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Optimal Reactive Power Dispatch using Hybrid Grey Wolf Optimization Technique

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Abstract

In this paper, Hybrid Grey Wolf Optimization (HGWO) method is used to find the set of optimal control variables of Optimal Reactive Power Dispatch (ORPD) problem, such as generators terminal voltage, position of tap changers of transformers, and number of switchable capacitor banks. The performance and feasibility of the proposed algorithm are demonstrated through IEEE 30-bus system. Comparison of obtained results with simple GWO technique and other methods reported in the literature shows clearly the superiority of HGWO algorithm over other recently published algorithms in regards to real power transmission losses minimization hence confirmation of the efficiency of HGWO algorithm in providing optimal solution.

Keywords: Hybrid Grey Wolf Optimization, Loss Minimization, Optimal Reactive Power Dispatch

1. Introduction

The reactive power optimization problem has a significant influence on secure and economic operation of power systems and it affects the overall generation cost by the way of transmission loss. In the power system, reactive power optimization problem directly influences the power system stability and power quality. The reactive power can be controlled in order to improve the voltage profile and minimize the system loss. Generally, some load bus voltage might violate their upper or lower limits during system operation due to disturbances and/or system configuration changes. The power system operator can improve this situation and voltages can be maintained within their permissible limits by reallocating reactive power generation in the system.

Sometimes the reactive power variations lead to the blackouts. Such black outs occurred in northern USA after which the reactive power optimization became the major concern. The purpose of Optimal Reactive Power is mainly to improve the voltage profile in the system and to minimize system losses. The Reactive Power Optimization problem is one of the most important aspects in optimal operation of power system. It is a multi-constraint, multi-modal, mixed-variable and nonlinear planning problem. The main objective of ORPD problem is to minimize the active power losses and to maintain the voltage profile in the power system, which can be achieved by adjusting controllable variables, such as generator voltages, transformer taps, shunt capacitors/inductors, etc. Since the generator voltages are continuous, whereas the transformer ratios and shunt capacitors/inductors are discrete, reactive power optimization is a complex nonlinear, multi-constraints, non-differentiable and mixed-integer problem.

In the past, very intensive and exhaustive efforts were being made by various power system researchers in the direction of developing the robust and efficient solution technique for complex optimization problems like ORPD. Various traditional solution techniques such as classical coordination equation method, interior-point linear programming[1], quadratic programming[2] and nonlinear programming methods have been widely adopted to solve the Optimal Power Flow (OPF) problem for large-scale power systems. A detailed review of all these traditional optimization techniques is presented[3]. However, these techniques have severe limitations in handling nonlinear, discontinuous functions having multiple local minima or maxima and constraints[4]. Besides these traditional techniques[1–3], many non-

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traditional Artificial Intelligence (AI) based optimization techniques also have been introduced in literature such as Particle Swarm Optimization (PSO)[4,5], ant colony optimization approach[6], seekers optimization algorithm[7], stochastic search technique, Evolutionary Programming (EPs)[8–10] and Genetic Algorithms (GAs)[11–13]. All these non- traditional optimization methods are preferred over conventional numerical techniques because of their superiority to handle the nonlinear complex constraints and capability to reach near the global optimal solution efficiently. Another advantage of these non-traditional optimization techniques is their ability to provide the multiple optimal solutions near the global minima or maxima.

2. Mathematical Formulation of ORPD

The objective (F) is to minimize the total real power loss in the transmission network

$$F = \sum_{k \in N_L} P_{k,loss} = \sum_{k \in N_L} g_k [V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j)]$$
$$k = (i, j); i \in N_B, j \in N_i$$

Where $P_{k,loss}$ is the real power loss in kth transmission line between i^{th} and j^{th} buses; N_L is total number of transmission lines; g_k is the conductance of the k^{th} transmission line; V_i, V_j are bus voltages in p.u. and δ_i, δ_j are phase angles in radians at the end buses i.e. ith and j^{th} of the k^{th} transmission line, respectively.

2.1 System Constraints in ORPD

The above objective functions F is minimized subject to all the system equality and inequality constraints as given:

Equality constraints

$$P_{G,i} - P_{D,i} - V_i \sum_{j \in N_i} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) = 0; \forall i \in N_B$$

$$Q_{G,i} - Q_{D,i} - V_i \sum_{j \in N_i} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) = 0; \forall i \in N_B$$

