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Optimal Power Flow Using Modified Grey Wolf Optimizer

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Abstract— *This paper presents the use of an artificial intelligence tool Grey Wolf Optimizer (GWO) for solving Optimal Power Flow (OPF) problem. The Optimal Power Flow (OPF) is a non-linear optimization problem in which the control parameters of the power network are optimized for a specific objective. Optimal Reactive Power Dispatch (ORPD) is a sub-problem of optimal power flow. The meta-heuristic tool Grey wolf optimizer is tested on two test cases IEEE-30 bus system and IEEE-118 bus system for minimization of active power Losses and voltage deviation. The Grey Wolf Optimizer was then modified and newly developed Modified Grey Wolf Optimizer (mGWO) was tested on both the test case IEEE-30 bus test case and IEEE-118 Bus system Again. The simulation results are compared with other artificial intelligence methods in literature.*

Keywords—*optimal power flow,grey wolf optimizer,optimal reactive power dispatch*

I. INTRODUCTION

An Optimal Power Flow (OPF) is a non-linear and non-convex problem. An OPF is a very important in ever-increasing power system network in today's era as it is necessary to meet the load demands with best operational condition. One of the many problems of OPF is a Optimal Reactive Power dispatch (ORPD) Problem which usually deals with objectives like minimum cost, minimum losses and maintaining voltage profile. These Objectives can be fulfilled by obtaining the optimum values of control parameters like Generator voltages, Generator Active power injection, Tap-changing transformer ratios and values of Shunt reactors. Equality and inequality constraints should not be violated while obtaining values of all these parameters.

Many methods like linear programming[1], non-linear programming[2], quadratic programming[3], interior point methods[4] and Newton-based techniques[5] were used earlier for solving ORPD problems. These methods suffered with different drawbacks like algorithmic complexity, large computational time and inefficient convergence characteristics. With the development in artificial intelligence, Optimization tools in AI became popular because of its merits like flexibility and easy implementation.
The Grey Wolf Optimizer[6] technique is Population based meta-heuristic method. It is inspired from behavior of Grey Wolves. The social and hunting behavior of grey wolves has inspired the optimization procedure. The Grey Wolf Optimizer is modified with inclusion of operators like Crossover and mutation.
This paper proposes Modified Grey Wolf Optimizer (mGWO) technique for solving ORPD problem. The mGWO technique is used for minimization of active power losses and voltage deviation. For both the Objectives two test case systems IEEE-30 bus system and IEEE-118 bus test system is taken. The simulation results are then compared with BBO[7], conventional PSO [8], GPAC [8], LPAC [8], CA [8] and IP-OPF [8].

II. PROBLEM FORMULATION

A. Optimal Reactive Power Dispatch(ORPD)

The Optimal reactive power dispatch problem objective can be formulated as

$$\text{Minimization of } f(p,q)$$

Where f(p,q) is the objective function. Where, p is the vector of dependent variables and q is the vector of control variables. The solution to function needs to take care of equality constraints as well as inequality constraints.

Now,

$$g(p,q) = 0$$
$$h(p,q) \leq 0 \qquad (1)$$

Where, $g(p, q) = 0$ is the equality constraint, $h(p, q) \leq 0$ is the inequality constraint.

The objective function to be minimized is the total transmission losses,

$$p_{loss}(p,q) = \sum_{l=1}^{nl} p_{loss} \qquad (2)$$

and voltage deviation at load buses,

$$VD(p,q) = \sum_{k=1}^{nd} |v_k - v_k{}^{sp}| \qquad (3)$$

Where Nl is the number of transmission lines, Nd is the number of load buses, V_k is the voltage at load bus k , $v_k{}^{sp}$ is the specified value which is usually set to 1.0 p.u .

The equality constraints are the power balanced load flow equations,

$$P_{Gi} - P_{Di} = V_i \sum_{j \in N_i} \mathrm{V_j}\,(G_{ij}cos\theta_{ij} + B_{ij}sin\theta_{ij}\,)$$
$$Q_{Gi} - Q_{Di} = V_i \sum_{j \in N_i} \mathrm{V_j}\,(B_{ij}cos\theta_{ij} - G_{ij}sin\theta_{ij}\,) \qquad (4)$$

Where P_{Gi} is the power Demand, P_{Di} is real power generation, Q_{Gi} is the generation of reactive power . G_{ij} and B_{ij} are conductance and susceptance respectively.

