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Improved Mayfly Algorithm for Optimizing Power Flow with Integrated Solar and Wind Energy

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ABSTRACT- Across the globe, the transition towards sustainable energy systems necessitates seamless implementation of Renewable Energy Sources (RES) into traditional power grids. Such RESs include solar and wind power. The current research work intends to overcome the challenges associated with Optimal Power Flow (OPF) problem in power systems in which the traditional operation parameters ought to be optimized for effective and trustworthy integration of the RESs. The current study proposes an innovative nature-inspired approach by enhancing the Mayfly algorithm on the basis of mating behaviour of mayflies. The aim of this approach is to tackle the complexities introduced by dynamic and discontinuous nature of solar and wind power. The improved Mayfly algorithm aims at minimizing power losses, emission, optimize voltage profiles, and ensure reliable integration of solar and wind power. The current study outcomes provide knowledgeable insights towards power flow optimization in power systems with high penetration of renewable energy. The application results reveal that the improved mayfly algorithm achieved better efficacy compared to the classical mayfly algorithm and the rest of the optimization algorithms.

Keywords: Improved Mayfly Algorithm (IMA); Wind power; Solar Photovoltaic; Optimal Power Flow; Operation Cost; Voltage Deviation; Voltage Stability Index; Emission.

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1. INTRODUCTION

The increasing demand for electric power coupled with environmental concerns and the depletion of conventional non-renewable energy resources have eventually increased the interest towards renewable energy sources such as wind and solar power [1]. Renewable Energy Sources (RES), specifically wind and solar power, have gained significant attention in the recent years as viable alternatives to conventional energy resources [2]. However, the increasing penetration of RESs introduces other types of complexities due to the unpredictability and intermittency associated with wind and solar power sources [3]. In this background, it is challenging for the power system operators to integrate such variable and intermittent energy sources into power grid, especially in maintaining a stable and efficient power flow [4]. Furthermore, the integration of these variable energy sources into power systems necessitates advanced optimization techniques in order to ensure grid stability, reliability, and efficiency [5]. Traditional power flow studies have played an essential role in optimizing the operation of power systems. The Optimal Power Flow (OPF) problem aims at optimizing the operating parameters of the power system to enhance efficiency, reliability, and economic viability [6]. The solution to address the OPF problem gets heavily intricate with the integration of RESs [7]. The imperative to undergo a paradigm shift towards sustainable energy sources underscores the need for effective methodologies that can handle the challenges posed by the integration of RESs [8]. Hamdi Abdi et al., provided a comprehensive review of the existing optimization algorithms in order to resolve the OPF problem experienced in smart grids and micrograms [9]. Furthermore, the authors also discussed about their strengths and limitations, thus emphasizing the need for innovative approaches to address the challenges encountered. In literature [10], optimal power flow problem faced during the incorporation of renewable energy sources was addressed using Success history-based parameter adaptation technique of Differential Evolution (SHADE). The objective function considered reserve cost for overestimation and penalty cost for underestimation of the intermittent renewables. In the study conducted earlier [11], the multi-objective optimal power flow was handled using two constraint multi-objective optimization approaches with the incorporation of solar and wind power sources. The study incorporated four optimization objectives such as generation cost, real power loss, voltage deviation, and emissions. In literature [12], a Multi-Objective Optimization Power Flow (MOOPF) problem with stochastic wind, solar power and tidal power models was resolved. The researchers [13] proposed a robust multi-objective method to determine the Pareto optimal solutions of a multi-objective optimal power flow framework which was inclusive of thermal, wind, and solar PV energy sources in a hybrid power system. Both single and multi-objective optimal power flow was validated with the integration of solar and wind power sources using moth flame optimization algorithm [14]. In the study conducted earlier [15], multi-objective optimal power flow problem, encountered with the integration of thermal, wind, and PV systems, was handled using a multi-objective evolutionary algorithm based on decomposition and the summation of normalized objectives with an improved diversified selection method was proposed.

