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An optimal power flow solution to deregulated electricity power market using meta-heuristic algorithms considering load congestion environment

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ABSTRACT

In this article, the Improved Mayfly Algorithm (IMA) is used as an upgraded form of the Mayfly Algorithm (MA), featuring simulated binary crossover and polynomial mutation operators replacing the arithmetic crossover and standard distribution mutation operators of the MA. With MA, IMA's achievements and significance are acknowledged. The algorithms achieve a final best solution for the investigated objective functions of the optimal power flow problem in a deregulated electrical power market under different load conditions. The overall load of the power system varies between half of the base load (-50%) and twice the base load (+100%). The investigated objective functions are associated with the financial worth of generators, dissipation of active power in transmission lines, variation of voltage magnitudes at the system bus, and voltage stability index at the load bus of the power system networks. The result achieved by GA, PSO, MA and IMA are attained using the IEEE-30 bus test system in a deregulated power system. Investigations are conducted on the best solutions for each objective function; offers of generators and bids of loads; generator sales and load purchases; and system revenues associated with different load scenarios. The simulated outcomes have confirmed that IMA would triumph over GA, PSO and MA.

1. Introduction

The process of deregulation in the energy power market is being launched to boost the power sector's efficiency and offer competition among the stakeholders (i.e., GENCOs and DISCOs) to reduce the price of electricity. With the advent of deregulation in the electric power market over the last two decades, the framework of the electricity market has transitioned from a vertical model in which greater importance is given to GENCOs, then to TRANSCOs, and finally to DISCOs, to a horizontal model in which equal importance is given to all companies. As a result, these enterprises operate freely in the electricity market [1]. In a deregulated energy market, firms that generate power (GENCOs) are assigned to the generator bus, firms that transfer power (TRANSCOs) are assigned to the transmission lines, and firms that distribute power (DISCOs) to the load bus [2]. By adopting a bidding strategy, suppliers' profits (GENCOs) are maximised while customers' payments (DISCOs) are reduced. GENCOs give the offers, whereas DISCOs provide the bids [3]. Deregulation occurs in underdeveloped nations owing to a lack of financial resources for the growth of the power sector [4]. The pricing structure in the deregulated electrical power market is complicated and multi-layered, with pricing as blocks of providers and customers [5].

Nowadays, the electrical market is deregulated, encouraging competition among various market actors such as GENCOs and DISCOs, resulting in lower power rates. The decisions on selling and purchasing energy are left to the sellers (GENCOs) and customers in a deregulated electricity market (DISCOs). The emphasis of the deregulated energy market is mainly on the problems of offers for power sales and bids for power purchases [6]. Because offers and bids are accessible in blocks, the market clearing price (MCP) plays a vital role in strategic bidding problems. The MCP identifies the functional blocks for the market clearing process. Sellers make offers, and buyers make bids to sell and acquire power. The market operator takes offers and bids from sellers and buyers and grades seller offer concerning buyer bids. When determining the grades, the market operator creates a supply and demand curve for the supplier and buyer. The MCP is defined as the point at which the supply curve created by suppliers and the demand curve

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developed by customers intersect [7]. The Central Electricity Regulatory Commission (CERC), Independent System Operator (ISO), Transmission Utilities (TU), Central Generation Utilities (CGU), Power Pool Controller (PPC), State Electricity Regulatory Commission (SERC), State Utilities (SU), and Regional Load Dispatch Center (RLDC) are the components of India's deregulated electricity power system [8].

Aside from research studies, one of the important tools useful for operation and control of deregulated energy market is optimum power flow (OPF). An OPF's purpose is to compute the state and control variables of every portion of the system at any moment. The values of the system control variables are often set via market decision-making [9]. The pricing mechanism of suppliers and customers in any market is influenced by (a) the number of sellers and buyers in the market; (b) the size and location of the market; (c) bidding and settlement of the market in future markets; (d) available information about the correlated markets; and (e) choice availability and risk management for competitors (suppliers' and customers') [11]. For example, suppliers are compensated for services delivered to clients, while customers are paid for services gained from suppliers through marginal pricing [10].

GENCOs are concerned with effective load distribution and using available generating capacity. TRANASCOs are concerned about low bus voltage magnitude, line congestion, and line losses [12]. There are two sorts of electricity markets. The first is the real-time market, while the second is the day-ahead market. A real-time market is a one-way market in which the competitor buys or sells power for the whole operational day. Prices for that electricity are established based on daily or hourly demand and supply. The day-ahead market is a two-way market in which the competitor buys or sells power ahead of the working day. Electricity prices are established based on daily or hourly demand and availability [13].

In earlier days, the power market was regulated and designed as vertical architecture in which power is transmitted from GENCOs to TRANSCOs and then to DISCOs. The customer has no choice but to purchase the power at their own cost. TRANSCOs must purchase according to the cost fixed by GENCOs, or GENCOs must generate the power at the cost fixed by TRANSCOs. Similarly, DISCOs must buy the power that TRANSCOs fix. The customers have to pay DISCOs at a price fixed by them. With the deregulated system in the power market, the vertical structure is redesigned into horizontal architecture in which GENCOs, TRANSCOs, DISCOs and customers can make their own decisions. In deregulated power market, GENCOS can generate power at different prices and transmit it to different TRANSCOs. TRANSCOs can buy power from different GENCOs at different prices and distribute to different DISCOs at different prices. Finally, the customer has a choice to buy the power from different DISCOs based on their preference. This increases the researchers' interest in working on the deregulated power market. The best solution to the optimal power flow problem in regulated power systems is obtained by setting the optimal values for the objective functions' decision variables and control variables while satisfying the equality and inequality constraints. This helps power engineers in the planning and operation of the power system. The optimal power flow solution in a deregulated power system gives the compromise solution for both GENCOs and DISCOs. GENCOs provide offers for the generating capacities, and DISCOs provide bids. The optimal solution gives the compromise solution between the GENCOs sales and DISCOs purchase. For better optimal solutions, meta-heuristic algorithms are implemented.

In the literature, several meta-heuristic algorithms have been designed to solve complex, undefined problems in different applications. Each of these algorithms has unique advantages in dealing with the specific nature of the problem. An algorithm's performance is evaluated by its explorative and exploitative capabilities and the intrinsic characteristics of the sample data used. Modified algorithms attempt to merge two or more meta-heuristics so that another can address the deficiencies of one method. For example, an algorithm with good investigation ability can be combined with one with good enslavement ability to achieve a good trade-off between the overall system's explorative and exploitative capabilities. Presently, this would be an aggressive field of research. According to the No Free Lunch (NFL) theorem, the performance of any solution method would be the same if averaged across all problems in the category. This indicates that new algorithms may lead to different outcomes for a given problem, but on the whole, they are equivalent. This has urged researchers to focus on early research and adopt novel problem-specific strategies for enhanced performance. The authors propose a hybrid algorithm, the Improved Mayfly Algorithm (MA), based on GA, PSO, and FA and simulated binary crossover and polynomial mutation operators to solve the OPF problem in this paper. MA is a recently proposed metaheuristic that has been demonstrated to be effective in dealing with real-world problems. Despite being similar to PSO, MA appears to have a more remarkable ability than PSO to find a more optimal solution and thus has a better chance of finding the globally optimal solution. However, in some cases, premature convergence degrades the final solution's effectiveness. As previously stated, an algorithm with high exploitation ability can be combined with another algorithm with high exploration ability. The PSO algorithm effectively explores the search space, whereas the FA algorithm exploits and improves existing relevant features. The relevant features highlight that we should use MA to solve the OPF problem. When the simulated binary crossover and polynomial mutation operators are combined in the MA, the IMA algorithm can find a better solution. As a result, IMA can result in higher search space exploitation and overall performance enhancement. The advantages of IMA are the convergence rate and convergence speed to obtain the best solution. The parameters of IMA, nuptial dance nonstop and random flight co-efficient enhance the balance between exploration and exploitation and assist in escaping from local optima.

The work's contribution has been as described in the following:

- For the first time, the OPF problem is solved under deregulated environment considering different load levels.
- In a deregulated electricity market, fuel cost, active power losses, voltage deviation, and voltage stability are being used as objective functions to solve the OPF problem.
- This paper considers Improved Mayfly Algorithm (IMA) that incorporates simulated binary crossover and polynomial mutation into the original Mayfly Algorithm (MA) for solving the problem
- The proposed IMA's performance is analysed for different mathematical test functions having unimodal, multimodal, fixed-dimension test functions and is compared with GA, PSO and MA
- The comparison of optimum solutions obtained from IEEE-30 bus system are reported to assess the performance of evolutionary algorithms via., GA, PSO, MA and IMA.
- The performance of IMA is evaluated under a diversity of load scenarios.
- The generator offers and load bids, as well as system revenues gained by applying the IMA, are presented.

The following is the structure of this paper: Section II formulates the optimal power flow problem in a deregulated electricity market with objective functions such as total fuel cost, total active power losses, total voltage deviation, and total voltage stability index while taking equality and inequality constraints into account, followed by Section I. Section III describes the framework of the Improved Mayfly Algorithm, and Section IV reports the validation and comparison results of IMA with GA, PSO and MA with +100% overload and −50% under load. This section also includes the generator sales and load purchases at +100% base load, at base load, and −50% base load, as well as the system revenues utilizing IMA. Finally, section V brings this study to a close with conclusions and future initiatives.

