Solution of Optimal Power Flow problems using Enhanced Hunter Pray Optimization Algorithm

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***Abstract*—This work presents a new algorithm specifically developed to solve the Optimal Active Power Dispatch (OAPD) problems. The OAPD problem aims to minimize total voltage deviation, quadratic fuel cost, and complex nonlinear fuel cost, while considering the impact of valve point loading (VPL) effects and prohibited operating zone (POZ). This is done to maintain an economically efficient operational condition in a power system. The proposed hybrid algorithm combines the non-uniform mutation process with the Hunter-Prey Optimization Algorithm (HPOA) in order to improve the local search capabilities of HPOA. HPOA manages the global search process, whereas non-uniform mutation process and HPOA operate together for local search process. This combined technique effectively addresses complex nonlinear optimization problems. The proposed method is applied to determine the optimal settings to minimize real power loss, simple quadratic fuel cost and the fuel cost with VPL and POZ. The IEEE 30 bus system is used to evaluate the algorithm that is being considered. After that, its results are compared to those of other published algorithms.**

Keywords— Hunter-Prey Optimization Algorithm; OPF; non-uniform mutation

I. Introduction

Optimal Power Flow (OPF) is an essential problem in the operation and control of power systems (PS). This mathematical optimization problem seeks to determine how an electric power system can be operated in the most secure and cost-effective manner. While satisfying numerous operational constraints, the principal objective of OPF is to reduce the overall cost of producing and transmitting electricity [1]. In this study, the proposed algorithm is used to determine the optimal control variables to minimize Ploss in transmission line, quadratic fuel cost, and fuel cost with VPL.

Over the years, several traditional approaches have been used to address OPF issues, using nonlinear program method [2], interior-point method [3], and Newton's method [4]. In addition, metaheuristic algorithms like gravitational search algorithm (GSA) [5], teaching learning-based optimization (TLBO) [6], and Dwarf Mongoose Optimization Algorithm (DMOA) [7] have previously been used solving OPF problems. According to the literature review, some evolutionary algorithms have unavoidable problems, such as sluggish convergence rate and becoming stuck in local optima [8]. It is clear that hybrid algorithms are useful for solving these problems and finding global optimal solutions to power system difficulties with varying degrees of complexity [9]. Mutualism phase based Pelican Optimization Algorithm (MPOA) in [10], and Enhanced Butterfly Optimization algorithm (EBOA) in [11] have emerged, aiming to improve search capabilities.

This paper introduces a novel approach by hybridizing the Hunter-Prey Optimization Algorithm (HPOA) with SOSA, known for exploitation process. The mutualism phase of SOSA is integrated into each iteration of HPOA to enhance its exploitation capabilities. This hybridization shows potential for improved efficiency and search performance in solving power system optimization challenges.

The subsequent sections of this manuscript are as follows:

Section II discuss about Problem Formulation, Section III and Section IV delve into the discussions on HPOA and non-uniform mutation, respectively. Section V covers the discourse on the proposed algorithm, Section VI provides a summary of the acquired results and Section VII concludes the paper.

II. Problem Formulation

The OPF serves as an optimization tool of PS aiming to optimize specific objectives and determine the optimal operating state of the PS while adhering to physical and operational constraints. The OPF can be formulated as:

Minimize $f(u,v)$

$$\text{Subject to} \begin{cases} g(u,v)=0 \\ h(u,v)\le 0 \end{cases} \tag{1}$$

Where the objective function is denoted as f(u,v). u and v refer to vectors of dependent variables and control variables.

$$u^T = \left[P_{G1}, V_{L1} \cdots V_{LPQn}, Q_{G1} \cdots Q_{GGn}\right] \tag{2}$$

Where, P_{G1} signifies the power of slack bus, $V_{L1} \cdots V_{LPQn}$ represents the voltage at the PQ bus, $Q_{G1} \cdots Q_{GGn}$ represents the reactive power output.

$$v^T = \left[V_{G1} \cdots V_{GGn}, Q_{C1} \cdots Q_{CCn}, T_1 \cdots T_{Tn}\right] \tag{3}$$