2. MATHEMATICAL FORMULATION OF OPTIMAL POWER FLOW

2.1. Objective functions

2.1.1. Mitigation of generating cost

When the generation cost of thermal generators gets reduced in the presence of specific physical constraints, the ELD problem gets articulated without valve point loading [7]. The ELD challenge is mathematically expressed in *equation (1)*.

Minimize

$$F_0(P_g) = \sum_{j=1}^{k}(a_j + b_jP_{gj} + c_jP_{gj}^2) \quad (1)$$

Here, a_j, b_j and c_j corresponds to the j[th] generating unit's operation cost efficiency, while k denotes the overall set of generating units while the power generated by the j[th] generator is denoted as P_{gj} in MW.

2.1.2. Reduction of generation cost through valve point loading effect

According to the literature [7], the formulation of economic dispatch problem is simple to accomplish by leveraging the valve point effect and initiating a sinusoidal term into fitness function (5), as shown in *equation (2)*.

$$F(P_g) = \sum_{j=1}^{k}(a_j + b_jP_{gj} + c_jP_{gj}^2) + |e_j\sin(f_j * (P_{gjmin} - P_j)| \quad (2)$$

Here, the j[th] unit's operation coefficients are denoted by e_j and f_j and these values are utilized to portray the valve point effect.

2.1.3. Total emission reduction

In OPF, the emission objective function is strategically created in order to mitigate the environmental impact of power system operations, by reducing the emissions associated with electricity generation. Here, the objective is to optimize the dispatch of generation units in which not only economic factors are considered, but also the environmental considerations such as greenhouse gas emissions. As per the literature [7], *equation (3)* quantifies the overall emission of the atmospheric pollutants produced by the thermal generators in terms of t/h.

$$E(P_g) = \sum_{j=1}^{k}[10^{-2}(\alpha_j + \beta_jP_{gj} + \gamma_jP_{gj}^2) + \varsigma_i\exp(\lambda_jP_{gj})] \quad (3)$$

In this equation, $\alpha_j, \beta_j, \gamma_j, \varsigma_j$ and λ_j correspond to the emission coefficients of the j[th] generation unit.

Energy production facilities across the globe are under pressure from their respective governments to reduce their carbon emission levels, as a strategic move to confine the effects of global warming [16]. In addition to the existing taxes, carbon tax (C_{tax}) is additionally levied upon for every quantity of GHG emitted. The aim of this taxation is to increase the investments made in clean energy production methods using renewable energy sources such as solar and wind [16]. The emission cost is shown in *equation (4)* in terms of t/h.

Emission cost, $F_E = C_{tax}E(P_g)$ (4)

2.1.4. Mitigation of Real Power Loss

As the consumption of energy increases, there is an increase observed in the amount of power losses too. This phenomenon emphasizes the power system operators to reduce the power losses [17]. Accordingly, the following equation is used to determine the transmission line loss.

$$F(P_{loss}) = P_{loss} = \sum_{n=1}^{NL} g_n\,[V_j^2 + V_k^2 - 2V_jV_k\cos(\delta_j - \delta_k)] \quad (5)$$

Here, the n[th] line's conductance is denoted by g_n and it integrates the buses j and k while *NL* corresponds to the count of transmission lines.

2.1.5. Mitigation of L-Index

Voltage stability determination gained importance in power system analysis since the modern-day power systems function near stability limits. Since voltage stability is one of the critical elements of power system operation, voltage stability indices enact a crucial role in both evaluation and stabilization of the power system. Voltage stability indices help in detecting the proximity to voltage collapse conditions. Therefore, the following *equation (6)* exhibits the defined objective.

$$L - Index = \min VSI = Minimize(\max(L_j)) \quad (6)$$

The following expression [18] characterizes the L_j of the j[th]bus.

$$L_j = \left|1 - \sum_{i=1}^{N_{PV}} F_{ji} X \frac{V_i}{V_j}\{\theta_{ji} + (\delta_i - \delta_j)\}\right| j = 1,2,\dots,N_{PQ}$$

With

$$F_{ji} = |F_{ji}|\theta_{ji}, V_i = |V_i|\delta_i, V_j = |V_j|\delta_j F_{ji} = -[Y_1]^{-1}[Y_2]$$