2. OPF problem formulation

The OPF problem [14] can be arithmetically represented as f (x,u) exposed to

$$e\ (x,u) = 0 \tag{1}$$

$$ie\ (x,u) \leq 0 \tag{2}$$

f: The value of the objective function to be reduced or raised, i.e., total fuel cost (TFC), total active power loss (TAPL), total voltage deviation (TVD), voltage stability index (VSI); e: A set with equality constraints; ie: A set with inequality constraints x: The vector contains state variables,

$$x = \left[P_S, V^T_{L_n}, Q^T_{G_n}, S^T_{TL_n}\right] \tag{3}$$

P_S: Active power of node located at the slack bus;

$V^T_{L_n}$: Voltage magnitude of n^{th} node located at load bus;

$Q^T_{G_n}$: Reactive power of n^{th} node located at generator bus;

$S^T_{TL_n}$: Apparent power of n^{th} node of transmission lines; u: The vector contains control variables,

$$u = \left[P^T_{G_n}, V^T_{G_n}, Q^T_{C_n}, T^T_{T_n}\right] \tag{4}$$

$P^T_{G_n}$: Active power of n^{th} node located at generator bus;

$V^T_{G_n}$: Voltage magnitude of n^{th} node located at generator bus;

$Q^T_{C_n}$: Reactive power of n^{th} node placed with VAR compensator;

$T^T_{T_n}$: Tap setting ratio of n^{th} transformer

The objective functions considered for the OPF problem are TFC, TAPL, TVD and VSI [15]. The mathematical expressions for analysing the objective functions are given below.

Total Fuel Cost (TFC) is the cost of all the generators committed to generating power. The minimum TFC indicates the lowest generation cost.

$$\begin{aligned} &TFC : F1 = TFC_G - TFC_{DL} \\ &TFC_G = \sum_{k=1}^{N_G} P^{coQ}_{G\ k} * P^{coP}_{G\ k} \\ &TFC_{DL} = \sum_{k=1}^{N_{DL}} P^{cbQ}_{DL\ k} * P^{cbP}_{DL\ k} \end{aligned} \tag{5}$$

$P^{coQ}_{G\ k}$: Cleared offer quantity of k^{th} node of generator bus;

$P^{coP}_{G\ k}$: Cleared offer price of the k^{th} node of generator bus;

$P^{cbQ}_{DL\ k}$: Cleared bid quantity of k^{th} node of dispatched load;

$P^{cbP}_{DL\ k}$: Cleared bid price of the k^{th} node of dispatched load;

N_G: Total number of generator bus;

N_{DL}: Total number of dispatched loads;

Total Active Power Losses (TAPL) is the sum of real power losses at the transmission lines. The minimum TAPL indicates the maximum power transfer capability of the lines.

$$\text{TAPL}: \ F2 = \sum_{k=1}^{N_{TL}} \sum_{j=1}^{N_{TL}} G_{jk}\left(V_j^2 + V_k^2 - 2V_jV_k\cos\delta_{jk}\right) \tag{6}$$

G_{jk}: Conductance between k^{th} and j^{th} node of the transmission line;

V_j: Voltage magnitude of j^{th} node at transmission line;

V_k: Voltage magnitude of k^{th} node at transmission line;

δ_{jk}: Voltage phase between the k^{th} and j^{th} node of the transmission line;

N_{TL}: Total number of transmission lines of the system;

Total Voltage Deviation (TVD) is the deviation of the system from the ideal condition. The minimum TVD indicates the system operation in ideal condition.

$$\mathbf{TVD} : \mathbf{F}3 = \sum_{\mathbf{k}=1}^{\mathbf{N_L}} |(\mathbf{V_{L\ k}} - 1)| \tag{8}$$

$V_{L\ k}$: Voltage magnitude of k^{th} node at load bus;

N_L: Total number of load bus;

Voltage Stability Index (VSI) is the ability of the system to withstand away from collapse. The minimum VSI indicates that the system is far away from voltage collapse.

$$\mathbf{VSI} : \mathbf{F4} = \min(\max(\mathbf{L_n})); \mathbf{n} = 1, 2, ..., \mathbf{N_L} \tag{9}$$

$$\mathbf{L\ index},\ \mathbf{L_n} = \left|1 - \sum_{\mathbf{k}=1}^{\mathbf{N_G}} \mathbf{H_{jk}} \frac{\mathbf{V_j}}{\mathbf{V_k}}\right| \ \mathbf{j} = 1, 2, \ldots,\ \mathbf{N_L} \tag{10}$$

H_{jk}: Partial inversion matrix of Y_{BUS} between j^{th} node at load bus and k^{th} node at generator bus

The solution to the OPF problem is generally agreed upon with the confirmation of the constraint. The restrictions shackled to the OPF problem are equality and inequality constraints. Equality constraints are confined to nullifying the active power in the power system (smart grid) [16], and inequality constraints are confined to the limits of active power and voltage magnitude at generator bus, transformer's tap percentage and VAR values of shunt compensators.

The equality constraint is given by below Eq. (11)

$$\sum_{\mathbf{K}=1}^{\mathbf{N_B}} \mathbf{P_{G\ k}} - \mathbf{P_{L\ k}} - |\mathbf{V_k}| \sum_{\mathbf{j}=1}^{\mathbf{N_B}} |\mathbf{V_j}| \left(\mathbf{G_{kj}}\mathbf{cos}\delta_{\mathbf{kj}} + \mathbf{B_{kj}}\mathbf{sin}\delta_{\mathbf{kj}}\right) = 0 \tag{11}$$

$P_{G\ k}$: Active power of k^{th} node at generator bus;

$P_{L\ k}$: Active power of k^{th} node at load bus;

V_k: Voltage magnitude of k^{th} node at the bus;

V_j: Voltage magnitude of j^{th} node at the bus;

G_{jk}: Conductance between the k^{th} and j^{th} node at the bus;

B_{jk}: Suspectance between the k^{th} and j^{th} node at the bus;

δ_{jk}: Voltage phase between the k^{th} and j^{th} node of the bus;

N_B: Total number of the bus;

The inequality constraints are given by below Eqs. (12) – (15)

$$\mathbf{Real\ power}, \mathbf{P^{LP}_{G\ k}} \leq \ \mathbf{P_{G\ k}} \leq \ \mathbf{P^{HP}_{G\ k}};\ \mathbf{k} \in \ \mathbf{N_G} \tag{12}$$

$$\mathbf{Voltage\ magnitude}, \mathbf{V^{LP}_{G\ k}} \leq \ \mathbf{V_{G\ k}} \leq \ \mathbf{V^{HP}_{G\ k}};\ \mathbf{k} \in \mathbf{N_G} \tag{13}$$

$$\mathbf{Transformer\ ratio}, \mathbf{T^{LP}_k} \leq \mathbf{T_k} \leq \mathbf{T^{HP}_k};\ \mathbf{k} \in \mathbf{N_T} \tag{14}$$

$$\mathbf{VAR\ compensator}, \mathbf{Q^{LP}_{C\ k}} \leq \mathbf{Q_{C\ k}} \leq \mathbf{Q^{HP}_{C\ k}};\ \mathbf{k} \in \mathbf{N_C} \tag{15}$$

LP: Lowest position;

HP: Highest position;

$V_{G\ k}$: Voltage magnitude of k^{th} node located at generator bus;

$\mathbf{T_k}$: Tap ratio of the k^{th} transformer;

$\mathbf{Q_{C\ k}}$: VAR value of k^{th} shunt compensator;

N_C: Total number of shunt compensators;

3. Improved mayfly algorithm

The Mayfly Algorithm (MA) is a perspective of Konstantinos Zervoudakis in 2020 that seems to be motivated by mayfly community behavior [17]. The term was adopted because mayflies appear solely during May in the British Empire. MA is enhanced as a composite design using a combination of PSO, FA, and GA [18]. GA is a population-based evolution design founded on social theories drawn from Darwin's theory, which was introduced by Holland in 1960 and further examined by Goldberg in 1989. GA is used to attain the objective of complex challenges. GA responses are produced in the form of chromosomes. Genetic operators such as crossover and mutation are used to renovate the chromosomes. The best alternative result is obtained by replacing the worst result through the phases of selection and recombination. PSO is also a population-based swarm intelligence approach developed by Kennedy and Ebelhart in 1995 to deal with recurring optimization problems based on the swarm behavior of fishes or birds of prey. The location of the particles in the swarm represents the result obtained by PSO during the search period. The present location of the particles is renewed using a simple mathematical method of increasing with particle position change [19]. The particle's velocity is determined by its previous local and global positions. In addition to GA and PSO, FA is a population-based swarm intelligence process based on the behavior of fireflies, proposed by Xin She Yang in 2008 to resolve two simultaneous and different combinatorial undefined problems. The intensity divergence of light decides the effectiveness of FA. Each firefly is represented by light intensity, which is a fitness rating. The firefly that is accompanied by lower intensity is lured to high intensity. The fireflies that accompany the same light intensity fluctuate in any direction. High-quality findings are achieved by keeping the current location, attraction coefficient, and random constant updated with the latest [20].