The Inequality constraints are

- For generator the constraints are generator real and reactive power Generation limits and voltage limits:

$$P_{gk}^{min} < P_{gk} < P_{gk}^{max}$$
$$Q_{gk}^{min} < Q_{gk} < Q_{gk}^{max}$$
$$V_{gk}^{min} < V_{gk} < V_{gk}^{max} \qquad (5)$$

k=1,…,Ng ; Ng= number of generators

- For transformers the constraints are their tap setting limits:

$$T_k^{min} < T_k < T_k^{max} \qquad (6)$$

k = 1,…,N_k ; N_T= number of transformers.

- Reactive compensators limits:

$$Q_{ck}^{min} < Q_{ck} < Q_{ck}^{max} \qquad (7)$$

k = 1,…,N_C ; N_C= number of the shunt compensators.

Both functions of ORPD problem need to be minimized while satisfying the equality and inequality constraints. Number of parameters should be set to optimum values for obtaining such objective.

III. GREY WOLF OPTIMIZER

The Grey Wolf Optimizer is Swarm Intelligence tool. It was first introduced by S.Mirjalili[6]. The grey wolf optimizer is inspired from the behavior of grey wolves. The grey wolves usually live in a pack of 4-10 wolves. The Group consists of one leader which is on top of its hierarchy. The leaders are alpha wolves which dominate the whole pack and they take decisions for the pack. The alphas are followed by betas ,they help alphas in decision making and they, too, dominate rest of the pack. The deltas are third in order and they control rest of the wolves. The omegas are at last on the hierarchy and they follow the commands from top orders. The social hierarchy is shown in figure 1.

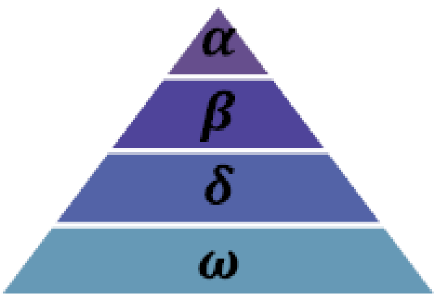

Fig. 1 Social hierarchy of grey wolves[6]

The Hunting Behavior of grey wolves consists of chasing the prey, encircling the prey and attacking the prey. These behaviors help in exploration and exploitation in search space for optimization problems.

A. Mathematical Approach

The mathematical approach of social hierarchy and hunting behavior of grey wolves is explained below.

- Social Hierarchy

To mathematically formulate the social hierarchy for grey wolf optimizer, we consider the best solution as the alphas. The second best solution is called beta, followed by delta as the third best solution. The rest of the population is called omega.

- Hunting Behaviour

The hunting behavior of grey wolves comprises of searching the prey, encircling the prey, attacking the prey.

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right|$$
$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \qquad (8)$$

The Encircling Behavior can be formulated by above equation. Where, t indicates the current iteration, A and C are coefficient vectors, Xp is the position vector of the prey,X indicates the position vector of a grey wolf. Vectors A and C are calculated as follows,

$$\vec{A} = 2a.\vec{r}_1 - a$$
$$\vec{C} = 2.\vec{r}_2 \qquad (9)$$

Where, a is in [2,0] and decreased from 2 to 0 with every iteration while r1, r2 are random vectors in [0, 1].
The three best solutions namely alpha, beta and delta are chosen and rest of the population called omega change their positions according to these best three population. This can be done mathematically as below,

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_1.\vec{X}_\beta - \vec{X}\right|,$$
$$\vec{D}_\delta = \left|\vec{C}_1.\vec{X}_\delta - \vec{X}\right|$$
$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta)$$
$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta)$$
$$\vec{X}_p(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \qquad (10)$$

The third behavior which is to attack the prey can be controlled by value of A which is [-2a,2a] . So, as mentioned before value of a is between [0,2], we can balance exploration which is |A|>1 and exploitation which is |A|<1 by defining the change in value of a with each iteration. , if C>1 it emphasize or if C<1 it deemphasize the effect of distance D.