2.2. Constraints of Equality and Inequality

In order to accomplish efficient Optimal Power Flow (OPF), it is crucial to consider the transmission line losses. The current study followed Newton-Raphson method to obtain the OPF solution in order to find out the real power loss *i.e.*, P_{loss}. Equation [7] corresponds to active power loss, when it is exposed to equality constraints.

$$P_{gj} - P_{Dj} - V_j \sum_{j=1}^{NB} V_k \left[G_{jk}\cos(\delta_j - \delta_k) + B_{jk} sin(\delta_j - \delta_k)\right] = 0 \quad (7)$$

$$Q_{gj} - Q_{Dj} - V_j \sum_{j=1}^{NB} V_k \left[G_{jk}\sin(\delta_j - \delta_k) + B_{jk} cos(\delta_j - \delta_k)\right] = 0 \quad (8)$$

As per the literature [7], the real power generation output of each and every generating unit must be kept under control with minimum and maximum threshold levels.

$$P_{gimin} \le P_{gi} \le P_{gimax} \quad (9)$$

P_{gi} denotes the *i*[th] generating unit's actual power output. On the other hand, P_{gimax} denotes the maximum real power output of the *i*[th] generating unit while its minimum real power output is denoted by P_{gimin}.

$$Q_{gimin} \le Q_{gi} \le Q_{gimax} \quad (10)$$

$$V_{gimin} \le V_{gi} \le V_{gimax} \quad (11)$$

Equation (12) corresponds to the tap changer of transformers that is employed to regulate the voltage magnitude. *Equation (13)* is linked to the output achieved from the overall number of switchable shunt components.

$$T_r^{min} \le T_r \le T_r^{max} \quad (12)$$

$$Q_{C_s}^{min} \le Q_{C_s} \le Q_{C_s}^{max} \quad (13)$$

$$V_{L_k}^{min} \le V_{L_k} \le L_{L_k}^{max} \quad (14)$$

$$|S_{l_t}| \le S_{l_t}^{max} \quad (15)$$

3. IMPROVED MAYFLY ALGORITHM

The inspiration behind the development of Mayfly algorithm is the social behaviour of mayflies, especially its mating phenomenon [19]. In conventional mayfly algorithm, random functions are employed to create new parameters, thus contributing to indigenous optimality. In order to enhance the searching capability of Mayfly Algorithm (MA) and foster the creation of optimal solutions, the researchers have integrated MA and Levy Flight (LF) approach [20]. When the latter is used for system identification, it accomplishes rapid convergences while it has no provisions for derivative information. The contribution of LF towards confining the optimal solution from suffering local trapping and local search avoidance is huge. [21].

The steps involved in the operations of the suggested IMA are given herewith.

Step-1: This step involves the random generation of two mayfly sets that imply male and female populations respectively. This candidate solution is denoted by d-dimensional vector $P_{Gi} = (P_{G1}, \dots, P_{Gd})$. Then, the enactment is assessed on the basis of the predefined fitness function $f(C_T(P_{Gi}))$

Step-2: The velocity of the mayfly *i.e.*, $v = (v_1, \dots v_d)$ gets started when its location changes. To be precise, every mayfly tends to modify its path as per the own finest location (*pbest*) up to that point. Additionally, the trajectory is influenced by the best location attained by some other mayfly of the swarm (*gbest*).

Step-3: In this step, the mayfly male population is primed as $P_{Gmi}(i = 1,2,\dots,NG)$ whereas its velocity stands at v_{mi}. At time t, the current location of the mayfly i in the exploration space is denoted by P_{Gi}^t. This location is modified by adding the velocity v_i^{t+1}, to the present location. This symbolization is articulated as given below.

