	0.75
	Global learning co-efficient (a3)	1.5		Learning co-efficient	a1=0.8, a2=1.2
	Mutation rate	20 %			
	Crossover probability index	3			
	Mutation probability index	18			

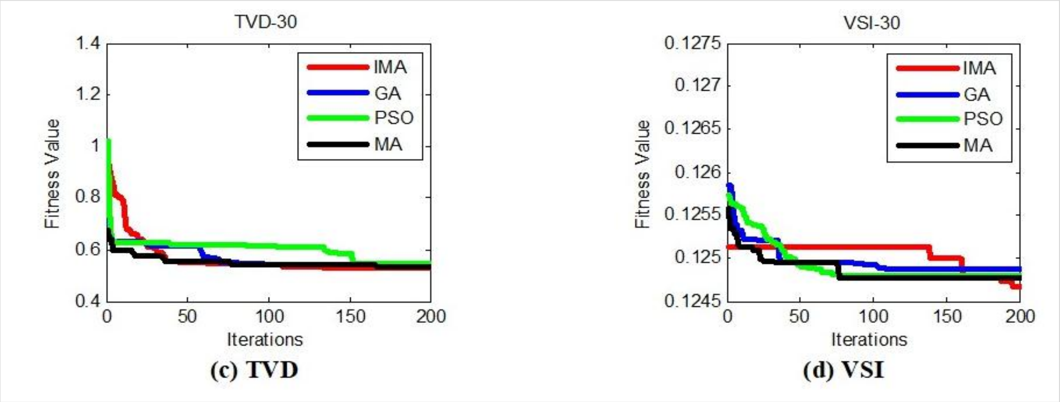
4.1Test system-1: IEEE-30 bus system

This test system consists of 25 control variables in which 6 are real power at various generator bus, 6 are voltage magnitudes at various generator bus, 4 are transformer tap settings and 9 are VAR compensators that minimize objective functions. The real power at PV bus is restricted between 10 MW and 200 MW. The voltage level at PV bus is bounded within 0.95 and 1.1p.u. The ratio of transformer tap settings is limited between 0.9 and 1.1p.u. The cutoff range of shunt compensators is (0, 5) MVAR. The convergence characteristics of Test system-1 for different objective functions are shown in *Figure 2 (a)-(d)*. The values of variables to minimize TFC, TAPL, TVD, VSI for Test system-1 using IMA is tabulated in *Table 3*. The optimal solution attained by IMA for TFC is 802.1448 \$/hr, the TAPL is 3.6487 MW, TVD is 0.5279 pu and VSI is 0.1247. The comparison of optimal solution of objective functions with different EAs is listed in *Table 4*.

In comparison, the best optimal solution is achieved by implementing IMA for all objective functions. The worst optimal solution for TFC is 802.2899 \$/hr with PSO, the TAPL is 3.6687 MW with GA, TVD is 0.5442 pu with PSO and VSI is 0.1249 with GA. The effectiveness of different EAs with each objective function is acknowledged with the performance metrics that are indexed in *Table 5*. The statistical measures of optimal solution of EAs are pictured in *Figure 3(a)-(d).*



(a) TFC **(b) TAPL**



(c) TVD **(d) VSI**

Figure 2 Convergence curves of test system-1

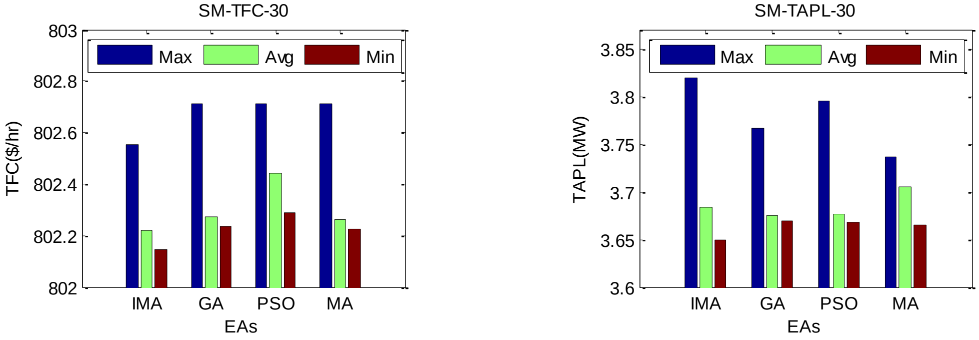
Table 3 Optimal values for test system-1with IMA