Where, $T_1 \cdots T_{Tn}$ stands for the quantity of tap-changing transformers, $Q_{C1} \cdots Q_{CCn}$ represents the count of shunt VAR compensators, $V_{G1} \cdots V_{GGn}$ denotes the output voltages at PV buses

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A. Objective function

1) Total Voltage Deviation: Minimizing the load bus voltage deviation (VD) may allow an improvement in the voltage profile, as the power system operates more securely. Minimization of the VD can be formulated as: [11]:

$$TVD = \sum_{i=1}^{NL} \left| V_i - V_{ref_i} \right| \qquad (4)$$

Where, NL denotes the overall transmission line, Vi and Vrefi represents the magnitude of i^{th} bus and reference voltage.

2) Quadratic Fuel Cost:

The quadratic cost function can be mathematically expressed by

$$F_{\cos t} = \sum_{n=1}^{NG} \left[v_n + w_n P_{Gn} + x_n P_{Gn}{}^2 \right] \$ / hr \qquad (5)$$

Where v_n, w_n, and x_n cost coefficient of nth generator. P_{Gn} the real power output of nth generator. NG the number of generator bus.

3) Minimization of Total Environmental Emission

The environmental emissions from each thermal generating unit can be modeled as:

$$F_{emission}^{total} = 10^{-2} \times \sum_{n=1}^{NG} \left[\alpha_n + \beta_n P_{Gn} + \gamma_n P_{Gn}{}^2 + \left| \psi_n \exp\left(\zeta n P_{Gn} \right) \right| \right] ton/h$$

Where αn, βn, γn, ψn and ζn emission coefficient of nth generator.

B. Constraints

1) *Equality constraints:* In optimization problems, equality constraints are considered the most stringent constraints because they significantly reduce the feasible space [12].

$$P_G = P_D + P_{Loss} \qquad (7)$$

$$P_n = \left| V_n \right| \sum_{m=1}^{NB} \left| V_m \right| [G_{nm} \cos \theta_{nm} + B_{nm} \sin \theta_{nm}]$$

$$(8)$$

$$Q_n = \left| V_n \right| \sum_{m=1}^{NB} \left| V_m \right| [B_{nm} \cos \theta_{nm} - G_{nm} \sin \theta_{nm}]$$

Where Pn abd Qn represent the real and reactive power injection at bus n. and θnm is the angle between them. Bnm and Gnm denote the line susceptance and conductance.

2) *Inequality constraints:* In the OPF problem, Inequality Constraints (IC) are applicable to both independent and dependent variables. If any of these limitations is violated, the solution is considered unachievable. The mathematical expression representing the set of IC for both variables is as follows:

$$IC_{\min} \le IC \le IC_{\max} = \begin{cases} P_{Gn}^{\min} \le P_{Gn} \le P_{Gn}^{\max} \\ V_{Gn}^{\min} \le V_{Gn} \le V_{Gn}^{\max} \\ Q_{Gn}^{\min} \le Q_{Gn} \le Q_{Gn}^{\max} \\ T_{Gn}^{\min} \le T_{Gn} \le T_{Gn}^{\max} \\ Q_{cn}^{\min} \le Q_{cn} \le Q_{cn}^{\max} \\ V_{Ln}^{\min} \le V_{Ln} \le V_{Ln}^{\max} \\ S_{\ln} \le S_{\ln}^{\max} \end{cases} \qquad (9)$$

Where P_{Gn} and Q_{Gn} active and reactive power output. V_{Gn} represents the generator bus voltage. T_{Gn} represents the transformer tap settings. V_{Ln} the PQ bus voltage. Q_{Cn} the shunt VAR compensator. S_{ln} represents the total line flow. If any of the IC violates its boundary condition the value of the IC will be set as the boundary value.

$$F = Fobj + \begin{cases} \lambda_V \sum_{i=1}^{NPQ} (V_{Ln} - V_{Ln}{}^{\lim})^2 \\ \lambda_Q \sum_{i=1}^{NG} (Q_{Gn} - Q_{Gn}{}^{\lim})^2 \\ \lambda_Q \sum_{i=}^{TL} (S_l - S_l^{\lim})^2 \end{cases} \qquad (10)$$