The suggested IMA is a nature-inspired algorithm that combines the benefits of the evolutionary algorithm (GA), the swarm intelligence algorithm (PSO), and the population-based algorithm (FA). The critical phases of IMA are (i) initialisation, (ii) male mayfly updating, (iii) female mayfly updating, and (iv) male mayfly mating with female mayflies.

Initialise the positions and velocities of mayflies as given in Eqs. (16) – (19)

$$x_i^{mmf} = \left[x_1^{mmf}, x_2^{mmf}, x_3^{mmf}, \ldots\ldots, x_n^{mmf}\right] \tag{16}$$

$$v_i^{mmf} = \left[v_1^{mmf}, v_2^{mmf}, v_3^{mmf}, \ldots\ldots, v_n^{mmf}\right] \tag{17}$$

$$x_i^{fmf} = \left[x_1^{fmf}, x_2^{fmf}, x_3^{fmf}, \ldots\ldots, x_n^{fmf}\right] \tag{18}$$

$$v_i^{fmf} = \left[v_1^{fmf}, v_2^{fmf}, v_3^{fmf}, \ldots\ldots, v_n^{fmf}\right] \tag{19}$$

x_i^{mmf}: Positions of ith male mayfly, $i = 1, 2, 3\ldots n$;x_i^{fmf}: Positions of ith female mayfly, $i = 1, 2, 3\ldots n$;v_i^{mmf}: Velocities (change of positions) of ith male mayfly, $i = 1, 2, 3\ldots n$;v_i^{fmf}: Velocities of ith female mayfly, $i = 1, 2, 3\ldots n$;

The updated velocity of the male mayfly is given by Eqs. (20) & (21)

$$ff\left(x_{ij}^{mmf}(t)\right) \geq best\left(p_{ij}^{mf}\right), v_{ij}^{mmf}(t+1) = g * v_{ij}^{mmf}(t) + a_1 e^{-\beta r_p^2}\left(p_{ij}^{best} - x_{ij}^{mmf}(t)\right) + a_2 e^{-\beta r_g^2}\left(g_j^{best} - x_{ij}^{mmf}(t)\right) \tag{20}$$

otherwise

$$v_{ij}^{mmf}(t+1) = v_{ij}^{mmf}(t) + d * r \tag{21}$$

$v_{ij}^{mmf}(t+1)$: ith male mayfly velocity in jth dimension during $(t+1)^{th}$ iteration;

$v_{ij}^{mmf}(t)$: ith male mayfly velocity in jth dimension during tth iteration;

$x_{ij}^{mmf}(t+1)$: ith male mayfly position in jth dimension during $(t+1)^{th}$ iteration;

$x_{ij}^{mmf}(t)$: ith male mayfly position in jth dimension during tth iteration;

p_{ij}^{best}: The individual best position during $(t+1)^{th}$ iteration;

g_j^{best}: The global best position during tth iteration;

r_p: Cartesian distance between individual and personal best;

r_g: Cartesian distance between individual and global best; g: The gravitational coefficient; a_1 and a_2: The positive attractive co-efficient;

β: The fixed visible co-efficient;

d: The nuptial co-efficient;

r: The random number

The personal best solution of male mayfly is given in Eq. (22)

$$p_{ij}^{best} = \begin{cases} x_{ij}^{mmf}(t+1), & iff\left(x_{ij}^{mmf}(t+1)\right) \leq f\left(p_{ij}^{best}\right) \\ x_{ij}^{mmf}(t), & otherwise \end{cases} \tag{22}$$

The global best position is given by Eq. (23)

$$g_j^{best} = \min\left\{f\left(p_1^{best}\right), f\left(p_2^{best}\right), \ldots\ldots, f\left(p_j^{best}\right)\right\} \tag{23}$$

The updated velocity of the female mayfly is given by Eqs. (24) & (25)

$$iff\left(x_{ij}^{fmf}(t)\right) \geq f\left(x_{ij}^{mmf}(t)\right) v_{ij}^{fmf}(t+1) = g * v_{ij}^{fmf}(t) + a_2 e^{-\beta r_{mfmf}^2}\left(x_{ij}^{mmf}(t) - x_{ij}^{fmf}(t)\right) \tag{24}$$

otherwise

$$v_{ij}^{fmf}(t+1) = g * v_{ij}^{fmf}(t) + fl * r \tag{25}$$

$v_{ij}^{fmf}(t+1)$: ith female mayfly velocity in jth dimension during $(t+1)^{th}$ iteration;

$v_{ij}^{fmf}(t)$: ith female mayfly velocity in jth dimension during tth iteration;

$x_{ij}^{fmf}(t+1)$: ith female mayfly position in jth dimension during $(t+1)^{th}$ iteration;

$x_{ij}^{fmf}(t)$: ith female mayfly position in jth dimension during tth iteration;

p_{ij}^{best}: The individual best position during $(t+1)^{th}$ iteration;

r_{mfmf}: Cartesian space between the male and female mayflies; fl: Random walk co-efficient.

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

The simulated binary crossover [21] is implemented using Eq. (26) & (27)

$$mf_{new}^1 = 0.5\left[(1+\varepsilon) * v_{ij}^{mmf}(t) + (1-\varepsilon) * v_{ij}^{fmf}(t)\right] \tag{26}$$

$$mf_{new}^2 = 0.5\left[(1-\varepsilon) * v_{ij}^{fmf}(t) + (1+\varepsilon) * v_{ij}^{mmf}(t)\right] \tag{27}$$

$$\varepsilon = \begin{cases} 2r^d & if\ r \leq 0.5 \\ \left[\dfrac{1}{2(1-r)}\right]^d & if\ r > 0.5 \end{cases} \tag{28}$$

$$d = \frac{1}{(d_i + 1)} \tag{29}$$

The polynomial mutation [22] is implemented through Eq. (30)

$$mf_{new}(t+1) = mf_{new}(t) + \left\{mf_{new}^{max}(t) - mf_{new}^{min}(t)\right\}\sigma_m \tag{30}$$

$$\sigma_m = \begin{cases} 2r^{\frac{1}{m_i-1}} - 1 & ifr \leq 0.5 \\ 1 - 2(1-r)^{\frac{1}{m_i+1}} & ifr > 0.5 \end{cases} \tag{31}$$

m_i: The mutation index; d_i: The crossover index;

The IMA approach is most likely as follows:

Begin

Fix the positions and velocities of male mayflies at random.

Fix the positions and velocities of female mayflies at random.

Create the objective functions and measure the fitness value of each function.

Calculate the desired results using the selected mayflies.

While the finish condition is unsatisfactory,

Mayfly velocities should be increased.

Determine the fitness values of mayflies.

Consider the new outcome of those mayflies.

Sort the mayflies into groups.

Take advantage of crossover and mutation.

Table 1
The best solution for TFC and TAPL using different algorithms.

S.No	% Load	TFC ($/Hr)				TAPL (MW)			
		GA	PSO	MA	IMA	GA	PSO	MA	IMA
1	−50%	2973.9837	2972.6730	2970.9240	2968.4399	3.7348	3.6343	3.5971	3.3249
2	−40%	2976.8924	2975.6243	2973.1514	2969.9544	3.6564	3.5647	3.5303	3.3552
3	−30%	2979.0065	2977.8958	2975.7442	2971.8575	3.5824	3.4976	3.4701	3.3933
4	−20%	2981.6380	2979.4729	2978.7079	2974.0869	3.5135	3.4625	3.4191	2.2838
5	−10%	2984.9972	2983.7828	2982.0515	2976.6866	3.5267	3.4138	3.3746	2.2150
6	BL	2989.0348	2987.7254	2985.7816	2979.8076	3.7189	3.6939	3.6717	2.2653
7	+10%	2992.1276	2990.9735	2989.9058	2985.7408	3.8201	3.7947	3.7542	2.3221
8	+20%	2997.6429	2996.9365	2994.4324	2986.7876	3.9536	3.8962	3.8448	2.3936
9	+30%	3052.6492	3049.7846	3036.2447	2990.9480	2.9137	2.7030	2.6269	2.4692
10	+40%	3008.7153	3006.5927	3004.7283	2995.6013	4.1965	4.1249	4.0507	2.5579
11	+50%	3018.4839	3014.7829	3010.5153	3000.5081	4.2838	4.2521	4.1664	2.6584
12	+60%	3035.6926	3019.7924	3016.7402	3005.9261	4.4149	4.3527	4.2909	2.7639
13	+70%	3048.7290	3029.4519	3023.6829	3011.7815	4.5347	4.4648	4.4175	2.8864
14	+80%	3063.6493	3038.8391	3032.4084	3018.0857	4.9251	4.6854	4.5629	3.0097
15	+90%	3120.6830	3109.7382	3103.7230	3025.4211	5.1879	5.1276	5.0582	3.2251
16	+100%	3398.6429	3338.5693	3319.8683	3142.9432	5.7834	5.2325	5.1603	3.3755

Calculate the fitness of the offspring.
Divide the mayflies in whatever way.
Replace the worst mayflies with the greatest mayflies.
Improve the pbest and gbest
Finish while.
Find the best solution.
Quit

The following explains the IMA implementation procedure [23]: Initially, mayfly positions and velocities are to be indicated within the boundaries of the lower and higher values. Each mayfly's goal function value is to be calculated. Next, examine the mayfly's fitness value and the halting point. If the stopping criterion is not reached, bring the mayfly velocities, male and female, up to date at another time. Next, determine the fitness of current mayflies and sort the mayflies based on fitness value, from highest to lowest fitness value. Separate the mayflies into male and female mayflies after sorting. Perform the simulated binary crossover and polynomial mutation to improve the fitness value of mayflies. Replace the worst mayfly with the best mayfly to bring individual and global best fitness function values up to date. This procedure is repeated until meeting the stopping criteria to get the best possible outcome.