Variables	**OF-1**	**OF-2**	**OF-3**	**OF-4**
P_{G1}	140.1530	132.5523	76.2086	61.6193
P_{G2}	65.0809	43.3201	20.0234	79.0125
P_{G5}	48.9453	24.6005	35.0655	33.2128
P_{G8}	20.9349	34.1649	34.9900	22.0292
P_{G11}	28.6540	25.3987	17.2476	29.4276
P_{G13}	28.5730	26.5155	30.3874	28.4169
V_{G1}	1.0897	1.0777	1.0993	0.9618
V_{G2}	1.0218	1.0291	1.0904	0.9500
V_{G5}	1.0021	1.0979	0.9583	1.0379
V_{G8}	1.0373	1.0849	1.0763	0.9714
V_{G11}	1.0996	1.0787	1.0256	0.9647
V_{G13}	1.0584	1.0994	1.0083	1.0839
$T_{11(6-9)}$	0.9852	1.0000	1.0998	0.9759
$T_{12(6-10)}$	0.9682	0.9408	1.1000	0.9000
$T_{15(4-12)}$	0.9775	0.9739	1.0274	0.9767
$T_{36(28-27)}$	0.9650	0.9668	1.0358	0.9455
Q_{C10}	4.9967	4.4960	0.5653	1.8121
Q_{C12}	4.9875	2.9618	4.4367	0.8739
Q_{C15}	4.2984	4.9718	0.0677	3.9011

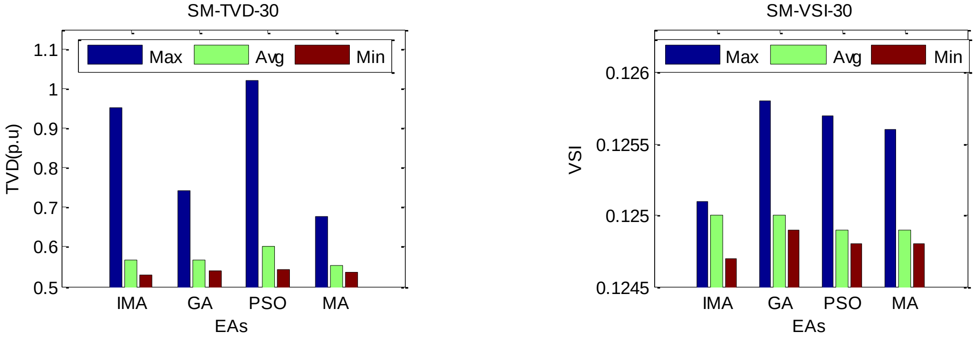
Variables	**OF-1**	**OF-2**	**OF-3**	**OF-4**
Q_{C17}	4.9841	4.9757	0.0203	4.0025
Q_{C20}	4.3637	3.7139	4.9848	3.1017
Q_{C21}	5.0000	4.9925	4.8965	2.6161
Q_{C23}	2.3790	2.5138	4.2796	2.4073
Q_{C24}	4.9967	4.9791	3.3790	0.9297
Q_{C29}	2.1974	2.2120	2.0547	0.1957
TFC ($/hr)	**802.1448**	802.1495	802.9744	802.5175
TAPL(MW)	3.6496	**3.6487**	3.8757	3.7508
TVD (pu)	2.0536	2.0526	**0.5279**	2.0243
VSI	0.1257	0.1258	0.1454	**0.1247**

Table 4 EAs with different objective functions for test system-1

EAs	**TFC**	**TAPL**	**TVD**	**VSI**
IMA	802.1448	3.6487	0.5279	0.1247
GA	802.2337	3.6687	0.5383	0.1249
PSO	802.2899	3.6681	0.5442	0.1248
MA	802.2270	3.6648	0.5362	0.1248