$$P_{Gmi}^{t+1} = P_{Gmi}^t + v_i^{t+1} \quad (16)$$

Male mayflies are assumed to be positioned on top of the water at a few meters height and are represented by $P_{Gim}^0\ U(P_{Gmmin}, P_{Gmmax})$ and tend to engage in a nuptial dance. This phenomenon leads to determining the velocity i of the male mayfly as given below [20]:

$$v_{ij}^{t+1} = g * v_{ij}^t + a_1 e^{-\beta r_p^2}(pbest_{ij} - P_{Gmij}^t) + a_2 e^{-\beta r_g^2}(gbest_j - P_{Gmij}^t) \quad (17)$$

In the above equation, the mayfly i's velocity is denoted by v_{ij}^t in dimension $j = 1,\dots,n$ at time step t, the mayfly i's position in dimension j is denoted by P_{Gmij}^t at time step t, the positive attraction constants are denoted by a_1 and a_2 which are used in augmenting the contribution of cognitive followed by social components correspondingly. Further, the best location ever visited by mayfly i is denoted by$pbest_i$. For the minimization problems that arise under deliberation, the personal finest location $pbest_{ij}$ at the next time step $t + 1$ is calculated as given below.

$$pbest_i = \begin{cases} P_{Gmi}^{t+1}, iff(P_{Gmi}^{t+1}) < f(pbest_i) \\ isleptthesame, otherwise \end{cases} \quad (18)$$

$$gbest \in \{pbest_1, pbest_2, \dots pbest_N, |f(cbest)\}$$

$$= \min\{f(pbest_1), f(pbest_2), \dots, f(pbest_{NG})\} \quad (19)$$

In this context, β corresponds to the fixed visibility coefficient used in *eq. (17)* and it is utilized to confine the perceptibility of one mayfly to others. Additionally, r_p signifies the Cartesian distance that is measured betweenP_{Gi} and $pbest_i$ whereas the Cartesian distance between P_{Gi} and $gbest$ is denoted by r_g. The following equation is used to determine the distances.

$$||P_{Gmi} - X_i|| = \sqrt{\sum_{j=1}^{n} (P_{Gmij} - X_{ij})^2} \quad (20)$$

Here, P_{Gmij} represents the j^{th} element of mayfly i whereas X_i signifies either $pbest_i$ or $gbest$. In order to have an efficient functioning of the technique, the best mayflies should mandatorily engage in up-and-down nuptial dance within the swam at a constant pace. So, it is important for the best mayflies to have dynamic velocity, which is determined as given below:

$$v_{ij}^{t+1} = v_{ij}^{t} + d \times r \quad (21)$$

Step-4: In this step, the female mayfly population is primed as $P_{Gfi}(i = 1,2, \dots, NG)$ with the corresponding velocity v_{fi}. Unlike males, female mayflies do not congregate in swarms. For females, P_{Gfi}^{t} is considered as the current location of female mayfly i in the exploration space, at time step t. The location of this mayfly gets modified by totalling the velocity $v_i^{t+1}$to the current position.

$$P_{Gfi}^{t+1} = P_{Gfi}^{t} + v_i^{t+1} \quad (22)$$

In this context, $P_{Gfi}^{0}\ U(P_{Gfmin}, P_{Gfmax})$ makes it impossible for the randomization of the attraction procedure. So, the model is fit to be a deterministic development. Eventually, the following equation is used as per the literature [20] to determine the velocities in the existence of minimization problems.

$$v_{ij}^{t+1} = \begin{cases} g * v_{ij}^{t} + a_2 e^{-\beta r_{mf}^2}(P_{Gmij}^{t} - P_{Gfij}^{t}), & iff(P_{Gfi}) > f(P_{Gmi}) \\ g * v_{ij}^{t} + fl \times r, & iff(P_{Gfi}) \leq f(P_{Gmi}) \end{cases} \quad (23)$$

Here, v_{ij}^{t} corresponds to the female mayfly i's velocity in dimension $j = 1, \dots, n$ at time step t, and P_{Gfij}^{t}denotes the female mayfly's position i in dimension j at time step t. The positive attraction constant is denoted by a_2 and it serves as a static discernibility coefficient. Additionally, g denotes the gravity coefficient while the Cartesian distance between male and female mayflies is denoted by r_{mf}. In this context, fl represents a random walk coefficient whereas r symbolizes a randomly generated value in the range of [-1, 1]. This value is calculated as per the *equation (20).*

