Marine predators algorithm for solving single-objective optimal power flow

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Abstract

This study presents a nature-inspired, and metaheuristic-based Marine predator algorithm (MPA) for solving the optimal power flow (OPF) problem. The significant insight of MPA is the widespread foraging strategy called the Levy walk and Brownian movements in ocean predators, including the optimal encounter rate policy in biological interaction among predators and prey which make the method to solve the real-world engineering problems of OPF. The OPF problem has been extensively used in power system operation, planning, and management over a long time. In this work, the MPA is analyzed to solve the single-objective OPF problem considering the fuel cost, real and reactive power loss, voltage deviation, and voltage stability enhancement index as objective functions. The proposed method is tested on IEEE 30-bus test system and the obtained results by the proposed method are compared with recent literature studies. The acquired results demonstrate that the proposed method is quite competitive among the nature-inspired optimization techniques reported in the literature.

Introduction

The optimal power flow (OPF) is an inevitable part of the energy management system for power system planning and operation over a couple of decades. The main objective of the OPF is to determine the most favourable operating conditions to meet the required demand by satisfying all the power system operational and security constraints [1]. In 1960, French scholar Carpentier proposed the concept of OPF to ensure reliable and economic power generation based on precise mathematics [2]. In this context, several selective objective functions, for instance, total generation cost, real/reactive power loss, and voltage deviation have been considered to obtain the optimal dispatch of generation by different numerical and artificial intelligence (AI) techniques [3]. Generally, the OPF problem is a static non-linear, non-convex, large scale, and highly constrained optimization problem in power system networks that deal
Abbreviations: ABC, Artificial Bee Colony Algorithm; AI, Artificial Intelligence; APL, Active Power Loss Minimization; BBBC, Big-Bang Big Crunch Algorithm; BBO, Biogeography-based Optimization; BHBO, Black-hole-based Optimization; CF, Convergence Factor; DEA, Differential Evolution Algorithm; DGWO, Developed Grey Wolf Optimizer; DSA, Differential Search Algorithm; EEA, Efficient Evolutionary Algorithm; EGA, Enhanced Genetic Algorithm; EM, Electromagnetism-like Mechanism Algorithm; FADs, Fish Aggregating Devices; FC, Fuel Cost; FHS, Fuzzy Harmony Search Algorithm; GA, Genetic Algorithm; GSA, Gravitational Search Algorithm; GSO, Glow worm Swarm Optimization Algorithm; GWO, Grey Wolf optimizer; HFPSO, Hybrid Firefly and Particle Swarm Optimization Algorithm; HS, Harmony Search Algorithm; HSHA, Hybrid Self-adaptive Heuristic Algorithm; IEEE, Institute of Electrical and Electronics Engineers; IEM, Improved Electromagnetism-like Mechanism Algorithm; JA, Jaya Algorithm; MFO, Moth-Flame Optimization Algorithm; MODE, Multi-objective Differential Evolution Algorithm; MOJA, Multi-objective Jaya Algorithm; OSCA, Modified Sine-Cosine Algorithm; MVO, Multi-verse Optimizer; MVP, Most Valuable Player Algorithm; OPF, Optimal Power Flow; PL, Power Loss; PSO, Particle Swarm Optimization; RPL, Reactive Power Loss Minimization; SCA, Sine-Cosine Algorithm; VD, Voltage Deviation; VSEI, Voltage Stability Enhancement Index; WOA, Whale Optimization Algorithm; Symbols u, Control variable; x, Vector of dependent variable; g, j, Equality constraints respectively; h, k, Inequality constraints at i-th limit; j, k, j-th and k-th limits; P_slack, Real power generation of slack bus; P_G, Real power generation; Q_G, Reactive power generation; S, L, Transmission line capacity; V_G, Generator voltage bus magnitude; Q_cap, Output of shunt VAR compensator; T, Tap settings of transformers; a, b, c, d, Generator cost co-efficient; N, Total number of generators; V, Voltage amplitude of from bus; V_m, Voltage amplitude of to bus; V_k, Voltage angle of from bus; V_m, Voltage angle of to bus; NL, Total number of transmission line; Algorithm X_min, Lower limit of dimensions; X_max, Upper limit of dimensions; X_0, Initial position; X_k, Top predator vector; d, Number of dimensions; X_i, jth dimension of ith prey; RB, Vector of random numbers; P = 0.5, Constant value; R, Vector of uniform random numbers in the range of [0, 1]; RL, Vector of random numbers based on Lévy with a set of independent and state variables. The control variables are the generator real power, generator bus voltages, reactive power injections of VAR compensators, and transformer tap settings while the state variables including the generator reactive power, load bus voltages, and the transmission lines limit [4]. Recently, the ever-increasing energy demand introduces a massive challenge to the prevailing networks to deliver quality power to the consumer end efficiently and economically [5]. Therefore, power utilities were repeatedly exploring several economic operational strategies in the power generation of power by enforcing equality and inequality constraints to deliver uninterrupted power supply [6]. Moreover, due to the ever-increasing power demand, the modern power system has been operating close to its power transfer capability limit that leads to stressed conditions of the system. Occasionally, a small change in the operating conditions results in system instability due to a dip in the voltage level that may cause blackouts or brownouts of the system as similar events have been witnessed in North America, Canada, India, Pakistan, and so on over the last few decades [7, 8]. Therefore, solving the OPF problem is most important to assess the voltage stability of the system.

Numerous optimization techniques have been employed to solve the OPF problems with different selective objective functions of generating cost, power loss, environmental emission, voltage deviation, and voltage stability assessment index. However, most of the work in the literature attempted to solve the OPF problem to minimize the power loss for the given operating loads. In general, the techniques to solve the OPF problem can be categorized into classical and heuristic-based techniques. The classical method includes the Newton method, gradient method, interior point method, linear programming, and non-linear programming [9]. These techniques were introduced with different theoretical assumptions of convexity, differentiability, and continuity which are not relevant to solve the OPF problems. Further, the convergence of all the classical methods is immensely gambled on the initial guess [10] and these also endure acute limitations in dealing with non-linear, discrete-continuous functions and control variables [11]. Moreover, the solution quality deteriorates when the number of the controlling parameters increases [12].

To overcome the aforementioned drawbacks of classical methods, researchers have proposed nature-inspired heuristic-based optimization techniques for solving the OPF problem due to the tremendous development of computer technology [13]. These techniques can be broadly categorized into evolutionary-based, swarm-based, physics-based, and human-based algorithms [14]. Due to the easy implementation and effectiveness in securing the global optimality, many heuristic-based techniques have been employed to solve OPF problems considering various objective functions in the power system [15]. Kwang Y. Lee Xiaomin Bai [16], presented a modified version of the conventional genetic algorithm (GA) to deal with OPF problems in the power system. The main goal of this study was to reduce the reactive power loss of the system and the obtained results were compared with successive linear programming. In [17], the load flow and the economic dispatch problem were considered to verify the viability of using GA to solve the OPF problems. Xiaohui Yuan et al., have proposed an improved Pareto evolutionary algorithm to solve OPF problems considering fuel cost and emission as objective functions [9]. A Biogeography-based Optimization (BBO) technique has been used to solve several objective functions as a single-objective OPF problem by A. Bhattacharya et al. [18]. Similarly, physics-based optimization techniques namely Big-Bang Big Crunch Algorithm (BBBC) [19], Gravitational Search Algorithm (GSA) [20] were applied to solve the OPF problem. Moreover, many researchers have also employed several human-based techniques in solving OPF problems. Based on the influence of a teacher on learners, Teaching-Learning-Based Optimization (TLBO) [21], Harmony Search Algorithm (HS) [22], Tabu Search Algorithm (TS) [23] were used to deal with the constrained OPF problems to get a
better optimal solution. In some cases, these techniques demonstrate promising results but stuck in local optima. Hence, several swarming behaviour-based techniques got attention for solving OPF problems in the literature. A Particle Swarm Optimization (PSO) [24] was proposed to solve OPF problems including fuel cost minimization, voltage profile improvement, and voltage stability enhancement. Further, some meta-heuristic based techniques, for example, Whale Optimization Algorithm (WOA) [25], Moth-Flame Optimization Algorithm (MFO) [26], Glowworm Swarm Optimization Algorithm (GSO) [27], Jaya Algorithm (JA) [28], Artificial Bee Colony Algorithm (ABC) [29] were employed to solve OPF problem effectively and accurately. Lately, a hybrid self-adaptive heuristic algorithm was used to solve OPF problems considering the total fuel cost, active power losses, and the emission in [30]. Based on the trophy-winning behaviour of players, the most valuable player algorithm (MVPA) belonging to the family of swarm intelligence was proposed by Koganti Srilakshmi et al., for solving OPF problems on several bus test systems [31]. On the other hand, the authors in [32] proposes a Turbulent flow of water-based optimization using the concept of nature search phenomenon to solve the economic load dispatch problem of fuel cost minimization considering the effects of valve points and ramp rate limits. A multi-objective backtracking search algorithm has been proposed to solve the disparate combinations of multi-objective (fuel cost, power loss, voltage deviations) OPF for IEEE 57-bus and 118-bus system [33]. Several other optimization approaches of phasor based PSO, improved wind driven algorithm and adaptive quasi-oppositional differential evaluation algorithm with migration operator of BBO were proposed to enhance the exploration and exploitation search ability of agents to reach the global minima in order to solve the different combinations of OPF problems [34–36]. However, As the rule of thumb states that all the optimization techniques proposed in literature do not provide optimal solutions for all kind of engineering optimization problems. Because, each technique has certain limitations to solve the particular type of problems like their own merits and demerits to solve OPF problems. Therefore, researchers continuously were looking for powerful nature-inspired optimization techniques to solve the OPF problems. In view of this, a recently developed optimization technique has been used to solve the OPF problem because of its distinct foraging strategy and Brownian movements as well as the biological interaction between predators and prey to get the optimal solution. The prime contributions of this paper are as follows:

- Solving single-objective OPF problem using MPA technique to minimize the fuel cost, real power loss, reactive power losses, voltage deviation and voltage stability index of the power system.

- The effectiveness of the method is tested on the IEEE 30-bus test system for different selective single objectives by satisfying the equality and inequality constraints of the network.

- The result obtained is compared with other well-known optimization techniques presented in recent literary works.

- The robustness of the proposed MPA based OPF method is validated for large-scale power system of IEEE 118-bus system.

The remainder of the paper is organized as follows: Section 2 deals with the OPF problem formulation which describes the various single-objective problem formulation mathematically including equality and inequality constraints. While section 3 presents the proposed intelligence-based MPA technique with a dynamic levy flight strategy. The results and discussion of the proposed method technique with other well-known nature-inspired methods of optimization are presented in section 4. Finally, section 5 portrays the conclusion and future scope of the work.
2. OPF problem formulation

This section presents the mathematical formulation of OPF and different selective objectives for the smooth and reliable operation of power networks. The OPF is a highly non-linear, non-convex and constrained optimization problem. The optimal power flow problem can be solved as a single or multi-objective function while satisfying equality and inequality constraints. In many research works, several objectives, for instance, fuel cost, real power loss, environment emission, voltage stability improvement have been considered individually or collectively that will be either maximized or minimized. In terms of optimization of real power generation, the generator bus voltage, reactive power compensator and transformer tap settings are the principles controlling parameters.

2.1 Single objective function

The objective function to be minimized is defined as,

\[
\text{Optimize, } f_i(x, u) \quad i = 1, 2, 3, \ldots, N
\]

Subject to equality and inequality constraints represented as,

\[
g_j(x, u) = 0 \quad j = 1, 2, 3, \ldots, N
\]

\[
h_k(x, u) \leq 0 \quad k = 1, 2, 3, \ldots, N
\]

where, \( f \) is the \( i \)th objective function, \( N \) denotes the total number of objective functions, \( u \) and \( x \) are the control and dependent variable, respectively, \( g_j \) and \( h_k \) are the equality and inequality constraints in \( j \)th and \( k \)th limits. The control variable \( u \) can be stated as,

\[
u = [P_{G2}, \ldots, P_{GN}, V_{G1}, \ldots, V_{GN}, Q_{cap1}, \ldots, Q_{capN}, T_1, \ldots, T_N]
\]

where, \( P_{G2}, \ldots, P_{GN} \) denotes the real power generation of \( N \) generators except the slack bus, \( V_{G1}, \ldots, V_{GN} \) represents voltage magnitude of generator bus, \( Q_{cap1}, \ldots, Q_{capN} \) depicts the shunt VAR compensator and \( T_1, \ldots, T_N \) is the tap settings of transformers.

On the other hand, the vector of dependent variable \( x \) can be represented as,

\[
x = [P_{Gslack}, V_{L1}, \ldots, V_{LN}, Q_{G1}, \ldots, Q_{GN}, S_{L1}, \ldots, S_{LN}]
\]

where, \( P_{Gslack} \) denotes the real power generation of slack bus, \( V_{L1}, \ldots, V_{LN} \) is the voltage magnitude of all load buses, \( Q_{G1}, \ldots, Q_{GN} \) is the reactive power generation, and \( S_{L1}, \ldots, S_{LN} \) is the transmission line capacity limit.

The various selective objective functions considered in this work are as follows:

2.2 Fuel cost minimization

In general, most of the literature work is based on fuel cost minimization as utility requires to generate electricity with the least cost by considering the deregulation and open market policy. The fuel cost function can be represented as a quadratic function of real power generations of generators which can be mathematically defined as,

\[
f_i = \sum_{g=1}^{NG} a_g + b_g P_{Gi} + c_g P_{Gi}^2 \quad \$ / h \quad i = 1, 2, \ldots, N_G
\]

where, \( P_{Gi} \) is the total power generation in MW, \( a_g \), \( b_g \), and \( c_g \) denote the cost co-efficient of the specific generator, and \( N_G \) is the total number of generators in the system.

2.3 Active power loss minimization (APL)

To enhance the power quality to the consumer end, the APL is considered as an objective function which can be optimized by tuning the controlling parameters of the system by satisfying
the power flow constraints. Mathematically, APL can be described as,

\[ f_2 = \sum_{i=1}^{N_L} g_i [V_i^2 + V_m^2 - 2V_iV_m \cos(\delta_i - \delta_m)] \quad \text{MW} \quad i = 1, \ldots, N_t \]  

where, \( g_i \) is the transfer conductance, \( V_k \) and \( V_m \) represent the voltage magnitude of from and to buses, respectively, \( \delta_k \) and \( \delta_m \) depicts the phase angle, and \( N_t \) is the total number of transmission lines of the system.

### 2.4 Reactive power loss minimization (RPL)

To ensure a reliable power supply with balanced voltage, another significant factor of reactive power loss need to consider as an objective function. The RPL can be optimized by tuning the controlling parameters of the system by satisfying power flow constraints. The mathematical formulation of RPL is as follows,

\[ f_3 = \sum_{i=1}^{N_L} g_i [V_i^2 + V_m^2 - 2V_iV_m \cos(\delta_i - \delta_m)] \quad \text{MVari} = 1, \ldots, N_t \]  

### 2.5 Voltage deviation (VD)

Generally, the voltage deviation range lies between ±5% of nominal values to ensure the stable operation of the system. Mostly in the power network, the voltage magnitude at the bus should be maintained at 1 p.u. However, the deviation in bus voltage occurs due to a sudden increase in load demand, insufficient reactive power support, fault or any interruption may happen. Therefore, voltage deviation is considered to minimize and can be expressed as,

\[ f_4 = \sum_{i=1}^{NG} |V_i - 1| \quad i = 1, 2, 3, 4, \ldots, NG \]  

### 2.6 Voltage stability enhancement index

In addition to the fuel cost and loss function, this paper also considers the voltage stability index to assess the system stability. The voltage stability enhancement index (VSEI) is formulated as the sum of squared L-index for a given system operating condition, and is formulated as,

Minimize, \( f_5 = f_{\text{VSI}} = \max (L_f) \)  

where, the L-index gives the proximity of the system to voltage collapse and can be defined as,

\[ L_f = \left[ 1 - \sum_{i=1}^{NG} F_{ij} \frac{V_i}{V_j} \right] \]  

where, \( F_{ij} \) is a matrix generated from Y-bus while \( V_i \) and \( V_j \) are the voltage magnitude at \( i \) and \( j \) bus, respectively.

### 2.7 Equality constraints

The active and reactive power flow balance equation between the generated and absorbed power are generally referred to the equality constraints. These restrictions are one of the most important controlling parameters in the power system, while the load demands need to be satisfied by the generation. The equality constraints are defined as follows,

\[ P_i(V, \delta) - P_{Gi} + P_{Di} = 0 \quad (i = 1, 2, 3, \ldots, N) \]  

\[ Q_i(V, \delta) - Q_{Gi} + Q_{Di} = 0 \quad (i = 1, 2, 3, \ldots, N) \]
where, $P_i(V, \delta)$ and $Q_i(V, \delta)$ are the real and reactive power flow equations and can be defined as,

\[
P_i(V, \delta) = V_i \sum_{j=1}^{n} V_j (H_{ij} \cos(\delta_i - \delta_j) + M_{ij} \sin(\delta_i - \delta_j))
\]

\[
Q_i(V, \delta) = V_i \sum_{j=1}^{n} V_j (H_{ij} \sin(\delta_i - \delta_j) - M_{ij} \cos(\delta_i - \delta_j))
\]

\[
\sum_{i=1}^{NG} P_{Gi} = P_{Di} + P_{loss}
\]

where, $N_G$ is the number of generator buses, $N$ represents the number of bus, $P_i$ depicts the active power injection, $Q_i$ denotes the reactive power injection, $P_{Di}$ represents the active power load demand, $Q_{Di}$ is the reactive power load demand, $P_{Gi}$ is the active power generation, $Q_{Gi}$ is the reactive power generation, $V$ is the voltage magnitude in p.u, $\delta$ is the phase angle in rad, the admittance matrix can be defined as $Y_{ij} = H_{ij} + jM_{ij}$, $i$ and $j$ are the from and to buses, and $P_{loss}$ is the active power loss.