(a) TFC **(b) TAPL**



(c) TVD **(d) VSI**

Figure 3 Statistical measures of test system-1

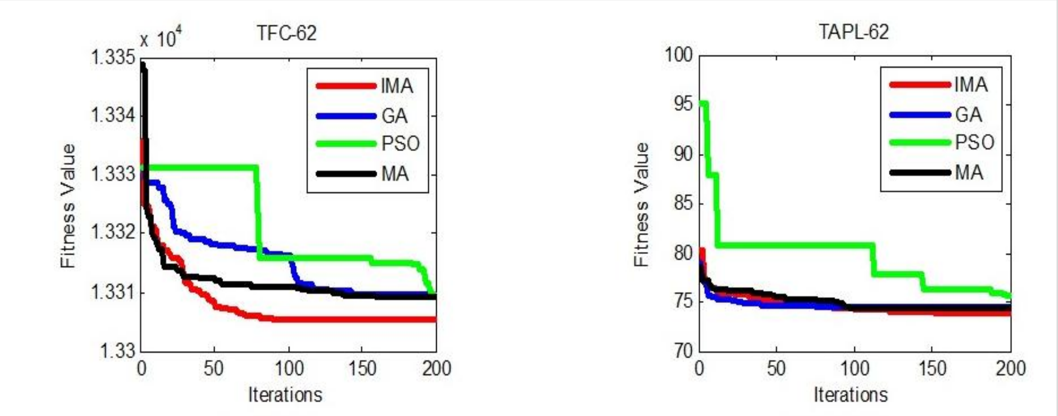
Table 5 Comparison of performance metrics of test system-1

OFs	**EAs**	**Max**	**Avg**	**Min**
TFC	IMA	802.5536	802.2181	802.1448
	GA	802.7109	802.2723	802.2337
	PSO	802.7111	802.4416	802.2899
	MA	802.7109	802.2621	802.2270
TAPL	IMA	3.8199	3.6842	3.6487

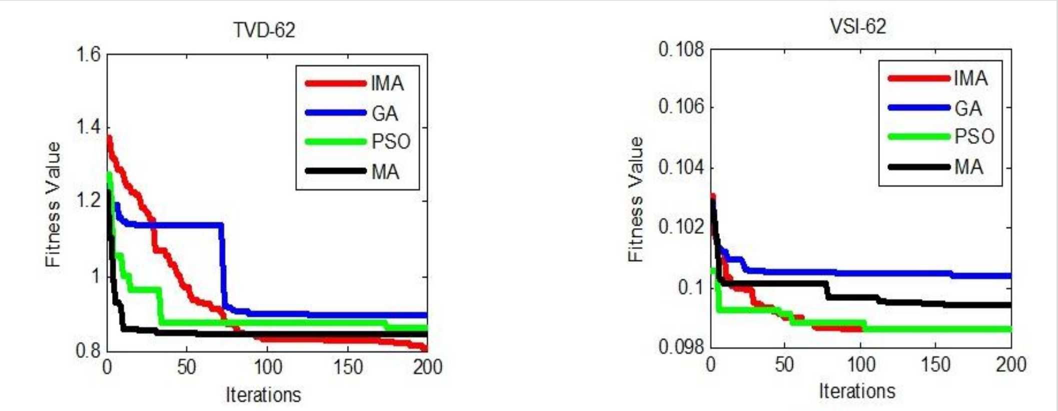
OFs	EAs	Max	Avg	Min
	GA	3.7658	3.6749	3.6687
	PSO	3.7954	3.6768	3.6681
	MA	3.7365	3.7053	3.6648
TVD	IMA	0.9517	0.5658	0.5279
	GA	0.7415	0.5667	0.5383
	PSO	1.0204	0.6005	0.5442
	MA	0.6759	0.5519	0.5362
VSI	IMA	0.1251	0.1250	0.1247
	GA	0.1258	0.1250	0.1249
	PSO	0.1257	0.1249	0.1248
	MA	0.1256	0.1249	0.1248

4.2Test System-2: 62-bus Indian utility system

The total number of control variables for the 62-bus Indian utility system is 49 in which 19 variables represent the real power at generator bus, another 19 variables represent voltage magnitudes at generator bus and the remaining 11 variables represent transformers' tap settings. The real power at PV buses is restricted to the maximum value of 600 MW. The voltage level at PV bus is bounded between 0.9 and 1.1 p.u. The ratio of transformer tap settings is in the range of 0.9 and 1.1 p.u. The convergence characteristics of Test system-2 for different objective functions are shown in *Figure 4 (a)-(d).*