IV. MODIFIED GREY WOLF OPTIMIZER

The simple grey wolf optimizer is conveniently very flexible and has given good results while tested on benchmark functions and other optimization problems as in the literature. However, there is always room for improvement. The operators like mutation and crossover are well known population based operators. These operators can be included in the simple grey wolf optimizer to improve its performance.

- Crossover

Cross over operator is used to improve the string/array values by interchanging the values between two strings/arrays. This is done by choosing a cross site and swapping the part/s of strings. Thus, two new strings are obtained.
Crossover is the first operator applied on population of Grey wolves. The crossover probability is defined first. For each population, according to probability crossover is executed. The cross site is selected randomly from size of population matrix and the values after cross site is swapped. The process is repeated for each population.

- Mutation

Mutation operator is used to further improve string/array after crossover. Mutation operator can be used to completely nullify some values by making them zero or to its initial state.
Mutation is the second operator applied here on grey wolf matrix. A mutation matrix of zeros and ones is generated according to mutation probability and is multiplied with grey wolf matrix element to element thereby changing some of the values.

A. Algorithm of mGWO for ORPD

The steps for implementation of grey wolf optimizer as well as modified grey wolf optimizer for ORPD problem are given below.

Step-1 Start with obtaining all the data of system like number of buses, number of branches, number of tap-changing transformers etc.
Step-2 Initialize Grey Wolf Optimizer by setting max number of iterations and max number of population for number of control variables.
Step-3 Define upper and lower limits for all variables.
Step-4 Start with random Alpha, Beta and Delta positions of three populations.
Step-5 Run Load flow for each population and obtain active power losses as well as voltage deviation.

Table 1 IEEE-30 bus data

IEEE-30 bus data	
No. of Buses	30
Slack bus number	1
Generators	6
Loads	24
Shunts	2
Transformer	4
Branches	41

Table 2 ORPD control parameters (IEEE-30 bus system)

ORPD Control Parameters	
Control parameters	Number
Generator bus voltage	6
Transformer tap ratio	4
Shunt Capacitor	2
Total	12

Step-6 The best results are those which give minimum active power losses and voltage deviation. Store best three solutions as Alpha, Beta and Delta.
Step-7 Update positions of other population by using alpha, beta and delta positions.
Step-8 Use crossover and mutation and get new population in case of mGWO (Skip this step in case of simple GWO).
Step-9 Check for all limits. Reject constrained violated values.
Step-10 Repeat from Step-5 till max number of iteration is reached.
Step-11 Print results for Best population.

V. TEST CASES AND RESULTS

A MATLAB programmed for simple GWO was developed and tested upon different test cases like IEEE-30 bus system and IEEE-118 bus system. The parameters like generators' voltages, transformer tap ratios, shunt reactive power are taken as control variables. The objective is to obtain the set of these values for best results that is minimum active power losses and minimum voltage deviation while satisfying the equality and inequality constraints. The population size for both test system is kept 20 while number of iteration count is 100. For mGWO crossover probability is 0.3 and mutation probability is 0.01 in mGWO.

We have considered two cases for results for both GWO and mGWO for both test cases.

1) Case A: Objective in this case is to obtain minimum active power losses only. We do calculate voltage deviation but we do not try to optimize it.
2) Case B: Objective in this case is to obtain minimum active power losses and minimum voltage deviation simultaneously.

I. IEEE-30 bus system

The IEEE-30 bus test case is considered to check the performance of GWO as well as mGWO. The IEEE-30 bus data was obtained from [9].The test case data summery is given in table 1. The Control parameters' summery is given in table 2. The limits for generator voltages are in range [0.9 p.u , 1.1 p.u] . The limits for tap changing transformers are between [0.9 p.u , 1.05 p.u]. The shunt reactive power from capacitor

Table 3 Results using GWO for IEEE 30 bus test case

Trail no.	CASE A			CASE B		
	Active Losses	Voltage Deviations	Constrains violated	Active Losses	Voltage Deviations	Constrains Violated
1	**4.9717**	**0.8284**	**0**	5.5740	0.1861	0
2	5.0074	0.3947	0	5.7671	0.1679	0
3	5.0620	0.3991	1	5.5925	0.1528	0
4	5.2420	0.3571	1	**5.4982**	**0.1648**	**0**
5	5.2253	0.7598	0	5.5690	0.1775	0