2.8 Inequality constraints
The inequality constraints are also called power system operating and security constraints which include the power generation limit of generating units, voltage magnitude of generator bus, transformer tap settings, and so on. These constraints are discussed as follows,

2.9 Generator constraints
The power generation and voltage limit can be expressed as follows for economic and reliable operation of the power system:

\[
P_{Gimin} \leq P_{Gi} \leq P_{Gimax} \quad (i = 1, 2, 3, \ldots, N_G)
\]

\[
Q_{Gimin} \leq Q_{Gi} \leq Q_{Gimax} \quad (i = 1, 2, 3, \ldots, N_G)
\]

\[
V_{imin} \leq V_i \leq V_{imax} \quad (i = 1, 2, 3, \ldots, N_G)
\]

2.10 Transformer constraints
The tap changing transformers in the power system is used to control the voltage magnitudes at a given bus to maintain the operational limits. The tap of transformers can be modelled in terms of a reactive power source which can be represented by,

\[
T_{imin} \leq T_i \leq T_{imax} \quad (i = 1, 2, 3, \ldots, N_T)
\]

2.11 Shunt compensator VAR constraints
Shunt compensator is used to maintain the voltage at the prescribed limit in order to improve the power factor. The system voltage can be maintained at the specified range by adding shunt or series reactors. The switchable shunt compensation can be designated to operate within the
limit as follows,
\[ Q_{\text{min}} \leq Q_i \leq Q_{\text{max}} \quad (i = 1, 2, 3, \ldots, N) \] (16)

### 2.12 Security constraints

Overhead lines absorb reactive power when it is fully loaded. The long transmission lines with light load act as reactive power generators due to the predominance of the line capacitance. In addition, the voltage magnitude of the healthy power system should be within the range of \( V_{\text{limin}} \) to \( V_{\text{limax}} \) as follows,
\[ V_{\text{limin}} \leq V_i \leq V_{\text{limax}} \quad (i = 1, 2, 3, \ldots, N) \] (17)
\[ S_{\text{limin}} \leq S_i \leq S_{\text{limax}} \quad (i = 1, 2, 3, \ldots, N) \] (18)

### 3. Application of MPA to OPF problem

MPA is a population-based meta-heuristic optimization technique proposed by Afshin Farzam [37]. The detailed steps for MPA based optimization are presented as follows:

#### 3.1 MPA formulation

Like other population-based methods, the initial solution in MPA is uniformly distributed over the search region in the first iteration as follows:
\[ X_0 = X_{\text{min}} + \text{rand}(X_{\text{max}} - X_{\text{min}}) \] (19)

where, \( X_{\text{min}} \) and \( X_{\text{max}} \) denote the lower and upper limit of control variables, respectively, and the rand is a random value in the range of (0, 1). According to the survival of the fittest theory, the top predators in nature are more talented in foraging. Therefore, the fittest solution is considered as a top predator to develop a matrix called Elite. The elements of this matrix can be used to find the prey based on the information of prey’s positions and which can be defined as:
\[
\text{Elite} = \begin{bmatrix}
X_{1,1} & X_{1,2} & \ldots & X_{1,d} \\
X_{2,1} & X_{2,2} & \ldots & X_{2,d} \\
\vdots & \vdots & \ddots & \vdots \\
X_{n,1} & X_{n,2} & \ldots & X_{n,d}
\end{bmatrix}_{n \times d}
\] (20)

where \( X^t \) represents the top predator vector, \( n \) is the number of search agents, and \( d \) is the number of dimensions. Both predator and prey are looking for their own food and are considered as the search agents. At the end of every iteration, the Elite matrix is updated by the better predator compared to the top predator in its previous iteration.

Another matrix is called prey which is framed with the same dimension as that of the Elite matrix. Generally, during the initialization process, the prey is constructed in which the predators update their position. Among the initial prey, the fittest one is used to construct the Elite matrix. The Prey matrix is presented as:
\[
\text{Prey} = \begin{bmatrix}
X_{1,1} & X_{1,2} & \ldots & X_{1,d} \\
X_{2,1} & X_{2,2} & \ldots & X_{2,d} \\
\vdots & \vdots & \ddots & \vdots \\
X_{n,1} & X_{n,2} & \ldots & X_{n,d}
\end{bmatrix}_{n \times d}
\] (21)
where, $X_{i,j}$ represents the $j^{th}$ dimension of the $i^{th}$ prey. The entire optimization process is mainly depending on the above specified two matrices.

### 3.2 MPA optimization scenarios

On considering the velocity ratio and mimicking pattern of predator and prey, the whole MPA optimization process can be categorized into three main phases. The various phases that occur based on the velocity of movement of prey to escape from predators are: high-velocity ratio, unit velocity ratio, and low-velocity ratio phases. In MPA, each phase is specified and assigned with a particular period of iteration. These phases are defined based on the rules overseen on the nature of predator and prey movement while mimicking it. The following phases are described in detail as follows:

**Phase 1:** During this phase, the prey is moving faster than the predator with a high-velocity ratio. This phase usually occurs in the initial stage of iteration where exploration is more important. Although the velocity ratio is higher than 10, the best strategy for the predator in this case is not moving at all. The mathematical model of the high-velocity ratio ($v > 10$) can be described as:

\[
\text{While Iter} < \frac{1}{3} \text{Max}_{\text{Iter}}
\]

\[
\text{Stepsize}_i = \frac{R}{\text{Elite} - \text{Prey}_i} \times \text{Prey}_i
\]

\[
\text{Prey}_i = \text{Prey}_i + P \times \frac{R}{\text{Stepsize}_i}
\]

(22)

where, $\frac{R}{\text{Elite} - \text{Prey}_i}$ is a vector of random numbers, $P = 0.5$ is a constant value, and $R$ is a vector of uniform random numbers in the range of [0, 1]. This scenario occurs when either the step size or the velocity of movement is high to achieve high exploration ability in the initial stage of the iterations.

**Phase 2:** In this case, both predator and prey move at the same velocity in order to search for their own food. This phase is also called the unit velocity ratio. In this phase, the transition from exploration to exploitation occurs which is considered as the intermediate phase of optimization. Thus, both exploration and exploitation happen in this phase, where half of the population is designated for exploration and the rest of the population for exploitation. Notably, the prey is responsible for exploitation while the predator for exploration. In the unit velocity ratio ($v \approx 1$), if prey direct in Lévy walk, and Brownian movement will be the best strategy for the predator to attack the prey. This phase can be mathematically expressed as follows:

\[
\text{While Iter} < \frac{1}{3} \text{Max}_{\text{Iter}} < \frac{2}{3} \text{Max}_{\text{Iter}}
\]

For the first half of the population

\[
\text{Stepsize}_i = \frac{L_{\text{R}}}{\text{Elite} - \text{Prey}_i} \times \text{Prey}_i
\]

\[
\text{Prey}_i = \text{Prey}_i + P \times \frac{L_{\text{R}}}{\text{Stepsize}_i}
\]

(23)

where, $\frac{L_{\text{R}}}{\text{Elite} - \text{Prey}_i}$ is a vector of random numbers based on Lévy distribution representing Lévy movement. As exploitation also occurs in the case of the second half of the populations during this
phase which can be presented as:

\[
\text{Stepsize}_i = R_b \times (R_b \times \text{Elite}_i - \text{Prey}_i)
\]

\[
\text{Prey}_i = \text{Elite}_i + P.CF \times \text{Stepsize}_i
\]

while \(CF = \left(1 - \frac{\text{Iter}}{\text{Max}_{\text{Iter}}}\right)^{\frac{1}{\text{Iter}_{\text{max}}}}\) is considered as an adaptive parameter to control the step size for predator movement. Multiplication of \(R_b\) and \( \text{Elite} \) simulates the movement of predator in Brownian manner. On the other hand, prey updates its position according to the movement of predators in Brownian motion.