To test the effectiveness of IMA, various test functions viz., unimodal, multimodal and fixed-dimension test functions that are reported in [23] are considered. The best objective function values of various test functions along with its convergence characteristics with respect to IMA, MA, PSO and GA are reported in Appendix A. Based on the results, it is noted that the performance of IMA is better than MA, PSO and GA in terms of convergence to the optimum value and speed of convergence for solving mathematical test functions.

4. Results and discussions

The significance of GA, PSO, MA and the proposed IMA, is tested using MATPOWER [15] in MATLAB on a standard test system, specifically, an IEEE-30 bus system in a deregulated power market with distinct load settings. The test system combines 30 buses, 41 branches, six fully committed generators, and 20 loads, 17 of which are fixed and 3 of which are dispatched. Two shunt compensators are installed between the transmission lines. The system's maximum generating capacity is 360 MW, although the actual operational generation is 215.3 MW. The average fixed load is 151.6 MW. The dispatched loads ranged from 60 MW to 90 MW. Each transmission line has a total power transfer capacity of 33.1 MW. 3.67 MW is the total active power loss. The solution to the OPF problem for the test system in a deregulated environment is simulated using 14 control variables. The load is changed between 50% of the base load (−50%) and 200% of the base load (+100%).

During the simulation, the following algorithm parameters are considered: For GA, maximum number of iterations is set as 200; the number of population is 40; crossover and mutation probabilities are 0.7 and 0.3 and the mutation rate is 0.1. For PSO, maximum number of iterations is set as 200; the number of particles is chosen as 40; inertia weight is 1 and damping ratio 0.9, personal and global learning coefficients are 1.5 and 2 respectively. For MA, For GA, maximum number of iterations is set as 200; the number of mayflies is 40; inertia weight is

Table 2
The best solution for TVD and VSI using different algorithms.

S.No	% Load	TVD (p.u)				VSI			
		GA	PSO	MA	IMA	GA	PSO	MA	IMA
1	−50%	0.6968	0.6814	0.6773	0.6650	0.0918	0.0809	0.0751	0.0750
2	−40%	0.6805	0.6708	0.6656	0.6497	0.0967	0.0855	0.0770	0.0769
3	−30%	0.6817	0.6711	0.6609	0.6361	0.0994	0.0889	0.0793	0.0791
4	−20%	0.6826	0.6723	0.6612	0.6379	0.1037	0.0928	0.0817	0.0802
5	−10%	0.6839	0.6734	0.6615	0.6197	0.1069	0.0969	0.0844	0.0827
6	BL	0.6847	0.6758	0.6618	0.6124	0.1085	0.0995	0.0874	0.0855
7	+10%	0.6850	0.6769	0.6622	0.6288	0.1138	0.1037	0.0905	0.0884
8	+20%	0.6889	0.6778	0.6627	0.6033	0.1164	0.1059	0.0939	0.0917
9	+30%	0.6907	0.6815	0.6704	0.6037	0.1196	0.1087	0.0960	0.0954
10	+40%	0.6917	0.6828	0.6706	0.6093	0.1236	0.1127	0.1013	0.0994
11	+50%	0.6959	0.6858	0.6771	0.6013	0.1269	0.1158	0.1053	0.1037
12	+60%	0.7086	0.6909	0.6838	0.6223	0.1297	0.1197	0.1095	0.1081
13	+70%	0.7156	0.7008	0.6910	0.6044	0.1326	0.1252	0.1139	0.1128
14	+80%	0.7197	0.7018	0.6978	0.6096	0.1367	0.1280	0.1179	0.1176
15	+90%	0.7455	0.7321	0.7236	0.6483	0.1398	0.1359	0.1220	0.1220
16	+100%	0.7507	0.7458	0.7206	0.6631	0.1407	0.1386	0.1261	0.1261

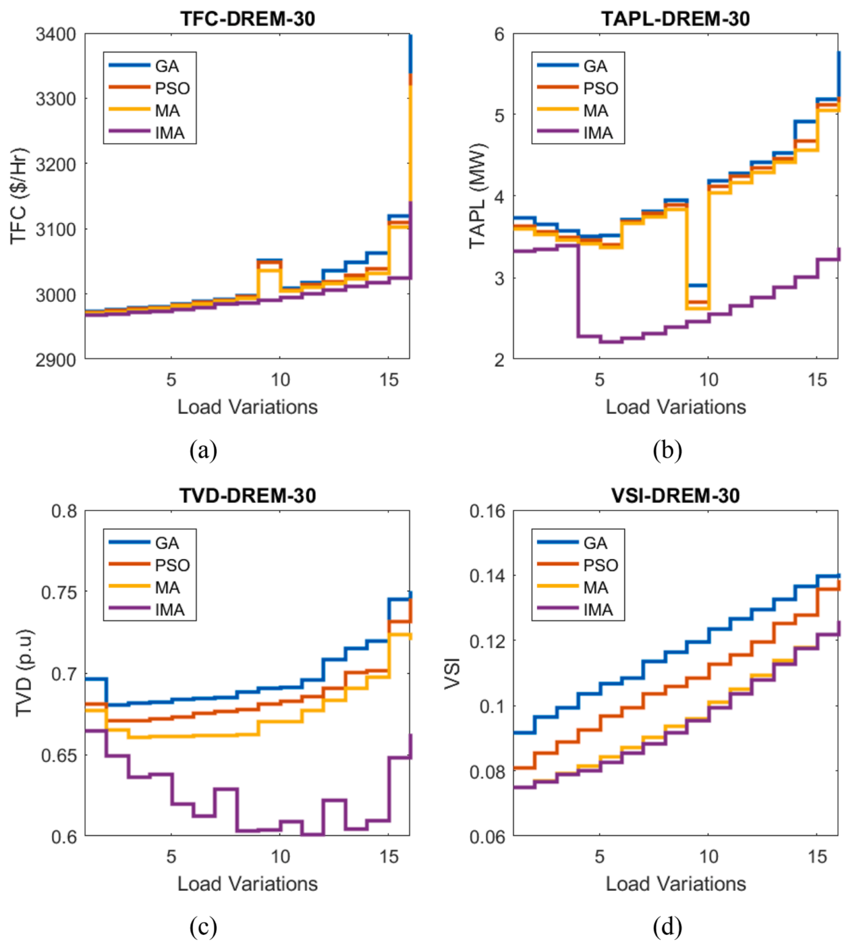

Fig. 1. Comparison of objective function's optimal solutions with MA and IMA, (a) TFC (b) TAPL, (c) TVD, (d) VSI.

0.8 and damping ratio 1, personal and global learning coefficients are 1 and 1.5 respectively; nuptial dance value is set to be 5; random flight value is fixed as 1 and the mutation rate is 0.01. For IMA, maximum number of iterations is considered as 200; the number of mayflies is 40; the crossover and mutation indices are chosen as 0.3 and 0.18. All other remaining parameters are set similar to MA.

In deregulated electrical power markets, suppliers' offers to sell power and consumers' bids to purchase power are designed based on blocks. OPF can compute the necessary allocations and pricing [24]. The following steps are taken into account in deregulated power markets: (i) The blocks containing offers and bids are translated to the associated generator capacities and costs; (ii) OPF is used to determine generator allocations and prices; and (iii) generator allocations and nodal prices are converted to a set of cleared offers and bids. The capacity and proposals for three blocks of six generators are gathered from [15].

The first block of all generators is assigned a capacity of 12 MW for $20/MWh, while the subsequent two blocks are allotted capacities of 24 MW each at various rates. [15] is used to tabulate the three blocks of dispatched load capacity and bids. Each load block is assigned a capacity of 10 MW, with the first block costing $100/MWh and the following blocks costing various amounts.

Tables 1 and 2 shows the best solution for each objective functions, TFC, TAPL, TVD, and VSI using GA, PSO, MA and IMA. From Table 1, the ideal solution for the objective function, TFC with GA, PSO, MA and IMA are 2973.9837 $/hr, 2972.6730 $/hr, 2970.9240 $/hr and 2968.4399 $/hr at −50% load. At base load condition, the best solutions are 2989.0348 $/hr, 2987.7254 $/hr, 2985.7816 $/hr and 2979 $/hr are achieved respectively with GA, PSO, MA and IMA. The ideal solution for the objective function, TFC with +100% load by using GA, PSO, MA and IMA are 3398.6429 $/hr, 3338.5693 $/hr, 3319.8683 $/hr and 3142.9432 $/hr. From Table 1, the ideal solution for the objective function, TAPL with GA, PSO, MA and IMA are 3.7348 MW, 3.6364 MW, 3.5971 MW and 3.3249 MW at −50% load. At base load condition, the best solutions are 3.7189 MW, 3.6939 MW, 3.6717 MW and 2.2150 MW are achieved respectively with GA, PSO, MA and IMA. The ideal solution for the objective function, TAPL with +100% load by using GA, PSO, MA and IMA are 5.7834 MW, 5.2325 MW, 5.1603 MW and 3.3755 MW.