(a) TFC **(b) TAPL**



(c) TVD **(d) VSI**

Figure 4 Convergence curves of test system-2

The comparison of optimal solution of objective functions considering IMA, GA, PSO and MA is listed in *Table 6*. Based on comparison, it is evident that the optimal solution is achieved by implementing IMA for all objective functions. The worst optimal solution for TFC is 13309.6423 \$/hr with GA, TAPL is 75.6726 MW with PSO, TVD is 0.8946 pu with GA and VSI is 0.1004 with GA. The values of variables to minimize TFC, TAPL, TVD, VSI for Test system-2 using IMA is tabulated in *Table 7*. The optimal solution attained by IMA for TFC is 13305.4267 \$/hr, the TAPL is 73.8746 MW, TVD is 0.8049 pu and VSI is 0.0986. The effectiveness of different EAs with each objective function is acknowledged with the performance metrics that are indexed in *Table 8*. The statistical measures of optimal solution of EAs are pictured in *Figure 5(a)-(d)*.

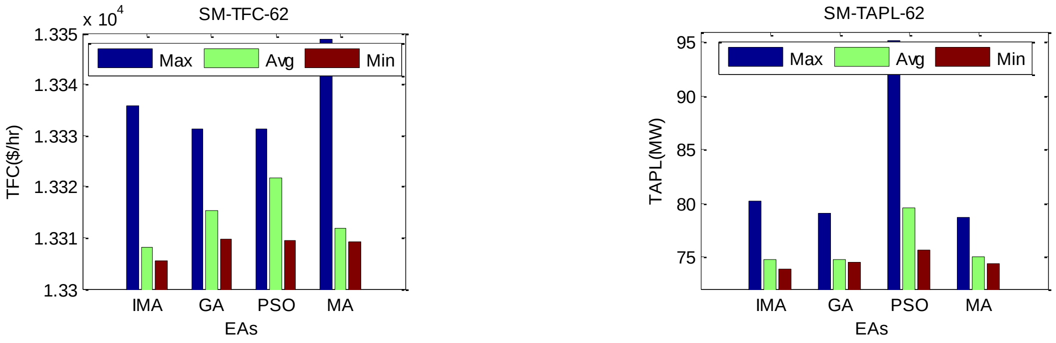
Table 6 Comparison of objective functions of test system-2

EAs	**TFC**	**TAPL**	**TVD**	**VSI**
IMA	13305.4267	73.8746	0.8049	0.0986
GA	13309.6423	74.4647	0.8946	0.1004
PSO	13309.4078	75.6726	0.8626	0.0986
MA	13309.3016	74.3201	0.8467	0.0994

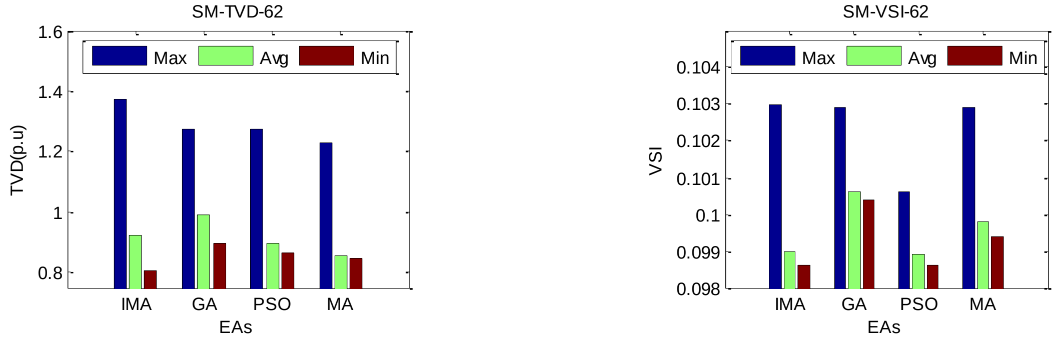
Table7 Optimal values for test system-2 with IMA