Phase 3: The low-velocity ratio is seen during this phase as the predator is moving faster than prey to attack it which happens in the last phase of the optimization. This low-velocity ratio \((v = 0.1)\) shows the high exploitation ability where the best strategy for the predator is Lévy. This phase can be modeled as:

\[
\text{While } \text{Iter} > \frac{2}{3} \text{Max}_{\text{Iter}}
\]

\[
\text{Stepsize}_i = R_b \times (R_b \times \text{Elite}_i - \text{Prey}_i)
\]

\[
\text{Prey}_i = \text{Elite}_i + P.CF \times \text{Stepsize}_i
\]

As observed from the literature study, the movement of the predator in the Lévy strategy is based on the Multiplication of \(R_L\) and \( \text{Elite} \). By adding the step size to the \( \text{Elite} \) position ensures the movement of the predator to update the prey position. Though, the Lévy and Brownian movement in the whole life span of a predator is the same percentage.

In the first stage, the predator is motionless but in the next stage, it moves in Brownian. Besides in the last stage, it shows the Lévy strategy. Since prey is considered as another potential predator for its mimicking behaviour of food. At the first phase of the movement, the prey is moving in Brownian, then in the second phase in the Lévy behavior. Each phase got one-third of the iterations which shows the better-optimized results comparing to the switching or repetition of the strategy. The entire exploration phases of the proposed MPA technique have illustrated in Fig 1.

### 3.3 Eddy formation and FADs’ effect

Environmental factors like eddy formation or Fish Aggregating Devices (FADs) affect the foraging pattern in a marine predator. The FADs are responsible for the local optima and the trapping behaviour in these points in the search region. To avoid such local optima during simulation, this method considers longer jumps. The mathematical representation of FADs is as follows:

\[
\text{Prey}_i = \begin{cases} 
\text{Prey}_i + \text{CF}[\bar{X}_{\text{min}} + R \times (\bar{X}_{\text{max}} - \bar{X}_{\text{min}})] \times \bar{U} & \text{if } r \leq \text{FAD}_s \\
\text{Prey}_i + [\text{FAD}_s (1 - r) + r](\text{Prey}_{r1} - \text{Prey}_{r2}) & \text{if } r > \text{FAD}_s
\end{cases}
\]

where \(r\) is the uniform random number in \([0, 1]\), \(\bar{X}_{\text{min}}\) and \(\bar{X}_{\text{max}}\) are the vectors containing the lower and upper bounds of the dimensions respectively, \(r1\) and \(r2\) subscripts denote the random indexes of the prey matrix. FADs are the probability of FADs effect and the value is
assumed as 0.2 in the optimization which generate a random vector in $[0,1]$. $\bar{U}$ denotes the binary vector of values zero or one. The array values changes to zero or one if the array value is lesser or greater than 0.2 respectively.

3.4 Marine memory
Marine predators have the quality memory that plays an important role in food foraging. Additionally, this memory enhances the capability of the exploration and exploitation in the MPA. The convergence criteria of the Elite are examined after updating the Prey and implementation of the FADs effect. The most fitted potential solution is updated after comparing the immediate solution with respect to the fitness function. Thus, the MPA determines the high-quality solution in the search space.

3.5 MPA phases, exploration and exploitation
The exploration and exploitation in the optimization process of MPA can be categorized into three distinct phases. At the first phase of optimization, the prey moves in Brownian motion within the search region. Though the distance between predator and prey is relatively large in Brownian motion but preys can explore their neighbourhood separately in this stage which results in good exploration of the domain. Then, the prey updates the new position after evaluating the fitness function based on the survival theory. Throughout the foraging process, prey can also be replaced as a dominant predator if it shows successful behaviour in food searching.

In the second phase, the algorithm moves from exploration into the exploitation stage. In this case, both prey and predator look for their own food where half of the populations engage for exploration and the other half for exploitation. In this journey, the predator follows the Brownian motion and the prey finds food in the Lévy strategy while in absence of food it takes
a long jump in the nearby area. At the end of this phase, predator and prey come closer and the jumping step size decreases, drastically. Additionally, the FADs effect minimizes the possibility of trapping into local optima for better optimization outcome. The foraging behavior switches from Brownian to Lévy strategy for high exploration ability. On the other hand, the search space is restricted by the defined convergence factor (CF) within the search space.

At the last phase, the computational complexity of the proposed method is the minimum and can be depicted as \( t(n^d + \text{Cof}^n) \), where \( t \) is the number of iteration, \( n \) is a number of agents, \( \text{Cof} \) is the cost of function evaluation, and \( d \) is the dimension of the problem to be solved. Fig 2 demonstrates the optimization process of the proposed method in a flowchart.
3.6 Application of MPA to the OPF problem

This section presents the step-by-step implementation of MPA in solving OPF problems as described below:

**Step 1:** Input the test system data (e.g., Bus and line data of the system) for the validation purpose.

**Step 2:** Set the MPA parameters such as number of populations, N and total number of iterations, t. The total number of populations will take part to optimize the formulated objective functions in the search space.

**Step 3:** Evaluate the objective functions to be optimized such as fuel cost, active power loss, reactive power loss, voltage deviation and Voltage Stability Enhancement Index considered as single-optimal power flow problems in Eqs 1–5 for each population.

**Step 4:** Now, construct Elite and Prey Matrix in order to get the optimal solution among the populations considered.

**Step 5:** Determine the top predator from elite and prey for updating its position and velocity of the prey for successive iterations.

**Step 6:** Exploration in three phase and update the position using Eqs 22–25

**Step 7:** Apply the FADs effect using Eq 26

**Step 8:** At this step, evaluate the objective function based on Eqs 1–5

**Step 9:** Check the stopping conditions of maximum number of iterations is reached using Eqs 7–18.

**Step 10:** Stop the program if the stopping criteria met, otherwise return to step 2.

4. Results and discussion

The effectiveness and feasibility of the proposed MPA-based optimization method was tested on a standard IEEE 30-bus test system. This test system model consists of six generators bus, four transformers, and nine shunt compensations. The location of the generator at buses 1, 2, 3, 8, 11, and 13, with shunt compensation at buses 10, 12, 15, 17, 20, 21, 23, 24, and 29. Besides, the IEEE 30-bus system has 24 load buses and 41 transmission lines of which 4 branches namely 6–9, 6–10, 4–12, and 28–27 are with the tap setting transformers [38]. It is worth mentioning that this test system has been widely used for OPF study with the maximum load demand of 283.4 MW, in which the total real and reactive power demands are 2.834 pu and 1.262 pu, respectively, with the base MVA of 100. On the other hand, the lower and upper bound limits of transformers tap and load busses were set in the range between [0.9, 1.1] pu and [0.95, 1.05] pu, respectively. Moreover, the minimum and maximum restrictions of the voltage magnitude of the generation units were set as [0.95, 1.1]. The proposed method was coded using MATLAB software in the PC with the subsequent characteristics: Intel core i5, CPU 2.60 GHz, RAM 4GB, and 64-bit operating system. The proposed technique was run with a maximum of 500 iterations and the comparative analysis was carried out for each case of selected objectives as detailed in the forthcoming subsections. The optimal settings of the controlling parameters for the proposed method have also been detailed in Table 1. The IEEE 30-bus system single line diagram has been showed in Fig 3.
To verify the effectiveness and performance of the proposed technique in solving the OPF problems, the quadratic fuel cost of each generating unit was considered to optimize as the single-objective function in this case. The mathematical formulation of the objective function is discussed in section 2. The proposed method was employed to analyze all the controlling parameters (i.e., real power generation dispatch) of the IEEE 30-bus test system to meet the required load demand by satisfying the power system constraints. The obtained optimal settings of controlling variables optimize the fuel cost (FC) of the system which is illustrated in Table 2. To generate the least cost power by satisfying all the lower and upper bound restrictions, the generators are initialized randomly in the search region for different iterations. Afterwards, the main optimizer MPA goes through several stages to meet the power demand by enforcing the lower and upper boundaries restriction of each controlling parameter. In the exploration and exploitation stage, the distinctive levy and Brownian movements demonstrated the best global optimum solution in the search space. After the exploitation process, the