III. HUNTER PRAY OPTIMIZATION ALGORITHM

I. Naruei et al. developed an algorithm named Hunter Pray Optimization Algorithm (HPOA) in 2021 [13]. HPOA is a bio-inspired algorithm that draws inspiration from the behavior of predator animals and their prey. According to the suggested method, there is a population of both prey and predators, and when one of the predators spots a prey that is trying to escape, it strikes. While the hunter shifts his position to get a better look at the distant target, the prey shifts his position to get out of a dangerous way. A secure location for the search agent was determined by its optimal fitness function value.

Step 1: Initialization

In this step, a set of random numbers are generated, which are depends on the population and dimension size and its lower and upper limit.

Step 2: Fitness calculation

In step 2, fitness of each individual of swarm population is computed and the positions of the best fitness is declared as the global optimal solution (T_{pos}).

Step 3: Position update

If a random number (R_1) is less than β then it is treated as a hunter and the positions are updated by equation (11) else it will be treated as a pray and the positions are updated by equation (12).

$$S_i^{t+1} = S_i^t + 0.5\left[A + B \right]$$

$$A = \left(\left(2 \times C \times Z \times P_{pos} \right) - S_i^t \right) \qquad (11)$$

$$B = \left(\left(2\left(1 - C \right) Z \times \mu \right) - S_i^t \right)$$

$$S_i^{t+1} = T_{pos} + \left(C \times Z \times \cos(2\pi R_2)\right) \times \left(T_{pos} - S_i^t\right)$$
$$C = 1 - itr\left(\frac{0.98}{T}\right) \quad (12)$$
$$Z = R_3 \times I + \overline{R_4} \times \left(\sim I\right)$$
$$P = \overline{R_5} < C$$

Where, Ppos represents the position of pray. μ represents the average of all the positions. R_2 represents a randomly generated number between [-1,1]. R_3 represents random number. $\overline{R_4}$ and $\overline{R_5}$ represents random vector generated between [0,1]. I represents the index of $\overline{R_5}$ that satisfies P=0.

Step 4: Limit Check

Validate the bounds of the modified location by assessing both lower and upper boundaries position and follow step 2.

Step 5: Stopping criteria

Check if maximum iteration is reached, declare the result otherwise follow the steps from 3 to 5 again.

IV. NON-UNIFORM MUTATION

Non-uniform mutation is a mutation operator often used in evolutionary algorithms and genetic algorithms to enhance the variety of potential solutions within the population. Non-uniform mutation differs from uniform mutation in that it applies different magnitudes of mutation to each gene in the solution, depending on a specified probability distribution. A mutation operator enhances the quality of offspring in relation to the number of iterations. This mutation refines the solution that previously hindered development. This operator is only applicable to integers and floating-point numbers. In the suggested technique, we have used the Non-Uniform Mutation process to enhance its exploitation feature. The solution is obtained using equations (13 and 14)

$$\Delta = \begin{cases} \left(ub_1 - d_1\right) \times \left(1 - a^Y\right) if & a > 0.5 \\ \left(lb_1 - d_1\right) \times \left(1 - a^Y\right) if & a < 0.5 \end{cases} \quad (13)$$

$$Y = \left(1 - \frac{t}{n}\right)^P \quad (14)$$

Where the value of ub1 is the uppermost boundary for updating all control variables. The value of lb1 is the lowest possible limit for updating all control variables. d1 is the variable that has to be changed as part of the control process. t denotes the current iteration number. n denotes the predetermined number of iterations required for achieving convergence.

V. PROPOSED ALGORITHM

The successful execution of any algorithm depends extensively on reaching an optimal equilibrium between exploration and exploitation [15]. An algorithm is prone to premature convergence when the act of exploitation process becomes more dominant than the act of exploration process. On the other hand, if the algorithm focuses too much on exploration rather than exploitation, it may spend an excessive amount of time thoroughly examining continuous areas, which might result in a failure to find the best solution [16]. Within this part, we combine the non-uniform mutation with the HPOA framework in order to improve its overall performance. The following steps provide a concise overview of the algorithm and its execution.