Variables	**OF-1**	**OF-2**	**OF-3**	**OF-4**
P_{G1}	249.1981	63.5661	101.4695	217.5901
P_{G2}	445.8175	317.1543	355.2195	181.3635
P_{G5}	271.8273	258.4950	227.6089	129.3750
P_{G9}	69.7900	27.8206	8.9707	79.6357
P_{G14}	214.8819	62.9465	95.0249	184.1375
P_{G17}	171.1465	287.1668	349.5991	420.0314
P_{G23}	81.6966	150.0535	96.0470	170.4820
P_{G25}	356.1602	493.0893	53.4551	135.3225
P_{G32}	412.6128	15.4413	301.2922	357.7379
P_{G33}	30.6705	97.6879	81.3264	99.0274
P_{G34}	125.6184	90.0975	100.8122	126.5673
P_{G37}	18.2039	15.0939	13.9983	49.4235
P_{G49}	100.2146	216.6395	218.8330	172.4761
P_{G50}	9.2126	48.9960	137.0072	148.0567
P_{G51}	422.8000	499.1912	447.2238	416.9448
P_{G52}	149.0000	117.6241	112.4641	51.3442
P_{G54}	90.6091	6.0321	63.7260	69.5483
P_{G57}	295.9691	116.3637	160.3197	220.0799
P_{G58}	476.6351	213.3705	592.6360	141.8322
V_{G1}	0.9307	0.9650	0.9481	1.0991
V_{G2}	0.9809	1.0181	0.9933	1.0283
V_{G5}	1.0748	1.0010	0.9518	1.0294
V_{G9}	0.9147	1.0530	1.0961	1.0180
V_{G14}	0.9480	0.9000	0.9597	0.9119
V_{G17}	1.0645	0.9235	1.0981	0.9650
V_{G23}	0.9075	0.9410	0.9456	1.0505
V_{G25}	0.9900	1.0228	0.9270	1.0415
V_{G32}	0.9489	0.9014	0.9615	0.9658
V_{G33}	0.9378	0.9552	0.9074	1.0910
V_{G34}	0.9236	1.0995	0.9074	1.0976
V_{G37}	1.0216	1.0425	1.0646	1.0847
V_{G49}	1.0409	1.0737	1.0466	0.9109
V_{G50}	0.9529	1.0114	1.0887	1.1000
V_{G51}	1.0994	1.0411	1.0367	1.0553
V_{G52}	0.9843	0.9607	1.0898	0.9097
V_{G54}	1.0373	1.0350	1.0329	1.0919
V_{G57}	0.9752	0.9293	0.9095	0.9746

Variables	OF-1	OF-2	OF-3	OF-4
V_{G58}	1.0464	0.9603	0.9828	0.9024
$T_{3(1-14)}$	0.9910	0.9884	0.9001	0.9401
$T_{11(14-15)}$	1.0099	1.0100	1.0575	1.0508
$T_{12(4-14)}$	0.9898	0.9890	0.9315	1.0446
$T_{13(13-14)}$	1.0216	1.0170	0.9581	0.9938
$T_{14(12-13)}$	1.0020	1.0008	1.0056	1.0703
$T_{37(14-19)}$	0.9502	0.9487	1.0751	0.9443
$T_{38(14-18)}$	0.9872	1.0216	0.9626	1.0023
$T_{39(14-16)}$	0.9952	0.9985	1.0669	0.9876
$T_{82(48-54)}$	0.9965	0.9980	1.0941	0.9605
$T_{83(48-50)}$	1.0454	1.0359	0.9220	0.9934
$T_{85(49-48)}$	0.9560	0.9639	1.0292	0.9582
TFC ($/hr)	**13305.4267**	13305.5903	13426.5556	13356.0800
TAPL (MW)	73.8767	**73.8746**	90.6879	81.1911
TVD (pu)	3.6232	3.6081	**0.8049**	3.5013
VSI	0.0991	0.0987	0.1393	**0.0986**



(a) TFC **(b) TAPL**



(c) TVD **(d) VSI**

Figure 5 Statistical measures of test system-2

Table 8 Comparison of performance metrics of test system-2

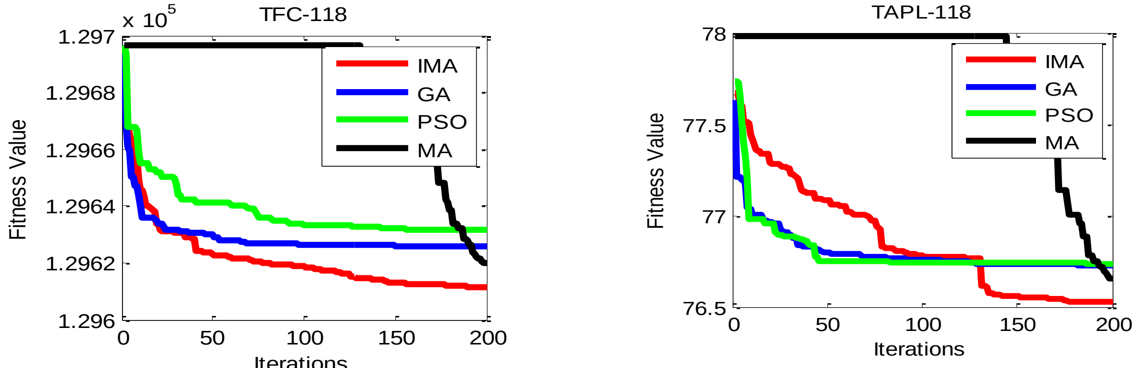
OFs	EAs	Max	Avg	Min
TFC	IMA	13335.7089	13308.1850	13305.4267
	GA	13331.3511	13315.2276	13309.6423
	PSO	13331.3511	13321.5952	13309.4078
	MA	13348.8223	13311.9007	13309.3016