From Table 2, the ideal solution for the objective function, TVD with GA, PSO, MA and IMA are 0.6968 p.u, 0.6814 p.u, 0.6773 p.u and 0.6650 p.u at −50% load. At base load condition, the best solutions are 0.6847 p.u, 0.6758 p.u, 0.6618 p.u and 0.6124 p.u are achieved respectively with GA, PSO, MA and IMA. The ideal solution for the objective function, TVD with +100% load by using GA, PSO, MA and IMA are 0.7507 p.u, 0.7458 p.u, 0.7208 p.u and 0.6631 p.u. From Table 2, the ideal solution for the objective function, VSI with GA, PSO, MA and IMA are 0.0918, 0.0809, 0.0751 and 0.0751 at −50% load. At base load condition, the best solutions are 0.1085, 0.0995, 0.0874 and 0.0855 are achieved respectively with GA, PSO, MA and IMA. The ideal solution for the objective function, VSI with +100% load by using GA, PSO, MA and IMA are 0.1407, 0.1386, 0.1261 and 0.1261. The solution attained by IMA is the best optimal solution than the solution accomplished by GA, PSO and MA for all objective functions.

Fig. 1 compares optimum solutions for objective functions, TFC, TAPL, TVD, and VSI using GA, PSO, MA and IMA. According to Fig. 1(a), the best solution for objective function TFC with GA, PSO, MA and IMA are ascendant, with load variation ranging from −50% to +100% of the base load. The best solution lowers for the following rise in load and then increases for the next increase in load. According to Fig. 1(b), the

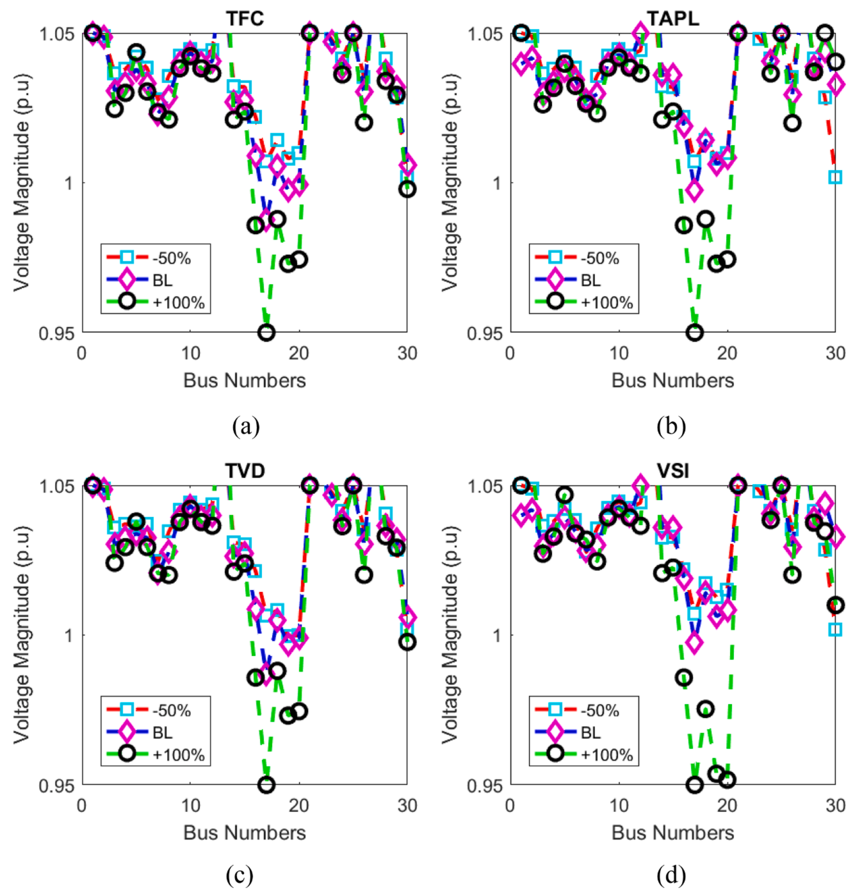

Fig. 2. Comparison of voltage magnitude for different objective function with load variation of −50%, BL and +100% using IMA, (a) TFC, (b) TAPL, (c) TVD, (d) VSI.

Table 3
Generator sales at −50% load using IMA.

OF	TFC		TAPL		TVD		VSI	
G	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)
G1	34.9995	46.8916	34.9995	46.8916	34.9995	46.8212	34.9995	46.9227
G2	36	47.1120	36	47.1120	36	47.0409	36	47.1431
G3	36	49.0947	36	49.0947	36	49.0702	36	49.1108
G4	36	47.0936	36	47.0936	36	47.0330	36	47.1221
G5	36	48.5289	36	48.5289	36	48.4870	36	48.5504
G6	36	47.7455	36	47.7455	36	47.6810	36	47.7749

optimal solution for the objective function TAPL with GA, PSO, MA and IMA are in the descendant direction with a load variation of 50% of the base load and the ascending direction with a load variation ranging from −50% to 100% of the base load. The ideal solution for the next rise in load increases for the following increase in load. According to Fig. 1(c), the ideal solution for objective function TVD with GA, PSO, MA and IMA are inconsistent, accompanied by load variation ranging from −50% to +100% of the base load. According to Fig. 1(d), the ideal solution for objective function VSI with GA, PSO, MA and IMA are ascendant, with load variation ranging from −50 to +100% of the base load.

Fig. 2 depicts the voltage magnitudes at various bus points for objective functions TFC, TAPL, TVD, and VSI using IMA with load variations of −50% of base load and +100% of base load. According to the figure, the voltage magnitudes for all objective functions with specified load fluctuation are violated at bus points 13, 22, and 27.

Table 3 summarises the sales of generators with IMA at −50% load

Table 4
Load purchases at −50% load using IMA.

OF	TFC		TAPL		TVD		VSI	
Load	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)
L1	30	48.3180	30	48.3180	30	48.2538	30	48.3496
L2	10.0307	49.9217	10.0307	49.9218	10.0118	49.8947	10.0279	49.9377
L3	20	51.7587	20	51.7587	20	51.6886	20	51.7905

Table 5
Generator sales at base load using IMA.

OF	TFC		TAPL		TVD		VSI	
G	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)
G1	35.1962	50.0000	0	59.2127	35.20948	49.9999	0	59.2186
G2	36	50.2390	36	59.0142	36	50.2387	36	59.0207
G3	36	52.8224	36	60.0000	36	52.8419	36	60.0000
G4	36	50.3054	36	58.5886	36	50.3106	36	58.5968
G5	36	52.0631	36	59.6618	36	52.0757	36	59.6653
G6	36	50.9993	50.5942	58.6529	36	51.0028	50.7938	58.6610

Table 6
Load purchases at base load using IMA.

OF	TFC		TAPL		TVD		VSI	
Load	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)
L1	30	51.5486	20.685	59.8509	30	51.5548	20.8839	59.8610
L2	10	53.6710	10	61.1354	10	53.6894	10	61.1368
L3	20	55.2538	10.0001	61.0559	20	55.2573	10.0001	61.0647

Table 7
Generator sales at +100% load using IMA.

OF	TFC		TAPL		TVD		VSI	
G	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)	Quantity Sold (MW)	Selling Price ($/MWh)
G1	34.9995	47.4057	0	58.8094	34.9995	47.3877	0	60.2409
G2	36	48.4676	36	58.6533	36	48.4702	36	63.0602
G3	34.3330	60.0000	36	60.0000	33.8235	60.0000	35.7656	61.0537
G4	35.9999	42.0000	36	57.7859	35.9999	42.0000	36	42.0001
G5	36	57.9984	36	59.7611	36	57.7855	36	57.4134
G6	43.6416	44.9478	53.5983	58.0097	44.1762	44.9445	60.0004	49.2307

with all objective functions. The capacity of generator G1 is 34.9995 MW. The quantity sold by generators G2 to G6 is the same for all objective functions, and it is 36 MW at different selling prices.

Table 4 summarises the purchasing of loads using IMA at −50% of the load with different objective functions. The quantity purchased by loads L1 and L3 is the same for all objective functions, and it is 30 MW and 20 MW for different purchase prices. The quantity purchased by load L2 is approximately 10 MW.

Table 5 summarises the sales of generators with IMA at base load with various objective functions. The quantity sold by generators G2 to G5 is the same for all objective functions, and it is 36 MW at different selling prices. Generator G1 sold 35.1962 MW and 35.2095 MW for objective functions TFC and TVD at 50 $/MWh.G6 sold 50.59419 MW and 50.79383 MW for objective functions TAPL and VSI at 58.6529 $/MWh and 58.6610 $/MWh, respectively. The generator G1 cannot serve the objective functions of TAPL and VSI.