Step-5: Levy flight methodology is employed in this stage in order to determine a candidate mayfly solution's velocity. For this, *equation (24)* is utilized to calculate the mayfly candidate solution's velocity [20].

$$v_{ij}^{t+1} = \begin{cases} V_{max,} if v_{ij}^{t+1} > V_{max,} \\ -V_{max,} if v_{ij}^{t+1} < -V_{max} \end{cases} \quad (24)$$

In this phase, the location of the global optimal element is adjusted using the Levy flight approach. Here, V_{max} is determined as follows:

$$V_{max} = Levy(\lambda) * (P_{Gmmax} - P_{Gmmin}) \quad (25)$$

Step-6: Determining the gravity coefficient value [22]: The value for gravity coefficient (g) is assumed to be a fixed number in the range of (0, 1].

$$g = g_{max} - \frac{g_{max} - g_{min}}{iter_{max}} \times iter \quad (26)$$

Here, g_{min} denotes the minimum value while g_{max}corresponds to the maximum value to be assumed by the gravity coefficient. Further, $iter$, the variable denotes the present iteration of the algorithm. The maximum iteration count is signified by $iter_{max}$.

Step-7: Mayflies undergo mating and the resulting offspring are subsequently assessed. This selection can be based on fitness function or random criteria. Such a crossover eventually leads to two offsprings and the formulation is as follows [19]:

$$offspring1 = L \times male + (1 - L) \times female$$

$$offspring2 = L \times female + (1 - L) \times male \quad (27)$$

Here, the male parent is denoted by $male$ whereas the female parent is denoted by $female$ while L corresponds to a random value in a specific range.

4. RESULTS AND DISCUSSION

Within the conventional IEEE 57-bus assessment system, seven generating units are distributed across the buses 1, 2, 3, 6, 8, 9, and 12. Among these, 17 transformers feature off-nominal tap ratios whereas three parallel compensators are present in bus 18, bus 25 and bus 53. The load demand for the current research work is specified as 12.508 p.u. From the study conducted earlier [16], the information for the cost coefficients, PDF factors and bus data was taken to develop the stochastic models of RESs.

Case I: Mitigation of operation cost

The optimization of the generation plan encompassed both thermal as well as RESs generators and is aimed towards reducing the total generation cost *via eq. (2)*. Based on the input data retrieved from literature [16] such as bus data, Probability Density Function (PDF) parameters, and cost coefficients, the convergence characteristics for minimizing the generation cost using MA and IMA algorithms are depicted in *figure 1*. Upon scrutinizing the cost convergence attributes of the proposed IMA algorithm, it is evident that the algorithm exhibits swift and even convergence in contrast to the rest of the optimization methods, as exemplified in Figure 1. In order to underscore the efficacy of the suggested IMA algorithm, the minimum, mean, standard deviation, and maximum values of operation cost attained from 100 test runs are associated with other optimization approaches and are depicted in Table 1. The results conclude that the solution achieved by the IMA method in the altered IEEE 57-bus system surpasses the outcomes obtained through alternative optimization techniques under consideration.

Table 1. Comparative analysis of optimization outcomes for Case I from a statistical perspective

Method	Min	Mean	Max	SD
IMA	29 648.1096	29 664.3074	29 701.9412	11.3018
MA	29 655.0982	29 671.0841	29 708.1092	11.8012
ISA [22]	29 661.7024	29 676.6147	29 714.1691	12.1473
CSA [23]	29 695.3057	29 731.6104	29 763.0951	17.7947
PSO [16]	29 701.3612	29 794.0231	29 927.3647	57.3651
DEEPSO [16]	29 666.3226	29 680.700	29 719.8178	12.75954
MSA [16]	29 700.5577	29 792.218	29 925.4365	56.10544
BSA [16]	29 706.2293	29 734.2686	29 764.5804	14.48449
DS [16]	29 698.6677	29 725.2608	29 770.0826	18.48107