OFs	EAs	Max	Avg	Min
TAPL	IMA	80.2085	74.6768	73.8746
	GA	79.0236	74.6967	74.4647
	PSO	95.2302	79.5121	75.6726
	MA	78.6067	75.0205	74.3201
TVD	IMA	1.3737	0.9232	0.8049
	GA	1.2739	0.9885	0.8946
	PSO	1.2755	0.8969	0.8626
	MA	1.2287	0.8552	0.8467
VSI	IMA	0.1030	0.0990	0.0986
	GA	0.1029	0.1006	0.1004
	PSO	0.1006	0.0989	0.0986
	MA	0.1029	0.0998	0.0994

4.3Test System-3: IEEE-118 bus system

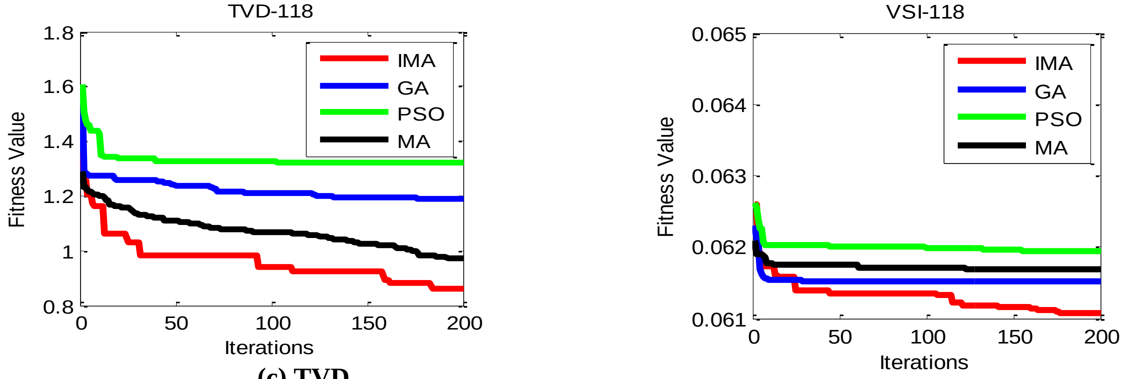
This test system contains 129 control variables in which 54 are representing real power at generator bus, 54 are for voltage magnitudes at generator bus, 9 are for transformers tap settings and 12 are for shunt VAR compensators. The real power at PV bus is restricted to the maximum of 550 MW. The voltage level at PV bus is bounded within 0.96 and 1.1 p.u. The ratio of transformer's tap settings is within 0.9 and 1.1 p.u. The cut-off range of shunt compensators is [0,40] MVAR.

The convergence characteristics of Test system-3 for different objective functions are shown in *Figure 6 (a)-(d).* The optimal solution attained by IMA for TFC is 129611.5389 $/hr, the TAPL is 76.5261 MW, TVD is 0.8632 p.u and VSI is 0.0611.