| Parameters | FC (MW) | Active PL | Reactive PL | VD | VSEI |
|------------|---------|-----------|-------------|----|-----|
| PG1 (MW)   | 177.032 | 51.250    | 51.309      | 175.172 | 171.845 |
| PG2 (MW)   | 48.688  | 80        | 80          | 48.703  | 47.874 |
| PG3 (MW)   | 21.305  | 50        | 50          | 21.515  | 22.800 |
| PG4 (MW)   | 21.081  | 35        | 35          | 22.328  | 23.382 |
| PG5 (MW)   | 11.912  | 30        | 30          | 12.300  | 12.808 |
| PG6 (MW)   | 12.004  | 40        | 40          | 13.184  | 13.128 |
| V1 (p. u.) | 1.1     | 1.1       | 1.1         | 1.035   | 1.100 |
| V2 (p. u.) | 1.088   | 1.098     | 1.1         | 1.019   | 1.087 |
| V3 (p. u.) | 1.062   | 1.080     | 1.092       | 1.010   | 1.082 |
| V4 (p. u.) | 1.069   | 1.087     | 1.1         | 1.001   | 1.095 |
| V5 (p. u.) | 1.1     | 1.1       | 1.1         | 1.062   | 1.099 |
| V6 (p. u.) | 1.1     | 1.100     | 1.1         | 0.997   | 1.100 |
| T1         | 1.045   | 1.057     | 1.002       | 1.083   | 1.021 |
| T2         | 0.9     | 0.900     | 0.966       | 0.909   | 0.905 |
| T3         | 0.987   | 0.984     | 0.995       | 0.956   | 0.999 |
| T4         | 0.967   | 0.973     | 0.986       | 0.969   | 0.981 |
| QC1 (MVAR) | 5.000   | 5.000     | 5.000       | 5.000   | 5  |
| QC2 (MVAR) | 5.000   | 5.000     | 5.000       | 5.055   | 4.998 |
| QC3 (MVAR) | 5.000   | 4.999     | 4.999       | 5.000   | 5.000 |
| QC4 (MVAR) | 5.000   | 5.000     | 5.000       | 2.300   | 5.000 |
| QC5 (MVAR) | 5.000   | 4.999     | 5.000       | 5.000   | 5.000 |
| QC6 (MVAR) | 5.000   | 5.000     | 5.000       | 5.000   | 5.000 |
| QC7 (MVAR) | 3.661   | 3.713     | 4.999       | 5.000   | 5.000 |
| QC8 (MVAR) | 5.000   | 5.000     | 5.000       | 5.000   | 5.000 |
| QC9 (MVAR) | 2.995   | 2.540     | 3.248       | 2.722   | 5.000 |
| Cost ($/h) | 799.0725| 999.8447  | 967.2060    | 803.9062 | 800.3773 |
| Real PL (MW)| 8.6223  | 2.8513     | 2.9102      | 9.8005   | 8.4383 |
| Reactive PL (MVAR)| 3.0807 | 24.3630   | 25.2040 | 7.2292 | 5.2224 |
| VD         | 1.8516  | 2.0479    | 2.1310      | 0.0992   | 2.1264 |
| LK         | 0.1164  | 0.1151    | 0.1142      | 0.1364   | 0.1131 |

4.1 Case 1 –Fuel cost minimization

To verify the effectiveness and performance of the proposed technique in solving the OPF problems, the quadratic fuel cost of each generating unit was considered to optimize as the single-objective function in this case. The mathematical formulation of the objective function is discussed in section 2. The proposed method was employed to analyze all the controlling parameters (i.e., real power generation dispatch) of the IEEE 30-bus test system to meet the required load demand by satisfying the power system constraints. The obtained optimal settings of controlling variables optimize the fuel cost (FC) of the system which is illustrated in Table 2. To generate the least cost power by satisfying all the lower and upper bound restrictions, the generators are initialized randomly in the search region for different iterations. Afterwards, the main optimizer MPA goes through several stages to meet the power demand by enforcing the lower and upper boundaries restriction of each controlling parameter. In the exploration and exploitation stage, the distinctive levy and Brownian movements demonstrated the best global optimum solution in the search space. After the exploitation process, the
Table 2. Comparison of proposed algorithm with other literature work for case 1.

| Parameters | MPA | DSA [39] | SCA [6] | MSCA [6] | GWO [40] | DGWO [40] | HSA [41] | FHSA [41] | WEA [5] | EEA [42] | PSO [43] | DEA [44] |
|------------|-----|----------|--------|----------|---------|---------|--------|---------|--------|---------|---------|---------|
| PG1 (MW)   | 177.032 | 1.76954 | 140.21 | 177.401 | 171.094 | 176.949 | 1.77747 | 1.76804 | 173.4593 | 1.7696 | 176.2592 | 176.2592 |
| PG2 (MW)   | 48.688 | 0.48713 | 49.00 | 48.615 | 48.615 | 48.519 | 0.48584 | 0.49229 | 47.7363 | 0.4898 | 48.5602 | 48.5602 |
| PG3 (MW)   | 21.305 | 0.21383 | 20.26 | 21.2376 | 21.123 | 21.326 | 0.21539 | 0.21147 | 23.7692 | 0.2130 | 21.3402 | 21.3402 |
| PG4 (MW)   | 21.081 | 0.21285 | 22.00 | 20.8615 | 22.068 | 21.571 | 0.21278 | 0.21043 | 23.2234 | 0.2119 | 22.0553 | 22.0553 |
| PG5 (MW)   | 11.912 | 0.12044 | 11.00 | 11.9385 | 15.479 | 12.026 | 0.11014 | 0.11977 | 11.3724 | 0.1197 | 11.7785 | 11.7785 |
| PG6 (MW)   | 12.004 | 0.12000 | 11.00 | 12 | 13.665 | 12.001 | 0.12266 | 0.12062 | 12.2530 | 0.1200 | 12.0217 | 12.0217 |
| V1 (p.u.)  | 1.100 | 1.08442 | 1.10 | 1.1 | 1.080 | 1.083 | 1.0951 | 1.1 | 1.0994 | 1.0855 | 1.0999 |
| V2 (p.u.)  | 1.088 | 1.06454 | 1.10 | 1.0867 | 1.062 | 1.063 | 1.0747 | 1.085 | 1.0878 | 1.0853 | 1.0653 | 1.0890 |
| V3 (p.u.)  | 1.062 | 1.03347 | 1.08 | 1.0604 | 1.030 | 1.031 | 1.0410 | 1.054 | 1.0618 | 1.0506 | 1.0333 | 1.0659 |
| V4 (p.u.)  | 1.069 | 1.03880 | 1.10 | 1.0923 | 1.036 | 1.035 | 1.0531 | 1.062 | 1.0692 | 1.0700 | 1.0386 | 1.0697 |
| V5 (p.u.)  | 1.100 | 1.09793 | 1.10 | 1.1 | 1.080 | 1.060 | 1.0976 | 1.098 | 1.0909 | 1.0735 | 1.0848 | 1.0965 |
| V6 (p.u.)  | 1.100 | 1.04266 | 1.10 | 1.1 | 1.054 | 1.050 | 1.0892 | 1.095 | 1.1 | 1.0976 | 1.0512 | 1.0996 |
| QC1 (MVAR) | 5.000 | 0.05000 | 5.00 | 0.0246 | 2.144 | 1.695 | 0.0138 | 0.04383 | 0.04 | 0.0198 | 2.2573 | 2.2573 |
| QC2 (MVAR) | 5.000 | 0.05000 | 4.80 | 2.56 | 2.929 | 3.394 | 0.0060 | 0.045 | 0.05 | 0.01 | 0.0220 | 4.4158 |
| QC3 (MVAR) | 5.000 | 0.05000 | 4.99 | 4.586 | 1.400 | 4.777 | 0.0398 | 0.041 | 0.0198 | 0.04 | 0.0198 | 4.1734 |
| QC4 (MVAR) | 5.000 | 0.05000 | 5.00 | 2.4098 | 3.526 | 4.153 | 0.0430 | 0.011 | 0.039657 | 0.03 | 0.0315 | 2.5171 |
| QC5 (MVAR) | 5.000 | 0.04991 | 4.60 | 4.6378 | 2.954 | 3.738 | 0.0346 | 0.038 | 0.024189 | 0.04 | 0.0454 | 2.0916 |
| QC6 (MVAR) | 5.000 | 0.05000 | 4.40 | 0.3635 | 3.588 | 4.941 | 0.0352 | 0.013 | 1.033 | 0.01 | 0.0381 | 4.1990 |

(Continued)
MPA shows the global optima value at 799.072$/h for fuel cost. The comparison results concerning other metaheuristic-based optimization techniques namely DSA, SCA, MSCA, GWO, DGWO, HAS, FHSA, WEA, EEA, PSO, and DEA reveals that the proposed method showed the global best results among other techniques presented. On the other hand, the DGWO shows the highest value at 801.4333 $/h and is stuck at a certain time. The computational performances in terms of real power generation, real power loss, reactive power loss, voltage deviation, and voltage stability enhancement index for case-1 have been illustrated in Table 2. Thus, from the numerical results, it is seen that the proposed MPA technique provides superior results for the selected single-objective cases among the mentioned literature work. Additionally, the obtained fuel cost using the proposed technique with its convergence characteristics is portrayed in Fig 4.