Table 4 Summary of Results using GWO for IEEE 30 bus test case

	CASE A			CASE B		
	BEST	AVG	STD DEV	BEST	AVG	STD DEV
LOSSES	4.9717	5.1017	0.1248	5.4982	5.6002	0.1000
VD	0.8284	0.5478	0.2267	0.1648	0.1698	0.0127

Table 5 Comparison of GWO with Other optimization techniques for IEEE-30 bus system

	GWO	BBO[7]	PSO[8]	GPAC[8]	LPAC[8]	CA[8]	IP-OPF[8]
V1	1.0717	1.1	1.01775	1.02942	1.02342	1.02282	1.1
V2	1.0614	1.0943	1.02458	1.00645	0.99893	1.09093	1.05414
V5	1.0282	1.0804	1.02466	1.01692	0.99469	1.03008	1.1
V8	1.0385	1.0939	1.01421	1.03952	1.01364	0.95	1.03348
V11	1.0361	1.1	1.01717	1.03952	1.01647	1.04289	1.1
V13	1.0614	1.1	0.99613	1.0487	1.01101	1.03921	1.01497
TC6-9	1.0445	1.1	1.09699	1.0425	1.04247	1.07894	0.99334
TC-6-10	0.9656	0.9058	0.92509	0.99417	0.99432	0.94276	1.05938
TC4-12	0.9815	0.9521	1.00048	1.00218	1.00061	1.00064	1.00879
TC-27-28	0.9624	0.9638	1.00714	1.00751	1.00694	1.00693	0.99712
Q10	27.8032	28.91	15.365	17.267	17.737	5.32	15.253
O24	11.7691	10.07	6.22	6.539	6.172	6.249	8.926
SVD	0.8284	0.155	-	-	-	-	-
Losses	4.9717	5.632	5.09219	5.09226	5.09212	5.09209	5.10091
computational time	~4	3.962	3.72	3.434	1.262	1.365	0.636

banks is in range of 0 MVAR to 30 MVAR. The matlab programme for GWO is run taking these variables as control variables for 5 times and the results are shown in table 3 and its summery is given in table 4. The best results for GWO are compared with results of other optimization methods in table 5. The mGWO programme is then run for same control variables for 10 times and the results obtained are shown in table 6 and its summery is given in table 7.

II. IEEE-118 bus system

The IEEE-118 bus test case is also tested upon for both cases A and B. The IEEE-118 bus data was taken from [10]. The test case data and control parameters in IEEE-118 bus system for ORPD are as shown in table 8. The limits for generator voltages and Transformer tap-settings is same as in IEEE-30 bus test case, The limits for shunt capacitor reactive power is between 0 MVAR and 40 MVAR. The results obtained by running GWO programme for

Table 6 Results using mGWO for IEEE 30 bus test case

Trail no.	**CASE A**					
	Active	**Voltage**	**Constrains**	**Active**	**Voltage**	**Constarins**
1	5.5858	0.5236	0	5.4517	0.2775	0
2	**4.8126**	**0.4907**	**1**	5.5725	0.2644	0
3	6.1956	0.5094	2	**5.3406**	**0.3335**	**0**
4	5.4814	0.4759	0	5.8239	0.2479	1
5	5.7902	0.7617	4	6.1298	0.5084	2
6	5.1917	0.6036	1	5.2084	0.5329	1
7	5.2538	0.4234	1	6.1240	0.3019	0
8	5.2493	0.7668	4	5.6520	0.2618	0
9	5.4900	0.3382	0	5.6988	0.2397	1
10	5.9344	0.7248	0	5.6330	0.3052	0

Table 7 Summary of Results using mGWO for IEEE 30 bus test case

	CASE A			CASE B		
	BEST	**AVG**	**STD DEV**	**BEST**	**AVG**	**STD DEV**
LOSSES	4.8126	5.4985	0.4022	5.3406	5.6635	0.3022
VD	0.4907	0.5618	0.1476	0.3335	0.3273	0.1059

Table 8 bus system data and ORPD control Parameters(IEEE-118)