Table 6 summarises the purchasing of loads using IMA at base load with different objective functions. For example, the quantity purchased by load L2 is the same for all objective functions, and it is 10 MW at various buying costs. However, for objective functions, TFC and TVD are 30 MW and 20 MW at various purchase rates.

Generators offer quantities at varied selling prices for distinct objective functions. Table 7 summarises the sales of generators with IMA at +100% of the base load with different objective functions. For TFC, generators G3 and G6 sold 34.3330 MW and 43.6416 MW for 60 $/MWh and 44.9478 $/MWh, respectively. The amounts sold by generators G3 and G6 to the objective function TAPL are 36 MW and 53.5893 MW at 60 $/MWh and 58.0097 $/MWh, respectively. G3 and G6 generators sold 33.8235 MW and 44.1762 MW for 60 $/MWh and 44.9445 $/MWh, respectively, for TVD. The quantity sold by generators G2 and G6 is 36 MW and 60 MW to the objective function VSI at 63.0602 $/MWh and 49.2307 $/MWh, respectively. As a result, the generator sells a maximum quantity at a minimum price and a minimum quantity at a maximum price.

Table 8 summarises the purchasing of loads using IMA at base load with different objective functions. As a result, the loads buy a minimum quantity at a maximum price and a maximum quantity at a minimum price. For example, load L2 purchased a minimum quantity of 10 MW,

Table 8
Load purchases at +100% load using IMA.

OF	TFC		TAPL		TVD		VSI	
Load	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)	Quantity Bought (MW)	Purchase Price ($/MWh)
L1	30	50.1299	22.5787	59.5404	30	50.1591	18.543	65.1365
L2	10	62.4484	10	61.4042	10	62.4405	9.4434	68.6326
L3	24.3103	49.5935	10.0003	60.1192	24.3182	49.5932	20	53.3097

Table 9
Earnings of the system for objective function TFC and TAPL with load variation using different algorithms.

S. No	Loadvariation	TFC GA	PSO	MA	IMA	TAPL GA	PSO	MA	IMA
1	−50%	6091.74	6093.58	6093.43	6095.01	6090.59	6092.48	6093.43	6095.01
2	−40%	6082.56	6084.49	6086.65	6089.81	6079.32	6083.59	6086.56	6089.81
3	−30%	6592.92	6595.64	6598.40	6601.17	6591.16	6594.46	6598.28	6601.13
4	−20%	6598.73	6601.96	6604.98	6607.14	6400.99	6403.27	6406.85	6409.90
5	−10%	6602.80	6605.39	6609.56	6613.45	6386.64	6397.94	6399.58	6402.67
6	BL	6610.83	6612.29	6616.78	6620.19	6394.73	6395.16	6397.98	6401.39
7	+10%	6619.26	6622.16	6628.14	6630.98	6484.16	6486.83	6389.08	6394.06
8	+20%	6627.74	6628.86	6632.40	6634.51	6375.83	6379.64	6382.77	6385.40
9	+30%	6635.98	6636.09	6639.21	6642.39	6376.68	6378.82	6381.86	6386.94
10	+40%	6642.37	6644.73	6646.68	6650.78	6363.05	6366.37	6368.98	6372.18
11	+50%	6649.92	6652.24	6655.46	6659.78	6357.49	6359.15	6361.97	6369.15
12	+60%	6659.85	6662.18	6666.89	6669.42	6361.72	6364.24	6368.93	6370.92
13	+70%	6667.72	6669.29	6675.78	6679.80	6362.56	6365.04	6368.56	6372.86
14	+80%	6682.39	6684.32	6688.74	6691.02	6364.98	6366.75	6369.99	6374.94
15	+90%	6946.16	6948.95	6950.38	6955.29	6362.63	6365.78	6367.57	6371.09
16	+100%	6714.34	6716.73	6719.87	6724.74	6435.75	6438.92	6441.54	6446.55

Table 10
Earnings of the system for objective function TVD and VSI with load variation using different algorithms.

S. No	Loadvariation	TVD GA	PSO	MA	IMA	VSI GA	PSO	MA	IMA
1	−50%	6074.74	6076.38	6079.63	6089.70	6084.47	6087.56	6090.11	6095.96
2	−40%	6586.56	6589.48	6591.89	6598.00	6083.83	6085.48	6088.98	6090.37
3	−30%	6595.83	6596.65	6599.67	6603.35	6594.62	6595.95	6597.15	6601.11
4	−20%	6597.27	6598.73	6601.76	6608.83	6384.49	6386.72	6389.67	6397.93
5	−10%	6602.18	6604.75	6609.93	6614.46	6392.05	6394.64	6395.89	6402.67
6	BL	6611.32	6614.46	6616.59	6620.49	6406.62	6408.38	6409.67	6412.18
7	+10%	6620.90	6623.03	6626.87	6630.98	6386.74	6389.95	6391.67	6399.42
8	+20%	6621.63	6625.64	6629.74	6634.72	6376.84	6378.26	6382.59	6385.40
9	+30%	6633.27	6636.48	6638.29	6642.51	6377.62	6379.39	6382.95	6386.93
10	+40%	6641.38	6643.17	6645.76	6650.81	6364.15	6365.08	6368.86	6373.07
11	+50%	6354.94	6357.53	6359.98	6369.16	6354.38	6358.57	6361.83	6369.15
12	+60%	6658.18	6660.29	6662.86	6669.21	6356.96	6359.38	6362.74	6370.92
13	+70%	6367.53	6369.03	6371.98	6373.04	6364.36	6367.74	6369.52	6372.86
14	+80%	6368.28	6369.64	6372.55	6375.04	6365.28	6368.65	6371.87	6374.91
15	+90%	7352.74	7353.37	7355.87	7367.83	6921.86	6924.89	6927.89	6933.16
16	+100%	6708.56	6710.69	6712.54	6716.57	5553.98	5556.63	5559.89	5567.24

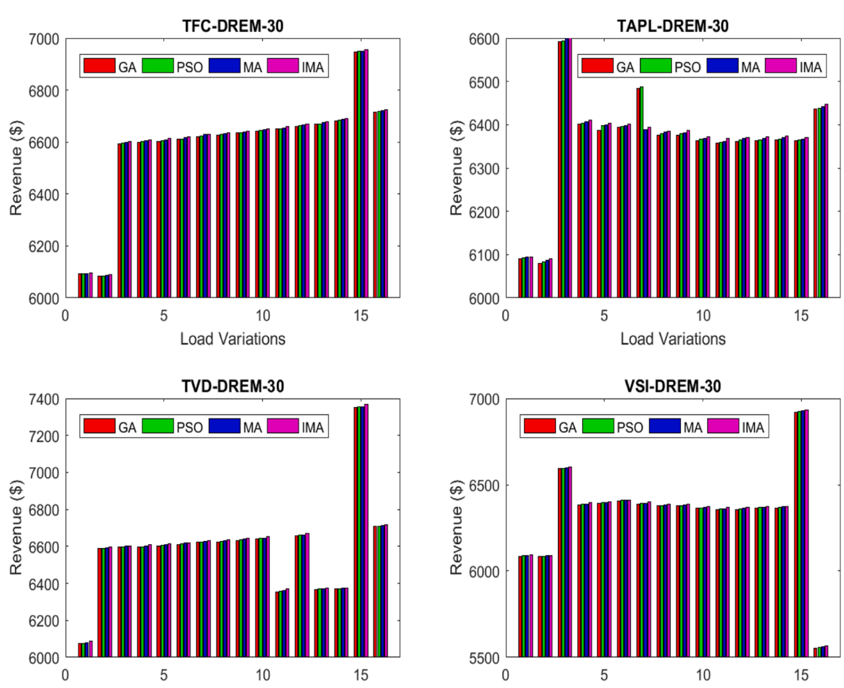

Fig. 3. Comparison of revenues for different objective function with GA, PSO, MA and IMA.

Table 11
Elapsed duration for objective function TFC and TAPL using different algorithms.

S.No	% Load	TFC GA	PSO	MA	IMA	TAPL GA	PSO	MA	IMA
1	−50%	16,649	15,793	14,419	13,289	16,539	15,759	14,272	13,887
2	−40%	16,728	15,950	14,715	13,505	16,893	15,658	14,417	13,278
3	−30%	16,957	15,871	14,708	13,477	16,048	15,835	15,017	13,584
4	−20%	16,826	15,539	14,946	13,788	16,752	15,895	15,748	13,327
5	−10%	16,046	15,902	14,019	13,313	16,859	15,892	14,614	13,195
6	BL	16,869	15,746	14,177	13,400	16,274	15,372	14,310	13,419
7	+10%	16,037	15,659	14,318	13,074	16,850	15,562	14,656	13,089
8	+20%	16,659	15,027	14,686	13,608	16,784	15,931	14,553	13,977
9	+30%	16,728	15,739	14,798	13,047	16,937	15,469	14,847	13,905
10	+40%	16,794	15,802	14,764	13,088	16,692	15,048	14,798	13,841
11	+50%	16,802	15,374	14,721	13,347	16,085	15,374	14,089	13,257
12	+60%	16,684	15,950	14,841	13,248	16,672	15,739	14,874	13,748
13	+70%	16,712	15,756	14,108	13,980	16,947	15,936	14,275	13,786
14	+80%	16,893	15,590	14,180	13,971	16,872	15,702	14,319	13,409
15	+90%	16,750	15,839	14,922	13,541	16,650	15,849	14,971	13,610
16	+100%	16,159	15,764	14,947	13,492	16,664	15,948	14,905	13,534

Table 12
Elapsed duration for objective function TVD and VSI using different algorithms.