4.2 Case 2 – Active power loss minimization (APL)

In this case, to verify the effectiveness and performance of the proposed technique for solving the OPF problems, the active power loss was considered to optimize as the single-objective
The mathematical formulation of this case is presented in section 2. For this case, the parameter setting for simulation is given in Table 1 and the result was obtained after several phases of exploration and exploitation by the presented approach. After the exploitation process, the MPA shows the global optimal value of 2.8513 MW for active power loss. The comparison results with respect to other metaheuristic-based optimization techniques namely DSA, SCA, MSCA, EEA, PSO, ABC, HS and EGA reveals that the proposed method showed the global best results among others in terms of active power loss minimization. On the other hand, the FEA technique shows the highest value at 3.3541 MW while PSO reveals the second highest at 3.318 MW. Although, the modified SCA give the second-best result of 2.9334 MW compared to the original SCA which performs to give 2.9425 MW active power losses. Further, the computational performances in terms of real power generation, real power loss, reactive power loss, voltage deviation, and voltage stability enhancement index for case-2 have been illustrated in Table 3. Thus, from the numerical results, it is seen that the proposed MPA technique provides superior results for the selected single-objective cases among the literature work. Additionally, the obtained power loss for the proffered technique with its convergence characteristics is portrayed in Fig 5.

| Parameters | MPA | SCA [6] | MSCA [6] | DSA [39] | PSO [42] | FEA [42] | ABC [39] | HS [39] | EGA [39] |
|------------|-----|---------|----------|----------|---------|---------|---------|--------|---------|
| PG1 (MW)   | 51.250 | 51.578 | 52.08    | 0.510945 | 56.6613 | 59.3216 | 0.510780 | 0.525327 | NR      |
| PG2 (MW)   | 80   | 79.78   | 79.28    | 0.800000 | 78.9597 | 74.8132 | 0.800000 | 0.795432 | 0.800000 |
| PG3 (MW)   | 50   | 50.00   | 50.00    | 0.500000 | 49.1795 | 49.8547 | 0.500000 | 0.498152 | 0.500000 |
| PG4 (MW)   | 35   | 34.99   | 35.00    | 0.350000 | 34.9084 | 34.5000 | 0.350000 | 0.347403 | 0.350000 |
| PG5 (MW)   | 30   | 29.99   | 30.00    | 0.300000 | 29.8242 | 28.1099 | 0.300000 | 0.297884 | 0.300000 |
| PG6 (MW)   | 40   | 40.00   | 39.97    | 0.400000 | 37.094  | 39.7538 | 0.400000 | 0.399480 | 0.400000 |
| V1 (p. u.) | 1.100 | 1.10    | 1.10     | 1.0605   | 1.0694  | 1.0547  | 1.0627   | 1.0754   | 1.0435   |
| V2 (p. u.) | 1.098 | 1.10    | 1.07     | 1.0566   | 1.0729  | 1.0418  | 1.0575   | 1.0728   | 1.0435   |
| V3 (p. u.) | 1.080 | 1.08    | 1.08     | 1.0378   | 1.0500  | 1.0247  | 1.0385   | 1.0540   | 1.0247   |
| V4 (p. u.) | 1.087 | 1.10    | 1.10     | 1.0453   | 1.0476  | 1.0335  | 1.0444   | 1.0637   | 1.0347   |
| V5 (p. u.) | 1.100 | 1.10    | 1.10     | 1.1000   | 1.0176  | 1.0229  | 1.0739   | 1.0991   | 1.0700   |
| V6 (p. u.) | 1.100 | 1.10    | 1.10     | 1.0474   | 1.0576  | 1.0776  | 1.0463   | 1.0967   | 1.0430   |
| T1         | 1.057 | 1.01    | 1.05     | 1.0329   | 0.95    | 1.0125  | 1.0500   | 1.0022   | 1.0375   |
| T2         | 0.900 | 0.93    | 0.95     | 0.9993   | 1.0125  | 0.9125  | 0.9375   | 0.9078   | 0.925    |
| T3         | 0.984 | 1.00    | 1.01     | 0.9913   | 0.9875  | 1.0125  | 0.9875   | 0.9593   | 0.975    |
| T4         | 0.973 | 0.97    | 0.99     | 0.9786   | 1.0375  | 1.0125  | 0.9750   | 0.9533   | 0.975    |
| QC1 (MVAR) | 5.000 | 2.81    | 3.15     | 0.5000   | 0.05    | 0.04    | 0.0500   | 0.0499   | 0.0500   |
| QC2 (MVAR) | 5.000 | 2.53    | 0.81     | 0.5000   | 0.05    | 0.02    | 0.0500   | 0.0486   | 0.0300   |
| QC3 (MVAR) | 4.999 | 3.99    | 4.49     | 0.5000   | 0.05    | 0.05    | 0.5000   | 0.0499   | 0.0000   |
| QC4 (MVAR) | 5.000 | 1.60    | 2.40     | 0.5000   | 0.03    | 0.01    | 0.5000   | 0.0488   | 0.0100   |
| QC5 (MVAR) | 4.999 | 2.99    | 1.48     | 0.5000   | 0.04    | 0.05    | 0.4000   | 0.0442   | 0.0400   |
| QC6 (MVAR) | 5.000 | 4.11    | 4.64     | 0.5000   | 0.05    | 0.00    | 0.5000   | 0.0499   | 0.0200   |
| QC7 (MVAR) | 3.713 | 1.86    | 3.17     | 0.4422   | 0.02    | 0.02    | 0.5000   | 0.0411   | 0.0500   |
| QC8 (MVAR) | 5.000 | 3.96    | 4.69     | 0.5000   | 0.00    | 0.05    | 0.5000   | 0.0499   | 0.0500   |
| QC9 (MVAR) | 2.540 | 3.12    | 1.80     | 0.3030   | 0.01    | 0.02    | 0.5000   | 0.0317   | 0.0500   |
| Cost ($/h) | 999.845 | 966.788 | 965.648 | 967.6493 | 954.348 | 952.3785 | 967.681 | 964.5121 | 967.86   |
| Real PL (MW) | 2.851 | 2.9425  | 2.9334   | 3.09450  | 3.318   | 3.3541  | 3.1078  | 2.9678   | 3.2008   |
| Reactive PL (MVAR) | -24.363 | - | - | - | - | - | - | - | - |
| VD         | 2.048 | 1.8161  | 1.5987   | -        | -       | -       | -       | -       | -       |
| LK         | 0.115 | -       | -        | 0.12604  | -       | -       | 0.1386  | 0.1154   | 0.12178  |

https://doi.org/10.1371/journal.pone.0256050.t003
4.3 Case 3—Reactive power loss minimization (RPL)

In this case, further to verify the effectiveness and performance of the propounded technique in solving the OPF problem, the reactive power loss was considered as the single-objective function. The mathematical formulation of this case is also detailed in section 2 with its optimal setting of the control parameter is portrayed in Table 1. The main goal of this objective function is to minimize the reactive power losses by the proposed MPA technique. This objective can be achieved by deducting the reactive power demand from reactive power generation. After the exploitation process, the MPA shows the global optima value of -25.204 MVAR for reactive power loss. The comparison results with respect to other metaheuristic-based optimization techniques reveals that the proposed method showed the global best results among others in the case of reactive power loss minimization. On the other hand, the BHBO technique shows the worst value of -20.1522 MVAR while EM reveals the second-highest value of -22.0196 MVAR. Although, the recently used hybrid HFPSO showed almost similar result. The computational performances in terms of real power generation, real power loss, reactive power loss, voltage deviation, and voltage stability enhancement index for case-3 have been illustrated in Table 4. Thus, from the numerical results, it is seen that the proposed MPA technique provides superior results for the selected single-objective cases among all mentioned literature work. Additionally, the obtained reactive power loss with its convergence characteristics is portrayed in Fig 6.

4.4 Case 4—Voltage deviation (VD)

In this case, the minimization of voltage deviation has been considered to be optimized as the fourth single objective function. The obtained optimal values of all controlling parameters of the power system by the proposed MPA for voltage deviation have been given in Table 4. To verify the effectiveness and performance of the proposed technique in solving the OPF problem comparing with other techniques, the numerical results obtained in the literature from
several recently developed meta-heuristic methods have been presented in Table 5. The mathematical formulation of this case is discussed in section 2. At the initial run of the MPA, the algorithm optimizes the parameter by exploring the search space and for the increase in iteration, the exploitation phase increases with a decrease in exploration in order to reach the global optimal solution. After the exploitation process, the MPA shows the global optima value at 0.099 for voltage deviation. The comparison results with respect to other metaheuristic-based optimization techniques namely SCA, MSCA, WEA, PSO, MOJA, and GSA reveal that the proposed method showed the global best results among others. It is observed that all other reported literature work has demonstrated quite similar results in voltage deviation. The computational performances in terms of real power generation, real power loss, reactive power loss, voltage deviation, and voltage stability enhancement index for case-4 have been illustrated in Table 5. Thus, from the numerical results, it is seen that the proposed MPA technique provides superior results for the selected single-objective cases among the presented technique in literature work. Moreover, the optimization of voltage deviation by the proposed technique is given in Fig 7.