IEEE-118 bus data		**ORPD Control Parameters**	
No. of Buses	118	Control parameters	number
Slack bus number	1	Generator bus voltage	54
Generators	54	Transformer tap ratio	9
Loads	64	Shunt Capacitor	12
Shunts	12	Total	75
Transformers	9		
Branches	186		

Table 9 Results using GWO for IEEE 118 bus test case

Trail no.	**CASE A**			**CASE B**		
	Active	**Voltage**	**Constrains**	**Active**	**Voltage**	**Constrains**
1	**127.14**	**2.6368**	**0**	130.00	1.4694	0
2	132.06	2.0255	0	128.05	1.7597	0
3	132.60	1.5675	2	**133.27**	**0.7863**	**0**
4	136.79	1.1571	0	133.14	1.0631	0
5	133.54	1.6090	1	139.25	1.3662	0

Table 10 Summary of Results using GWO for IEEE 118 bus test case

	CASE A			CASE B		
	BEST	**AVG**	**STD DEV**	**BEST**	**AVG**	**STD DEV**
LOSSES	127.1433	132.4247	3.4762	133.1383	132.7415	4.2531
VD	2.6368	1.7992	0.5601	1.0631	1.2890	0.3754

Table 11 Comparison of GWO with Other methods for IEEE 118 Test case

Algorithms	**GWO**	**BBO[7]**	**Conventional PSO[8]**	**GPAC [8]**	**LPAC 8[]**	**CA [8]**
Transmission loss(mw)	127.143	128.97	131.9146	131.9083	131.9010	131.8638
Computational time(s)	22.638	27.418	26.040	28.090	13.572	22.453

Table 12 Results using mGWO for IEEE 118 bus test case

Trail no.	**CASE A**			**CASE B**		
	Active Losses	**Voltage Deviations**	**Constrains Violated**	**Active Losses**	**Voltage Deviations**	**Constrains Violated**
1	135.0775	2.2967	0	133.5125	0.8089	0
2	130.4668	1.9673	0	128.3701	0.6993	1
3	138.3347	1.9814	1	135.9787	0.9311	0
4	130.2914	2.0817	0	134.3434	0.8587	0
5	127.7479	2.0047	1	131.4002	0.6682	1
6	127.0607	3.1127	0	127.2755	0.6176	2
7	122.9044	2.2595	2	134.2150	1.0395	0
8	131.7104	1.9099	0	129.7162	0.7422	3
9	125.8541	2.7211	1	131.5115	0.7607	0
10	125.4947	1.9984	1	133.7578	0.7676	0

Table 13 Summery mGWO for IEEE 118 bus test case

	CASE A			CASE B		
	BEST	**AVG**	**STD DEV**	**BEST**	**AVG**	**STD DEV**
LOSSES	127.0607	129.4943	4.6841	133.7578	132.0081	2.8464
VD	3.1127	2.2333	0.3923	0.7676	0.7894	0.1263

Table 14 Comparision of mGWO with other methods for IEEE 118 bus test case

	MGWO	**GWO**	**BBO[7]**	**PSO[8]**	**GPAC[8]**	**LPAC[8]**	**GA[8]**	**IP-OPF[8]**
SVD	0.768	1.063	1.025	-	-	-	-	-
Losses	133.76	133.14	172.54	131.91	131.91	131.90	131.86	132.11
computational time	25.000	25.000	27.534	26.040	28.090	13.570	22.430	11.870

This case is given in table 9 and it is summarized in table 10. It is compared with other methods in table 11. The modified version of this programme was run for 10 times and results are tabulated in table 12 with its summery in table 13. The results are then compared with results of other methods in table 14.

V. CONCLUSION

In this paper, The grey wolf optimizer was developed for ORPD problem of optimal power flow(OPF). The simple grey wolf optimizer was checked on IEEE-30 and IEE-118 bus system and the results were compared with other methods like BBO,PSO,GPAC,LPAC and GA. The results show that for IEEE-30 bus test system GWO gave better results than BBO and competativge results to other methods mentioned. The mGWO for the same test case gave even better results. For IEEE-118 bus test system the GWO gave slightly better results compared to other methods . For the same case mgwo gave better results than BBO and similar results to some extend compared to other methods.

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