(a) TFC

(b) TAPL



(c) TVD

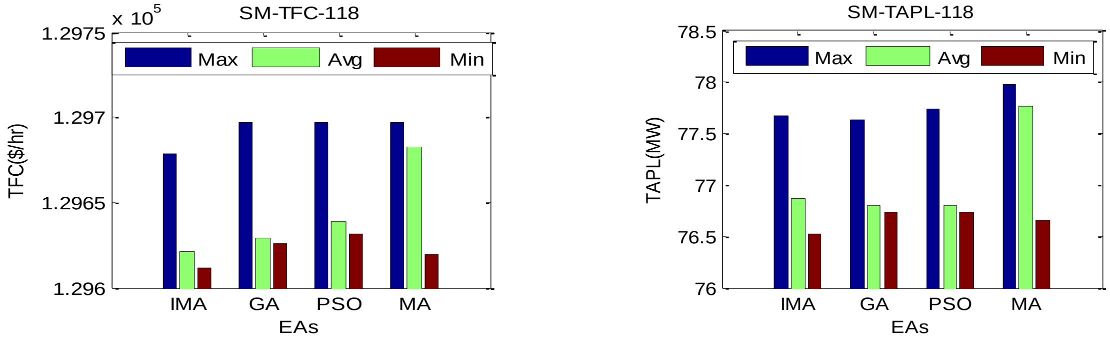
(d) VSI

Figure 6 Convergence curves of test system-3

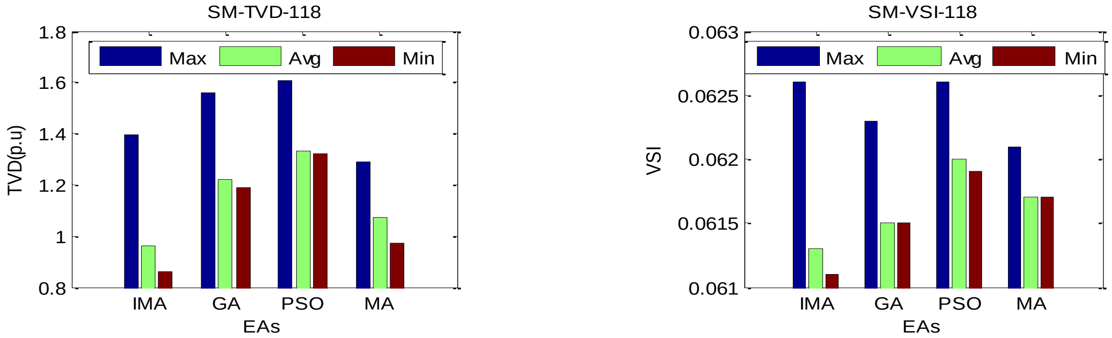
The comparison of optimal solution of objective functions considering various EAs is listed in *Table 9*. Based on comparison, it is clear that the optimal solution is achieved by implementing IMA for all objective functions is better. The worst optimal solution for TFC is 129631.5253 \$/hr with PSO, the TAPL is 76.7381 MW with PSO, TVD is 1.3193 pu with PSO and VSI is 0.0619 with PSO. The worst optimal solution is obtained by implementing PSO for all objective functions. The effectiveness of different EAs with each objective function is acknowledged with the performance metrics that are indexed in *Table 10*. The statistical measures of optimal solution of EAs are pictured in *Figure 7 (a)-(d).*

Table 9 Comparison of objective functions of test system-3

EAs	**TFC**	**TAPL**	**TVD**	**VSI**
IMA	129611.5389	76.5261	0.8632	0.0611
GA	129625.8773	76.7294	1.1864	0.0615
PSO	129631.5253	76.7381	1.3193	0.0619
MA	129619.7429	76.6517	0.9702	0.0617



(a)TFC **(b) TAPL**



(c) TVD **(d) VSI**

Figure 7 Statistical measures of IEEE-118 bus system

Table 10 Comparison of performance metrics of test system-3

OFs	**EAs**	**Max**	**Avg**	**Min**
TFC	IMA	129678.8340	129621.4057	129611.5389
	GA	129696.7749	129629.1012	129625.8773
	PSO	129696.7749	129638.3628	129631.5253
	MA	129696.7749	129682.3364	129619.7429
TAPL	IMA	77.6709	76.8604	76.5261
	GA	77.6344	76.8010	76.7294
	PSO	77.7342	76.8033	76.7381
	MA	77.9835	77.7662	76.6517
TVD	IMA	1.3938	0.9627	0.8632
	GA	1.5574	1.2208	1.1864

OFs	EAs	Max	Avg	Min
	PSO	1.6077	1.3317	1.3193
	MA	1.2897	1.0718	0.9702
VSI	IMA	0.0626	0.0613	0.0611
	GA	0.0623	0.0615	0.0615
	PSO	0.0626	0.0620	0.0619
	MA	0.0621	0.0617	0.0617