S.No	% Load	TVD GA	PSO	MA	IMA	VSI GA	PSO	MA	IMA
1	−50%	16,523	15,476	14,420	13,428	16,428	15,984	14,719	13,195
2	−40%	16,435	15,788	14,064	13,310	16,518	15,759	14,574	13,414
3	−30%	16,876	15,652	13,928	13,544	16,739	15,948	15,454	13,467
4	−20%	16,456	15,735	13,772	13,252	16,493	15,956	15,548	13,328
5	−10%	16,724	15,915	13,521	13,273	16,856	16,002	13,988	13,620
6	BL	16,983	15,167	14,654	13,865	16,026	15,679	14,179	13,541
7	+10%	16,672	15,624	14,046	13,529	16,736	15,786	14,998	13,172
8	+20%	16,294	15,809	14,689	13,137	16,813	15,924	14,093	13,801
9	+30%	16,730	15,371	14,335	13,191	16,147	15,087	14,556	13,685
10	+40%	16,892	15,643	14,834	13,874	16,583	15,745	14,526	13,214
11	+50%	16,739	15,783	15,446	13,278	16,724	15,835	14,332	13,257
12	+60%	16,546	15,694	14,218	13,408	16,803	15,925	14,447	13,107
13	+70%	16,783	15,067	14,248	13,127	16,649	15,863	14,749	13,923
14	+80%	16,926	15,915	14,788	13,964	16,826	15,629	14,127	13,484
15	+90%	16,453	15,893	14,409	13,486	16,883	15,683	14,584	13,810
16	+100%	17,021	15,989	15,191	13,962	16,037	15,963	14,088	13,507

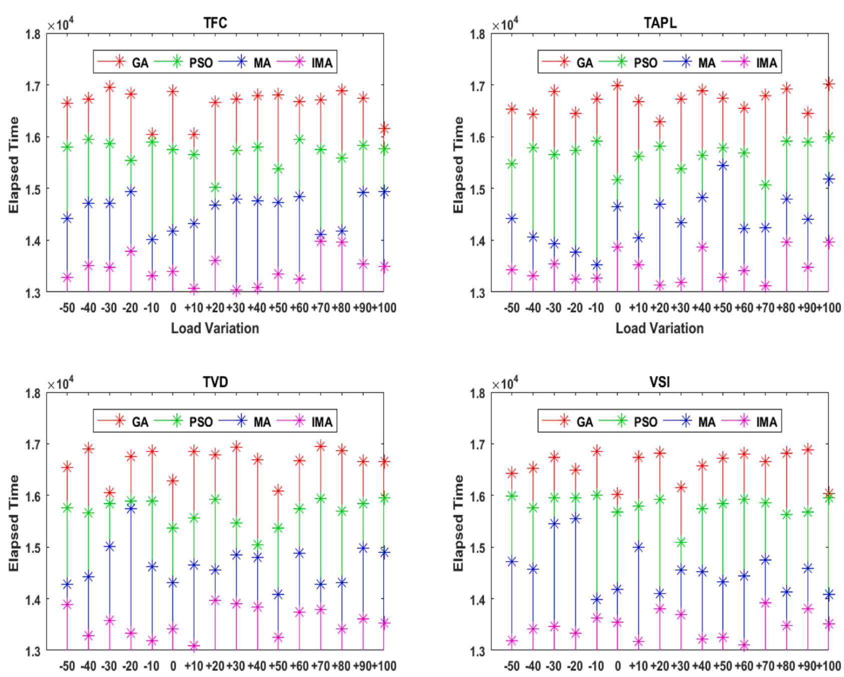

Fig. 4. Comparison of computation period for different objective function with GA, PSO, MA and IMA.

10 MW, 10 MW, and 9.4434 MW at 62.4484 \$/MWh, 61.4042 \$/MWh, 62.4405 \$/MWh, and 68.6326 \$/MWh, respectively for TFC, TAPL, TVD, and VSI.

In a deregulated energy market, the system's revenues are determined by the balance between the supplier's sales and the buyer's purchases. Table 9 and 10 shows the revenues of the test system employing GA, PSO, MA and IMA with load variations ranging from −50% to +100% of the base load. According to Table 9, for objective function TFC, as load rises, profits increase, and earnings decrease concerning the base load as load declines. In the case of objective function TAPL, revenues drop as load rises and increase as load decreases about the base load. According to Table 10, the objective function TVD, as load grew, profits climbed, and earnings decreased to the base load as load declined. In the case of objective function VSI, profits drop as load rises and increase as load decreases for the base load.

The comparison of revenues achieved for different objective functions by implementing GA, PSO, MA and IMA are shown in Fig. 3. It is observed that for objective function, TFC, the revenue is maximum when the load is increased to 90% of base load. For objective function, TAPL, the revenue is maximum when the load is decreased by 30% of base load. Maximum revenue is achieved at +90% load for the objective function TVD and VSI.

Table 11 and Table 12 shows the elapsed period for computation of each objective function using GA, PSO, MA and IMA in terms of CPU processing clock pulses. The table shows that the time taken by IMA is less than the time taken by MA, PSO and GA. The comparison of computation time required to execute the best solution of each objective function with different algorithms is represented in Fig. 4.

Table 1 and Table 2, Table 9 and Table 10, Table 11 and Table 12 illustrate the performance of IMA over MA, PSO and GA concerning about the best values of optimum solution, revenues earned and computation period for each objective function related to the OPF problem in the deregulated power market. The only limitation of IMA is that it suffers from the initial parameter tuning.

5. Conclusions

The IMA, MA, PSO and GA have been used in this research to find the best solution for the OPF problem with several distinct load conditions in deregulated electricity markets. The MA is a hybrid algorithm that considers the benefits of the GA, PSO, and FA to find the best solution. It is further improved to IMA by employing the simulated binary crossover operator for the arithmetic crossover operator and the polynomial distribution mutation for the standard distribution mutation operator. The aspects of GA used in the exploitation include simulated binary crossover and polynomial mutation. FA's random shuffle function improves exploration. The IMA, MA, PSO and GA were performed on an IEEE-30 bus system with varying loads, and their performance was assessed using the best solution, revenue earning and elapsed time. The system's load is changed from half load (−50%) to full load and double load (+100%). The ideal solutions of the objective functions determined by IMA are more acceptable than MA, PSO and GA for all load settings. The best solution achieved by implementing IMA for the objective functions' TFC and VSI is upstairs when the load is raised and downstairs when the load is lowered concerning the base load. Even if the load is raised or lowered with the base load, the ideal solutions for TAPL are found upwards. The best solutions for TVD fluctuate in an unspecified way with the load change. The provider provides a greater quantity at a higher price, while the customer purchases more quantity at a lower price. In a deregulated power market, using IMA to solve the OPF issue forces suppliers to sell the maximum amount at the lowest price and the minimum quantity at the highest price.

The decision-making gap between supplier sales and consumer purchases skews the system's profitability. Similarly, the buyer purchases the minuscule amount at the highest price and the most significant quantity at the lowest price. Earnings increase as load increases and decrease as load decreases with the base load for the objective functions TFC and TVD. Earnings for objective functions TAPL and VSI fall and rise as load increases and decreases relative to the base load. It is observed that there is an average additional earning of 2\$/Hr by implementing IMA. As a result, IMA outperforms the other evolutionary algorithms with respect to individual objective functions under different load conditions.

The research work might be expanded such that IMA is used to find the optimum solution to an OPF challenge, including contingency analysis such as generator bus outages, load bus outages, and line outages. The Improved Multi-Objective Mayfly Algorithm (IMOMA) is to be implemented to obtain an optimal solution for the multi-objective OPF problem under dynamic and random loading scenarios. Objective functions include fuel cost with valve point loading, fuel cost with various fuels, fuel cost with a piece-wise linear function, carbon emission, and penalty function. In addition, installation and optimum sizing of FACTS devices and DG with IMA and IMOMA might be considered for future work that will assist in analyzing operational and planning studies related to power systems in a deregulated environment.