Step 1: Initialization

In this step, a set of random numbers is generated, which are depends on the population and dimension size and its lower and upper limit.

Step 2: Fitness calculation

In step 2, fitness of each individual of swarm population is computed and the positions of the best fitness is declared as the global optimal solution (Tpos).

Step 3: Position update

In step 3, If a random number (R_1) is less than β then it is treated as a hunter and the positions are updated by equation (11) else it will be treated as a pray and the positions are updated by equation (12).

Step 4: Local search Improvement

The non uniform mutation process is applied for both the predators and pray process by the equation (13, and 14) and both the fitness are compared to the previous optimum solution and the best solution and its positions are updated for the next step.

Step 5: Limit Check

Validate the bounds of the modified location by assessing both the lower and upper boundaries.

Step 6: Stopping criteria

Check if maximum iteration reached, declare the result otherwise, follow the steps from 2 to 6 again.

VI. RESULTS AND DISCUSSION

In this manuscript, the efficacy of HPOA and NMHPOA is evaluated in solving a complex and highly nonlinear OPF problem. The efficacy of the proposed approach is assessed using the IEEE 30-bus standard test system. The NMHPOA program for the OPF issue was developed in MATLAB version 2022b and executed on i5 Core CPU and RAM of 16 GB. The selected system consists of 9 shunt VAR compensators, 4 tap-changing transformers and 6 generators. The system has active power 283.4 MW. For each of the three scenarios, a total of 50 test runs are performed, with each run consisting of 200 iterations. The most favorable outcomes of all the three case studies are then documented and presented. The statistical analysis presented in Table IV further affirms the efficacy of NMHPOA.

Case-1: Total Voltage Deviation

The proposed method is used in this case to minimize the PLoss, which is described in Equation (4), as the primary objective. Additionally, the penalty terms specified in equation (10) are taken into consideration. The first column of Table 1 presents the control variables necessary to minimize the TVD. The performance of NMHPOA is evaluated by comparing it with seven existing methods as well as the original HPOA. The suggested method achieves a TVD of 0.0893 pu, whereas the original HPOA achieves a power loss of 0.1127 pu. Figure 1 demonstrates that the convergence curve of NMHPOA surpasses that of the original HPOA. The superiority of NMHPOA over all the alternatives evaluated is clearly visible in this study.

TABLE I: TVD Comparison Result

Control Variable	ABC [10]	GSA [5]	BA [17]	ALO [17]	DMOA [7]	EDMOA [7]	BOA [11]	HPOA	NMHPOA
Vgen1	1.0025	0.9930	1.0186	1.0131	1.0371	0.9977	0.9839	1.0014	1.0020
Vgen2	1.0161	0.9552	0.9797	1.0262	0.9538	1.0956	0.9500	1.0025	1.0139
Vgen5	0.9927	1.0189	1.0193	1.0194	1.0021	1.0195	1.0514	1.0189	1.0196
Vgen8	1.0288	1.0189	1.0475	1.0264	1.0438	1.0010	1.0320	1.0362	1.0359
Vgen11	1.0646	1.0120	0.9938	0.9949	1.0895	0.9562	1.0346	0.9964	0.9872
Vgen13	1.0086	1.0360	0.9753	0.9732	0.9500	0.9944	1.0569	1.0223	1.0185
T6-9	0.9700	1.0578	0.9800	0.9900	1.1000	0.9828	1.0218	1.0198	1.0095
T6-10	1.0300	1.0500	0.9200	0.9200	0.9000	0.9049	0.9482	0.9000	0.9000
T4-12	0.9700	0.9000	0.9600	0.9500	0.9000	0.9697	1.0261	0.9940	0.9947
T27-28	0.9500	1.0500	0.9700	0.9700	0.9306	0.9750	0.9451	0.9690	0.9766
Qc10	2.5000	0.9660	3.4700	4.4000	1.5242	3.1038	4.1489	4.6303	5.0000
Qc12	0.0000	4.5000	2.4500	4.2000	5.0000	4.9633	2.4296	0.0000	0.0039
Qc15	5.0000	2.5000	3.3700	2.6000	0.6606	4.9761	1.4005	5.0000	5.0000
Qc17	0.0000	1.4000	3.6300	1.1000	2.5019	4.8995	0.7044	3.3707	0.0000
Qc20	5.0000	4.0000	4.3400	3.7000	4.8378	4.9955	3.9073	0.0000	5.0000
Qc21	5.0000	3.8000	3.6200	3.4000	1.8574	1.0314	3.6645	5.0000	5.0000
Qc23	5.0000	2.9000	3.4100	3.6000	0.6195	3.9246	3.5095	5.0000	5.0000
Qc24	4.7000	2.5000	4.0500	3.9000	1.3065	3.1007	1.1912	5.0000	5.0000
Qc29	0.0000	3.1000	2.3500	1.9000	0.0000	3.8681	0.8094	1.4169	2.6049
Ploss (MW)	0.1350	0.1180	0.1161	0.1177	0.1266	0.1097	0.1425	0.1127	**0.0893**