5.Discussions

From the simulated results, it is observed that MA has shown better performance than GA and PSO. By implementing simulated binary crossover and polynomial mutation operators in MA, the performance of the MA is once again improved. The crossover probability index is varied from 1 to 10 with step size of 1 and the mutation probability index is varied from 10 to 30 with step size of 2. It is observed that for crossover probability index at 3 and mutation probability index at 18, the obtained value gives the optimal solution of the OPF problem. For larger systems, the results obtained by GA and PSO have shown less effectiveness. The solution obtained through implementation of the IMA has given a better solution for both smaller as well as larger power systems. The performance of the evolutionary algorithms are evaluated and compared through the convergence characteristics as illustrated in *Figures 2*,*Figure 4*,*Figure 6*, the optimal solution as given in *Table 4, Table 7, Table 10* and statistical metrics viz., min (best), avg (mean), max (worst) values of each objective functions are tabulated in *Table 5, Table 7, Table 10.*

The limitation of the meta-heuristic algorithm is that for particular parameters only, the solution obtained by IMA is better than the other algorithms. If the parameters are varied then there is no surety for the best optimal solution. Thus, IMA requires fine tuning of parameters in order to get the best solution for OPF problem.

A complete list of abbreviations is shown in *Appendix I.*

6.Conclusion

In this paper, IMA, GA, PSO and MA are used to identify the solutions for solving the OPF problem by considering different objective functions. The best optimal solution is achieved by implementing IMA for all objective functions of the test systems. The OPF problem is investigated on three different systems. Based on the simulation results, it is observed that the IMA has performed better than GA, PSO, MA. The performance analysis is also carried out in terms of convergence curves, optimal solution and statistic measures. IMA is improved by the replacement of crossover and mutation operator in MA. The operators implemented in IMA are simulated binary crossover and polynomial mutation instead of arithmetic crossover and random distribution mutation in MA. The crossover and mutation operators of GA increase the convergence rate in IMA. The updating of mayflies in the IMA is similar to the updating of particles in PSO, which moves towards to the global optimal point. The random walk of mayflies is similar to that of random movement of fireflies in FA. IMA is a successful, productive optimization tool for solving OPF problems in regulated electrical power system networks.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author’s contribution statement

Vijaya Bhaskar K: Conceptualization, Investigation, Writing-original draft, review and editing. **Ramesh S:** Analysis and Interpretation of results, Supervision, Writing-review. **Chandrasekar P:** Analysis and Interpretation of results, Supervision, Writing-review. **Karunanithi K:** Investigation on challenges and Draft manuscript preparation. **Raja A:** Writing – editing.

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Appendix 1

S. No.	Abbreviation	Description
1	ACDE	Adaptive Constraint Differential Evolution
2	AIS	Artificial Immune System
3	AMTPG-Jaya	Adaptive Multiple Teams Perturbation Guided Jaya Algorithm
4	BAAMOA	Boundary Assigned Animal Migration Optimization Algorithm
5	CFA	Cuttle Fish Algorithm
6	COA	Coyote Optimization Algorithm
7	CS-GWO	Cross Over Grey Wolf Optimizer
8	DBN	Deep Belief Network
9	DE	Differential Evolution
10	ESCA	Enhanced Sine Cosine Algorithm
11	FA	Firefly Algorithm
12	FAHSA-PSOEA	Fuzzy Adaptive Harmony Search Algorithm With Particle Swarm Optimization Differential Evolutionary Algorithm
13	GA	Genetic Algorithm
14	IHOA	Improved Heap Optimization Algorithm
15	IMA	Improved Mayfly Algorithm
16	LAA	Learning Augmented Approach
17	MA	Mayfly Algorithm
18	MACO	Modified Ant Colony Optimization
19	MPIO-COSR	Modified Pigeon Inspired Optimization Through Constraint Objective Sorting Rule
20	MRFO	Manta Ray Foraging Optimization
21	MVPA	Most Valuable Player Algorithm
22	NISSOA	Novel Improved Social Spider Optimization Algorithm
23	NOKHA	Novel Oppositional Krill Herd Algorithm
24	NR	Newton Raphson
25	NSCA	Novel Sine Cosine Algorithm
26	OPF	Optimal Power Flow
27	PSO	Particle Swarm Optimization
28	TAPL	Total Active Power Losses
29	TFC	Total Fuel Cost
30	TSA	Tree Seed Algorithm
31	TVD	Total Voltage Deviation
32	VSI	Voltage Stability Index
33	WEA	Water Evaporation Algorithm