Author statements

Vijaya Bhaskar K – methodology, concept
Ramesh S – Supervision
Elena Verdu – Writing, draft correction
Karunanithi K – Visulaization
Raja S P - implementation

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Appendix

Mathematical Test Functions and the Best Objective Function Values obtained from IMA, MA, PSO and GA

S. No.	Function	LowerBound	UpperBound	Dim	Best Objective function value IMA	MA	PSO	GA
1	$f_1(x) = \sum_{i=1}^{n} x_i^2$	−100	100	10	2.36E-118	3.77E-83	5.78E-12	1.6041
2	$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	−10	10	10	1.59E-67	3.65E-55	1.51E-07	0.0164

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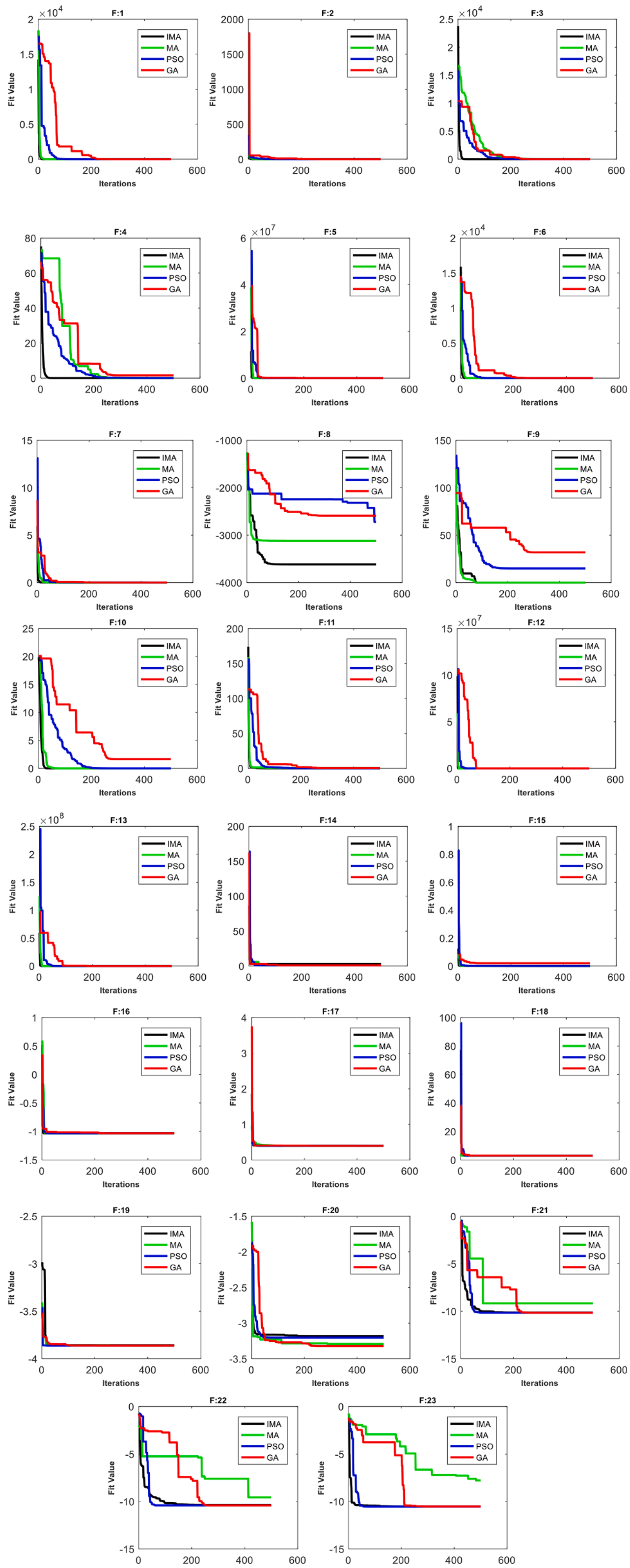

Fig. A. Convergence Characteristics of Mathematical Test Functions.

(*continued*)

S. No.	Function	LowerBound	UpperBound	Dim	Best Objective function value IMA	MA	PSO	GA
3	$f_3(x) = \sum_{i=1}^{n}\left(\sum_{j=1}^{i} x_j^2\right)$	−100	100	10	2.44E-47	0.0898	0.0065	7.0461

(*continued on next page*)

(*continued*)

S. No.	Function	LowerBound	UpperBound	Dim	Best Objective function value IMA	MA	PSO	GA
4	$f_4(x) = max_i\{\lvert x_i\rvert, 1 \le i \le n\}$	−100	100	10	3.78E-38	0.0174	0.0096	1.5419
5	$f_5(x) = \sum_{i=1}^{n-1}\{100(x_{i+1}-x_i^2)^2 + (x_i-1)^2\}$	−30	30	10	7.1761	6.5999	237.3175	72.9306
6	$f_6(x) = \sum_{i=1}^{n}([x_i+0.5])^2$	−100	100	10	0.0129	0.0001	3.50E-13	1.5722
7	$f_7(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1)$	−1.28	−1.28	10	0.0002	0.0011	0.0062	0.0074
8	$f_8(x) = \sum_{i=1}^{n} - x_i sin(\sqrt{\lvert x_i\rvert})$	−500	500	10	−2719.1977	−3121.53	−3617.37	−2589.37
9	$f_9(x) = \sum_{i=1}^{n}[x_i^2 - 10cos(2\pi x_i) + 10]$	−5.12	5.12	10	0	0	14.92438	31.8897
10	$f_{10}(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	−32	32	10	4.44E-15	7.99E-15	1.16E-06	1.6467
11	$f_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n}x_i^2 - \prod_{i=1}^{n}cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	−600	600	10	0	0.5497	0.1157	0.5507
12	$f_{12}(x) = \frac{\pi}{n}\{10\ sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i-1)^2[1+10\ sin^2(\pi y_{i+1})]\}$	−50	50	10	4.63E-12	0.0005	0.0016	0.0841
13	$f_{13}(x) = 0.1\{sin^2(3\pi x_i) + \sum_{i=1}^{n}(x_i-1)^2[1+sin^2(3\pi x_i+1)] + (x_n-1)^2[1+sin^2(2\pi x_n)]\} + \sum_{i=1}^{n}u(x_i,5,100,4)$	−50	50	10	0.0058	0.00092	0.0109	3.7801
14	$f_{14}(x) = \left[\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i-a_{ij})^6}\right]^{-1}$	−65.53	65.53	2	2.9821	0.9980	0.9980	0.9980
15	$f_{15}(x) = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2+b_ix_2)}{b_i^2+b_ix_3+x_4}\right]^2$	−5	5	4	0.0003	0.0007	0.0008	0.0204
16	$f_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	−5	5	2	−1.0316	−1.0316	−1.0316	−1.0316
17	$f_{17}(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1-\frac{1}{8\pi}\right)\cos x_1 + 10$	[−5,0]	[10,15]	2	0.3979	0.3979	0.3979	0.3979
18	$f_{18}(x) = [1+(x_1+x_2+1)^2(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)] \times [30+(2x_1-3x_2)^2X(18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)]$	−2	2	2	3	3.0001	3	3
19	$f_{19}(x) = -\sum_{i=1}^{4}c_i\ exp(-\sum_{j=1}^{3}a_{ij}(x_j-p_{ij})^2)$	0	1	3	−3.8626	−3.8572	−3.8628	−3.8627
20	$f_{20}(x) = -\sum_{i=1}^{4}c_i\ exp(-\sum_{j=1}^{6}a_{ij}(x_j-p_{ij})^2)$	0	1	60	−3.2935	−3.1826	−3.2031	−3.322
21	$f_{21}(x) = -\sum_{i=1}^{5}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	0	10	4	−10.1607	−10.1329	−10.1532	−10.1532
22	$f_{22}(x) = -\sum_{i=1}^{7}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	0	10	4	−10.5633	−10.3791	−10.4029	−10.4029
23	$f_{23}(x) = -\sum_{i=1}^{10}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	0	10	4	−10.7731	−10.5219	−10.5364	−10.5264

Highlights for Review

In this paper, Improved Mayfly Algorithm (IMA) is applied as enhanced variant of Mayfly Algorithm (MA), by replacement of stimulated binary crossover and polynomial mutation operators in the place of arithmetic crossover and normal distribution mutation operator's of MA. The accomplishment and influence of IMA is distinguished with MA. The algorithms are handled out to bring successful conclusion with optimum solution for the considered objective functions of the optimal power flow problem in deregulated electricity power market under distinct load environment. The total load of the power system is varied from half of the base load (−50%) to double of the base load (+100%). The objective functions that are treated, have connection with financial value of the generators, active power loss in the transmission lines, potential change and potential ability of the power system networks. The goal reached that has been accomplished by IMA is obtained on the IEEE-30 bus test system in deregulated environment. The investigations are performed on the optimal solution of each objective function, offers of generators and bids of loads, generator sales and load purchases, and earnings of the system accompanying distinct load conditions. The simulated results have guaranteed the predominance of IMA over MA.

The work's contribution has been as described in the following:

- For the first time, the OPF problem is solved under deregulated environment considering different load levels.
- In a deregulated electricity market, fuel cost, active power losses, voltage deviation, and voltage stability are being used as objective functions to solve the OPF problem.
- This paper considers Improved Mayfly Algorithm (IMA) that incorporates simulated binary crossover and polynomial mutation into the original Mayfly Algorithm (MA) for solving the problem
- The proposed IMA's performance is analysed for different mathematical test functions having unimodal, multimodal, fixed-dimension test functions and is compared with GA, PSO and MA
- The comparison of optimum solutions obtained from IEEE-30 bus system are reported to assess the performance of evolutionary algorithms via., GA, PSO, MA and IMA.
- The performance of IMA is evaluated under a diversity of load scenarios.
- The generator offers and load bids, as well as system revenues gained by applying the IMA, are presented. Fig. 3

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