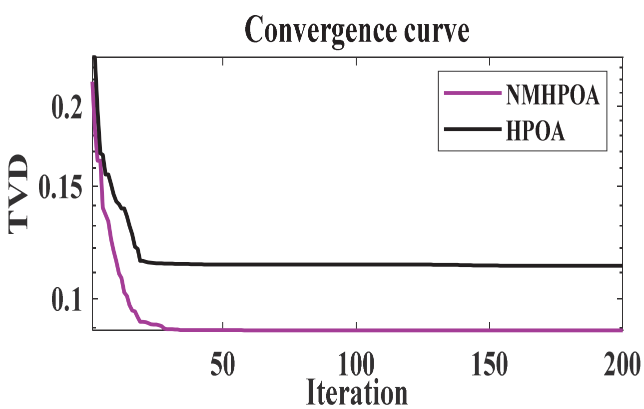

Fig. 1. Convergence curve of TVD

Case-2: Minimize Quadratic Fuel Cost:

In case 2, the suggested technique is used to enhance the TFC by using equation (5), in addition to the penalty component described in equation (10). According to Table II, the proposed algorithm achieved a TFC value of 798.9716 \$/hr whereas the original HPOA achieves TFC of 800.1043 \$/hr. It can be observed from Table II that the results of NMHPOA surpassing all previously reported result. The convergence curve of NMHPOA in Figure 2 demonstrates a smoother and quicker progression, suggesting that the proposed algorithm achieves a balanced combination of exploration and exploitation process.

TABLE II: TFC Comparison Result

Control Variables	GA [18]	FGA [18]	GA-OPF [18]	HBMO [19]	MHBMO [19]	BOA [11]	HPOA	NMHPOA
Pgen1	170.100	175.137	175.644	178.465	177.043	178.328	177.0608	177.0004
Pgen2	53.900	50.353	48.941	46.274	49.209	47.411	48.5226	48.4119
Pgen5	20.600	21.451	21.177	21.460	21.514	18.207	21.3298	21.1146
Pgen8	18.800	21.176	22.647	21.446	22.648	22.238	21.1750	21.6610
Pgen11	12.000	12.667	12.431	13.207	10.415	12.081	11.9433	11.7795
Pgen13	17.700	12.110	12.000	12.013	12.000	14.516	12.0000	12.0028
TFC	805.940	802.000	802.384	802.211	801.985	802.226	800.1043	**798.9716**

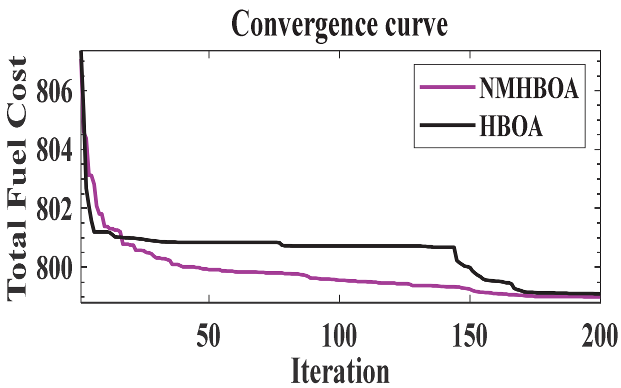

Fig. 2. Convergence curve of TFC

Case-3: Minimize Total Environmental Emission:

In this case, the NMHPOA is utilized to handle the TFC with VPL effect by using the equation (6). The inclusion of the VPL effect, the normal quadratic fuel cost, renders the objective function non-convex. According to Table III, the proposed algorithm achieved a TEE value of 0.2059 ton/hr whereas the original HPOA achieves TFC of 0.2059 ton/hr. The convergence curve depicted in Figure 3 illustrates the enhanced performance of NMHPOA compared over the HPOA. The evident superiority of NMHPOA over all the assessed alternative algorithms is a notable observation in this study.

TABLE III: TEE Comparison Result

Control Variables	PSO [20]	GA [20]	SLFA [20]	MSLFA [20]	GA [21]	PSO [21]	HPOA	NMHPOA
Pgen1	59.8079	78.2885	64.4840	65.7798	69.73	68.94	67.8158	66.8158
Pgen2	80	68.1602	71.3807	68.2688	67.84	67.13	68.11288	67.9221
Pgen5	50	46.7848	49.8573	50	49.73	49.86	50	50.0123
Pgen8	35	33.4909	35	34.9999	34.42	34.89	35	34.9834
Pgen11	27.1398	30	30	29.9982	29.15	29.67	30	29.0127
Pgen13	40	36.3713	39.9729	39.9970	39.29	39.94	40	39.9835
TFC-VPL	0.2096	0.2117	0.2063	0.2056	0.2072	0.2063	0.2067	**0.2059**

TABLE IV: Statistical analysis

	Case 1 (TVD)		**Case 2 (TFC)**		**Case 3 (TEE)**	
	HPOA	**NMHPOA**	**HPOA**	**NMHPOA**	**HPOA**	**NMHPOA**
Best Value	4.6196	4.5127	802.3359	798.9116	824.2036	822.572
Worst Value	4.6960	4.5498	805.8390	800.9577	830.9183	825.9968
Mean Value	4.6490	4.5280	804.1078	799.8811	827.9053	824.2031
STD Value	0.0279	0.0119	1.0412	0.5450	1.9376	0.9586

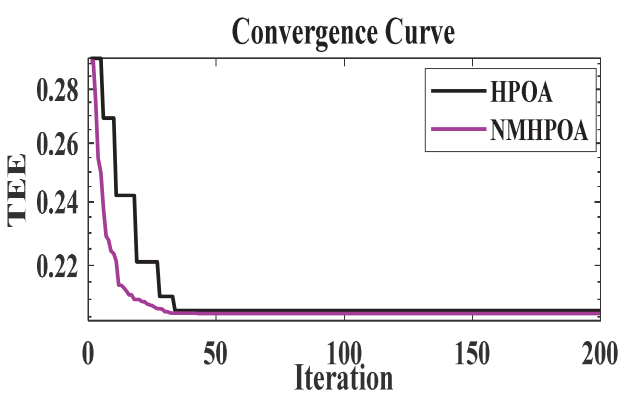

Fig. 3. Convergence curve of TEE

VII. RESULTS AND DISCUSSION

This study presents a new hybrid metaheuristic algorithm termed as the non-uniform Mutation-based Hunter-Prey Optimization Algorithm (NMHPOA). The technique is specifically developed to solve highly nonlinear OPF problems in power systems. The developed algorithm specifically tackles the problem of premature convergence that is noticed in the original HPOA. The hybrid method is implemented using MATLAB and is tested on the IEEE 30-bus standard system. The results are then compared to many previously published techniques. The effectiveness of the suggested approach is validated by statistical analysis, showcasing exceptional convergence properties for all three goals of the OPF problem. The outstanding performance of NMHPOA indicates its potential suitability for solving additional intricate optimization challenges.

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