Table 4. Comparison of proposed algorithm with other literature work for case 3.

| Parameters | MPA  | EM [45] | IEM [45] | HFPSO [46] | PSO [46] | BHBO [47] | MVO [48] |
|------------|------|---------|----------|------------|----------|-----------|---------|
| PG1 (MW)   | 51.309 | 64.0008 | 51.4349 | 51.3085 | 52.0175 | 73.6130 | 51.348 |
| PG2 (MW)   | 50.0000 | 75.0319 | 80.0000 | 80.0000 | 79.8978 | 79.9447 | 80.000 |
| PG3 (MW)   | 50.0000 | 48.1465 | 50.0000 | 35.0000 | 49.9998 | 48.5176 | 50.000 |
| PG4 (MW)   | 50.0000 | 32.7775 | 35.0000 | 50.0000 | 29.8163 | 31.7662 | 35.000 |
| PG5 (MW)   | 30.0000 | 28.9746 | 30.0000 | 35.0000 | 29.8163 | 25.5264 | 29.998 |
| PG6 (MW)   | 40.0000 | 37.9527 | 40.0000 | 40.0000 | 40.0000 | 36.7867 | 40.000 |
| V1 (p. u.) | 1.100  | 1.0927  | 1.1000  | 1.1000  | 1.0999  | 1.0817  | 1.1000  |
| V2 (p. u.) | 1.100  | 1.0885  | 1.1000  | 1.1000  | 1.0927  | 1.0784  | 1.1000  |
| V3 (p. u.) | 1.092  | 1.0764  | 1.0939  | 1.0919  | 1.0858  | 1.0651  | 1.093   |
| V4 (p. u.) | 1.100  | 1.0910  | 1.1000  | 1.1000  | 1.0999  | 1.0703  | 1.1000  |
| V5 (p. u.) | 1.100  | 1.0160  | 1.1000  | 1.1000  | 1.0999  | 1.0376  | 1.1000  |
| V6 (p. u.) | 1.100  | 1.0659  | 1.1000  | 1.1000  | 1.0999  | 1.0376  | 1.1000  |
| T1         | 1.002  | 1.0874  | 1.0121  | 1.0018  | 1.0603  | 1.0504  | 1.000   |
| T2         | 0.966  | 0.9879  | 0.9000  | 0.9657  | 1.0391  | 0.9973  | 0.937   |
| T3         | 0.995  | 1.0232  | 0.9870  | 0.9949  | 1.0241  | 1.0104  | 0.993   |
| T4         | 0.986  | 1.0461  | 0.9816  | 0.9863  | 1.0363  | 1.0284  | 0.983   |
| QC1 (MVAR) | 5.000  | 3.2124  | 0.6417  | 5.0000  | 0.3746  | 2.7586  | 0.775   |
| QC2 (MVAR) | 5.000  | 4.7420  | 0.0299  | 5.0000  | 4.9986  | 2.5341  | 3.857   |
| QC3 (MVAR) | 4.999 | 4.1200  | 4.4270  | 5.0000  | 4.9999  | 2.9776  | 3.668   |
| QC4 (MVAR) | 5.000  | 1.8437  | 0.0000  | 5.0000  | 1.3503  | 2.3622  | 2.923   |
| QC5 (MVAR) | 5.000  | 3.1539  | 5.0000  | 5.0000  | 4.9548  | 2.9648  | 4.170   |
| QC6 (MVAR) | 5.000  | 3.2219  | 4.9813  | 5.0000  | 0.6480  | 2.8198  | 2.113   |
| QC7 (MVAR) | 4.999 | 4.6849  | 0.0098  | 5.0000  | 2.7229  | 2.7216  | 3.390   |
| QC8 (MVAR) | 5.000  | 3.1210  | 0.0225  | 5.0000  | 4.9995  | 2.7057  | 5.000   |
| QC9 (MVAR) | 3.248  | 2.8779  | 4.0354  | 3.3162  | 1.4439  | 2.6123  | 2.952   |
| Cost ($/h) | 967.206| 939.4832| 967.2229| 967.2057| 966.95  | 924.1365| 967.250 |
| Real PL (MW) | 2.910 | 3.4851  | 2.9186  | 2.9101  | 2.9101  | 3.7545  | 2.948   |
| Reactive PL (MVAR) | -25.204 | -22.0196| -25.1422| -25.204 | -23.756 | -20.1522| -25.038 |
| VD         | 2.1310 | 0.7773  | 2.0860  | 2.1318  | 0.9126  | 0.4878  | 2.041   |
| LK         | 0.1140 | 0.1330  | 0.1162  | 0.1142  | 0.1323  | 0.1371  | 0.117   |

https://doi.org/10.1371/journal.pone.0256050.t004
Table 5. Comparison of proposed algorithm with other literature work for case 4.

| Parameters | MPA   | SCA [6] | MSCA [6] | WEA [5] | PSO [24] | MOJA [49] | GSA [50] |
|------------|-------|---------|----------|---------|----------|-----------|----------|
| PG1 (MW)   | 175.172 | 122.82  | 112.585  | 0.82313 | 1.7368   | 89.0808   | 1.73320940 |
| PG2 (MW)   | 48.703  | 74.98   | 79.76    | 0.67094 | 0.4910   | 78.6206   | 0.49263900 |
| PG3 (MW)   | 21.515  | 15.50   | 22.25    | 0.48874 | 0.2181   | 49.8306   | 0.21567799 |
| PG4 (MW)   | 22.328  | 31.40   | 25.09    | 0.31858 | 0.2330   | 34.6289   | 0.23274500 |
| PG5 (MW)   | 12.300  | 29.16   | 29.95    | 0.28385 | 0.1388   | 23.9941   | 0.13774500 |
| PG6 (MW)   | 13.184  | 18.04   | 20.85    | 0.29467 | 0.1200   | 12.0077   | 0.11964300 |
| V1 (p. u.) | 1.035   | 1.00    | 1.01     | 1.0055  | 1.0248   | 1.0284    | 1.026900  |
| V2 (p. u.) | 1.019   | 1.04    | 0.99     | 1.0028  | 1.0022   | 1.0143    | 1.009980  |
| V3 (p. u.) | 1.010   | 1.02    | 1.02     | 1.0191  | 1.0170   | 1.0127    | 1.014280  |
| V4 (p. u.) | 1.001   | 1.04    | 1.05     | 1.0037  | 1.0100   | 1.0071    | 1.008680  |
| V5 (p. u.) | 1.062   | 1.00    | 1.05     | 0.99844 | 1.0506   | 1.0441    | 1.050289  |
| V6 (p. u.) | 0.997   | 1.03    | 0.99     | 1.0047  | 1.0175   | 1.0004    | 1.016340  |
| T1         | 1.083   | 0.98    | 1.04     | 0.04149 | 1.0702   | 1.0646    | 1.071330  |
| T2         | 0.909   | 0.95    | 0.95     | 0.03150 | 0.9000   | 0.9010    | 0.900000  |
| T3         | 0.956   | 1.00    | 0.96     | 0.04979 | 0.9954   | 0.9574    | 0.996300  |
| T4         | 0.969   | 0.95    | 0.95     | 0.9703  | 0.9699   | 0.973200  |
| QC1 (MVAR) | 5.000   | 3.40    | 4.75     | 0.04999 | 0.0403   | 4.4080    | 0.04143700 |
| QC2 (MVAR) | 0.855   | 0.09    | 4.13     | 0.03514 | 0.0369   | 0.0000    | 0.03562000 |
| QC3 (MVAR) | 5.000   | 2.77    | 4.87     | 0.04081 | 0.0500   | 4.8290    | 0.05000000 |
| QC4 (MVAR) | 2.300   | 0.63    | 3.16     | 0.05    | 0.0000   | 0.0773    | 0.00000000 |
| QC5 (MVAR) | 5.000   | 4.50    | 4.93     | 0.00573 | 0.0500   | 4.9988    | 0.05000000 |
| QC6 (MVAR) | 5.000   | 4.19    | 4.91     | 1.0115  | 0.0500   | 4.8611    | 0.05000000 |

Fig 6. Convergence property of the proposed MPA for case 3.
4.5 Case 5—Voltage stability enhancement index (VSEI)

In this case, to verify the effectiveness and performance of the proposed technique in solving the OPF problem, the voltage stability enhancement index was considered to optimize as the fifth single-objective function. Generally, the voltage stability index should be in the range of zero (no-load case) to one (voltage collapse). This voltage stability index is used to find out the accurate voltage instability of the system in order to avoid the voltage collapse of the power network. Therefore, it is necessary to consider the VSEI in OPF problem solving. The mathematical formulation of this case is mentioned in section 2. The proposed method was employed to analyze all the controlling parameters of the IEEE 30-bus test system to meet the required demand by satisfying all the power system constraints. The obtained optimal settings of controlling variables to optimize the VSEI of the system which is illustrated in Table 6. In order to ensure the optimized outcomes, the proposed method of MPA undergoes through several stages to meet the power demand by enforcing the lower and upper boundaries restriction of each controlling parameter. In the exploration and exploitation stage, the distinctive levy and Brownian movements demonstrated the best global optimum solution in the search space. After the exploitation
The MPA shows the global optima value at 0.113 for VSEI. The comparison results with respect to other metaheuristic-based optimization techniques such as WEA, DSA, BBO, MODE, PSO, and GA reveals that the proposed method showed the global best results among others in terms of solution quality and convergence property. On the other hand, the WEA and BBO showed the global minima in case 5 at 0.0927 and 0.09803 respectively, although the other parameters like fuel cost showed the worst value which is are the major concern. The computational performances in terms of real power generation, real power loss, reactive power loss, voltage deviation, and voltage stability enhancement index for case-5 have been illustrated in Table 6. Thus, from the numerical results, it is seen that the proposed MPA technique provides superior results for the selected single-objective cases among all mentioned literature work. Additionally, the convergence characteristic for this case is portrayed in Fig 8.