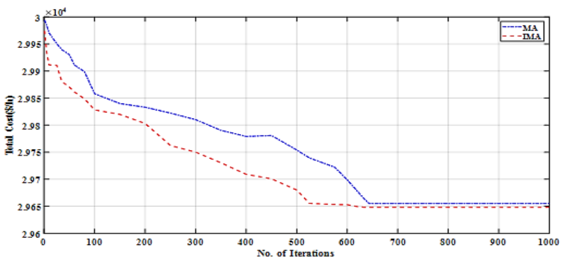

Figure 1. Operation cost convergence characteristic for Case I

Case II: Mitigation of operation cost with carbon tax

In this specific case, the primary focus is to minimize the overall generation cost by incorporating carbon tax, which is levied based on the emissions from conventional thermal power generators. *Equation (4)* denotes the cumulative cost that requires reduction while the carbon tax rate is set at $20/tonne [10]. The anticipated surge in the adoption of green energy sources, particularly wind and solar power, is attributed to the enforcement of carbon tax. It is evident that both emission volume as well as the imposed carbon tax rate enacts a crucial role in identifying the improvement levels in optimal generation schedule of RESs. *Figure 2* illustrates the cost convergence profiles for the suggested IMA and MA algorithms. The outcomes indicate that the proposed IMA displays a rapid and smooth convergence compared to the MA algorithm and it highlights the efficiency of the former. The optimization results affirm the robustness and enhanced accuracy of the suggested IMA in achieving optimal solutions. *Table 2* provides the numerical assessment outcomes of the optimization results for the altered IEEE 57-bus system. It is to be noted that the mean fuel cost achieved by the suggested IMA approach closely approaches its minimum value. The optimization results collectively suggest that the suggested IMA approach exhibits a notably commendable performance in comparison with the rest of the algorithms, including MA, CSA, DEEPSO, MSA, BSA, DS, and PSO.

Table 2. Comparative analysis of optimization outcomes for Case II from a statistical perspective

Method	Min	Mean	Max	SD
IMA	29 637.8146	29 651.0874	29 708.6017	12.0165
MA	29 643.0841	29 656.7019	29 715.8104	12.9157
ISA [22]	29 647.3059	29 661.0451	29 721.3610	13.5094
CSA [23]	29 692.0214	29 715.0345	29 759.3014	15.3017
PSO [16]	29 711.6207	29 779.3614	29 882.0649	41.0108
DEEPSO [16]	29 659.5505	29 673.024	29 730.5607	14.33206
MSA [16]	29 709.2692	29 776.655	29 880.4356	39.84685
BSA [16]	29 694.2836	29 716.6011	29 752.2188	14.08405
DS [16]	29 696.4717	29 720.1185	29 761.6953	15.3434

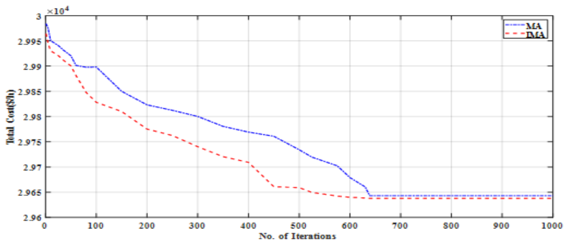

Figure 2. Operation cost convergence characteristic for Case II

5. CONCLUSION

The current research work focused on addressing the challenges posed by the incorporation of solar photovoltaic and wind power into conventional energy systems, in the perspective of the OPF problem. The successful application of the improved Mayfly algorithm underscores its potential to be a key player in addressing the challenges associated with OPF, in the era of renewable energy dominance. In both case studies, the proposed IMA algorithm outperforms the classical and other algorithms compared in terms of solution quality. In future research work, the possibility of further enhancements of the Mayfly algorithm with hybridizing with other optimization techniques to improve the convergence speed and solution accuracy will be explored.

AUTHOR CONTRIBUTIONS

All authors contributed to the study, conception and design. Material preparation, data collection and analysis were performed by KN, AR and MB. The first draft of the manuscript was written by KBNKR and NMG and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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