### 4.6 Case 6—Analysis of large-case test system

In this case, an IEEE 118-bus system data has been considered to verify the effectiveness of the proposed technique for solving the large-scale power system. The active and reactive power...
demand of this system are 4242 MW and 1439 MVAR, respectively. The quadratic fuel cost of each generating unit was considered to be optimize as the single-objective function to demonstrate the effectiveness of proposed method. The mathematical formulation of this objective function is discussed in section 2. The proposed method was employed to analyze all the controlling parameters (i.e., real power generation dispatch) of the IEEE 118-bus test system to meet the required load demand by satisfying the power system constraints of equality and inequality. The obtained optimal settings of controlling variables that optimize the fuel cost (FC) of the system which is illustrated in Table 7. To generate the least cost power by satisfying all the lower and upper bound restrictions, the generators are initialized randomly in the search region for different iterations. Afterwards, the main optimizer MPA goes through several stages to meet the power demand by enforcing the lower and upper boundaries restriction.

Table 7. Controlling variables of IEEE 118-bus system.

| Parameters | Value   | Parameters | Value   | Parameters | Value   | Parameters | Value   | Parameters | Value   |
|------------|---------|------------|---------|------------|---------|------------|---------|------------|---------|
| PG1        | 25.82641| PG65       | 4.68592 | VG1        | 1.03644 | VG65       | 1.05635 | T8         | 0.98167 |
| PG4        | 0.82954 | PG66       | 0       | VG4        | 1.05897 | VG66       | 1.07416 | T32        | 1.0042 |
| PG6        | 0       | PG69       | 0       | VG6        | 1.05142 | VG69       | 1.08738 | T36        | 0.98786 |
| PG8        | 0.82235 | PG70       | 16.74587| VG8        | 1.04061 | VG70       | 1.06097 | T51        | 0.97243 |
| PG10       | 396.3794| PG72       | 21.29686| VG10       | 1.05135 | VG72       | 1.05453 | T93        | 0.99825 |
| PG12       | 85.63114| PG73       | 0.38982 | VG12       | 1.04938 | VG73       | 1.06814 | T95        | 0.98374 |
| PG15       | 18.0197 | PG74       | 425.347 | VG15       | 1.04513 | VG74       | 1.05721 | T102       | 1.03342 |
| PG18       | 12.1527 | PG76       | 0.2663  | VG18       | 1.04572 | VG76       | 1.04863 | T107       | 0.9885 |
| PG19       | 20.64721| PG77       | 4.1874  | VG19       | 1.04579 | VG77       | 1.06263 | T127       | 0.98748 |
| PG24       | 0       | PG80       | 498.3164| VG24       | 1.05831 | VG80       | 1.07537 | QC5        | 22.1875 |
| PG25       | 192.3364| PG85       | 0       | VG25       | 1.07192 | VG85       | 1.05852 | QC34       | 15.642 |
| PG26       | 274.8895| PG87       | 0       | VG26       | 1.08589 | VG87       | 1.08615 | QC37       | 4.2751 |
| PG27       | 18.35485| PG89       | 0.4872  | VG27       | 1.05236 | VG89       | 1.07826 | QC44       | 22.3526 |

(Continued)
of each controlling parameter. In the exploration and exploitation stage, the distinctive levy and Brownian movements demonstrated the best global optimum solution in the search space. After the exploitation process, the MPA shows the global optima value of at 129422.56$/h for fuel cost and active power loss 74.64 MW, respectively. Additionally, the obtained fuel cost using the proposed technique with its convergence characteristics is portrayed in Fig 9.

Table 7. (Continued)

| Parameters | Value | Parameters | Value | Parameters | Value | Parameters | Value | Parameters | Value |
|------------|-------|------------|-------|------------|-------|------------|-------|------------|-------|
| PG31       | 7.17113 | PG90       | 0.3367 | VG31       | 1.04138 | VG90       | 1.06861 | QC45       | 15.2674 |
| PG32       | 26.24774 | PG91       | 225.6524 | VG32       | 1.045313 | VG91       | 1.07467 | QC46       | 2.3982 |
| PG34       | 12.85337 | PG92       | 38.4756 | VG34       | 1.06075 | VG92       | 1.07541 | QC48       | 7.826 |
| PG36       | 7.1522 | PG99       | 0           | VG36       | 1.06205 | VG99       | 1.0673 | QC74       | 11.6733 |
| PG40       | 33.82485 | PG100      | 7.4375 | VG40       | 1.07354 | VG100      | 1.07719 | QC79       | 24.1432 |
| PG42       | 31.39974 | PG103      | 34.8527 | VG42       | 1.05268 | VG103      | 1.06346 | QC82       | 5.3876 |
| PG46       | 18.0887 | PG104      | 6.2875 | VG46       | 1.05152 | VG104      | 1.05618 | QC83       | 7.9287 |
| PG49       | 193.61117 | PG105     | 147.94211 | VG49       | 1.06358 | VG105      | 1.06313 | QC105      | 14.6295 |
| PG54       | 49.00784 | PG107      | 0           | VG54       | 1.05604 | VG107      | 1.6288 | QC107      | 6.2836 |
| PG55       | 31.22416 | PG110      | 347.8255 | VG55       | 1.05829 | VG110      | 1.06429 | QC110      | 22.5176 |
| PG56       | 55.53385 | PG111      | 35.3524 | VG56       | 1.04872 | VG111      | 1.05344 | Fuel Cost ($/h) | 129422.56 |
| PG59       | 149.28334 | PG112      | 30.6253 | VG59       | 1.06105 | VG112      | 1.0611 | Active Power Loss (MW) | 77.64119 |
| PG61       | 349.00741 | PG113      | 0           | VG61       | 1.07251 | VG113      | 1.0521 | |
| PG62       | 462.83747 | PG116      | 0           | VG62       | 1.06084 | VG116      | 1.07613 | |

Fig 9. IEEE 118-bus convergence curve.

https://doi.org/10.1371/journal.pone.0256050.g009
5. Conclusion

In this work, a nature-inspired metaheuristic Marine predator-based optimization technique has been employed to solve several types of single objective OPF problems of fuel cost, real and reactive power loss, voltage deviation and voltage stability enhancement index by satisfying both the equality and inequality constraints of power system network. The effectiveness of the methods is tested on a standard IEEE 30-bus benchmark system and the convergence characteristic exhibits the proposed optimization techniques outperforms to optimal solution. The results obtained for various cases of single-objective function is compared with GA, PSO, BBO, WEA, DSA, and MODE. It is seen that the proposed MPA of fuel cost, active power loss, reactive power loss, voltage deviation, and voltage stability enhancement index was obtained to achieve the global optima of for each individual objective. This is attained through the unique foraging strategy of marine predators with Levy and Brownian movements attributed to getting the competitive optimized results for the formulated OPF problems. The results obtained demonstrated that the proposed method recorded the global minima comparing with other recently developed methods reported in the literature. In particular, the proposed MPA technique showed promising results of 799.0725 $/hr (case-1), 2.851 MW (case-2), -25.204 MVar (case-3), 0.099 (case-4) and 0.113 (case-5) in terms of solution quality for several objectives considered and this claim is also exhibited in convergence characteristics of for different OPF problems studied. Further, to demonstrate the robustness of the proffered technique, an IEEE 118-bus system is tested for the case of fuel cost minimization and the results obtained depicts the optimal fuel cost of 129422.56 $/hr. However, the study of placement of distributed generations and contingency ranking is the future scope of the proposed research work.

Acknowledgments

The authors gratefully acknowledge the Advanced Lightning, Power and Energy Research (ALPER), Universiti Putra Malaysia for providing facilities to carry out the research.

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