Inequality constraints

$$T_k^{\min} \le T_k \le T_k^{\max}; k \in N_T \; V_i^{\min} \le V_i \le V_i^{\max}; \forall \in N_B$$

$$Q_{G,i}^{\min} \le Q_{G,i} \le Q_{G,i}^{\max}; i \in N_{PV}$$

$$Q_{C,i}^{\min} \le Q_{C,i} \le Q_{C,i}^{\max}; i \in N_C$$

$$S_l \le S_l^{\max}; l \in N_L$$

$$P_{G,Slack}^{\min} \le P_{G,Slack} \le P_{G,Slack}^{\max}$$

2.2 Generalized Augmented Objective Function

The infeasible solutions are handled by applying a constant penalty to these infeasible solutions. The penalty functions corresponding to all the dependent variables such as voltage violations at all load buses ($\mu_{VL,i}$) , reactive power violations at all generator buses ($\mu_{QG,j}$), real power violations at slack bus ($\mu_{PG,slack}$) and power flow violations at all transmission lines ($\mu_{S,l}$) are included in objective function as follows:

$$F_n^{aug} = F_n + \sum_{i \in N_{PQ}} \mu_{VL,i} \left(V_i - V_i^{\lim} \right)^2 + \sum_{j \in N_{PV}} \mu_{QG,j} \left(Q_{G,j} - Q_{G,j}^{\lim} \right)^2 + \sum_{k \in N_{Gslack}} \mu_{PG,slack} \left(P_{G,k} - P_{G,k}^{\lim} \right)^2 + \sum_{l \in N_L} \mu_{S,l} \left(S_l - S_l^{\lim} \right)^2; \forall n = 1 : N_{obj}$$

where, F_n is n^{th} objective function value. The limits of dependent variables are defined as:

$$V_i^{\lim} = \begin{cases} V_i^{\max}; if V_i \rangle V_i^{\max} \\ V_i^{\min}; if V_i \rangle V_i^{\min} \end{cases}; \forall i = 1 : N_{PQ}$$

$$Q_{G,j}^{\lim} = \begin{cases} Q_{G,j}^{\max}; if Q_{G,j} \rangle Q_{G,j}^{\max} \\ Q_{G,j}^{\min}; if Q_{G,j} \rangle Q_{G,j}^{\min} \end{cases}; \forall j = 1 : N_{PV}$$

$$P_{G,k}^{\lim} = \begin{cases} P_{G,k}^{\max}; if P_{G,k} \rangle P_{G,k}^{\max} \\ P_{G,k}^{\min}; if P_{G,k} \rangle P_{G,k}^{\min} \end{cases} ; \forall k = 1 : N_{G,slack}$$

$$S_{l}^{\lim} = \begin{cases} S_{l}^{\max}; if S_{l} \rangle S_{l}^{\max} \\ S_{l}^{\min}; if S_{l} \rangle S_{l}^{\min} \end{cases} ; \forall l = 1 : N_{L}$$

For any reactive power optimization problem such as ORPD, the system variables include all control (decision) variables and all dependent variables. The system control variables are voltage magnitudes of all generators, transformer tap-settings and shunt capacitors/inductors. The system dependent variables are reactive power output of all generators, load bus voltage magnitudes and line flows.

3. Grey Wolf Optimization

Grey wolf optimization method is a meta-heurist technique inspired by the hunting behaviour and leadership hierarchy of Grey wolves[14]. Grey wolves prefer to live in a pack of size 5 to 12 and have a very dominant social hierarchy.

The leaders are called alphas. They are called decision makers as rest of the wolves follow his/her orders. Beta are the subordinate wolves that come on second level of the hierarchy, they help alpha in decision-making or other pack activities. They are the best substitute for alphas in case it dies or is old enough. It plays the role of manager of the pack and advisor to the alpha. The lowest ranking grey wolf is omega. They are at the bottom of the hierarchy they are allowed to eat at last and plays role of scapegoat. Omega have to report to all other wolves. If a wolf is not an alpha, beta, or omega, then it is called delta. They have to submit to alphas and betas, but they dominate omega.

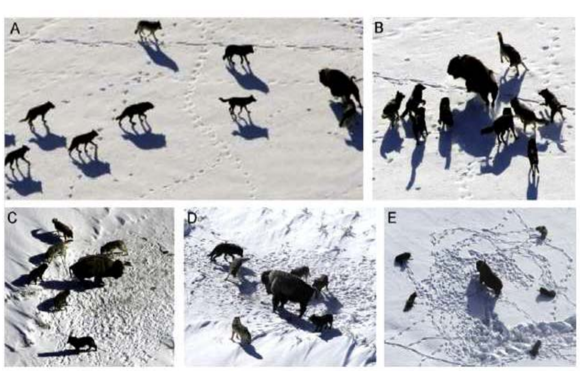

Figure 1. Hunting behaviour of grey wolves.

Scouts, hunters, elders, sentinels, and caretakers belongs to this category. Apart from the social hierarchy of grey wolves, they also depict another interesting behaviour of group hunting.

The main phases of grey wolf hunting are: (Figure 1) Tracking, chasing, and approaching the prey (A). Pursuing, encircling, and harassing the prey until it stops moving (B-D). Attack towards the prey (E).

Mathematical Model of GWO

The above social behaviour of Grey wolves is mathematically modelled and then optimization algorithm is developed.

Social Hierarchy: The fittest solution is considered as the alpha (α), the second and third best solutions are beta (β) and delta (δ) respectively.

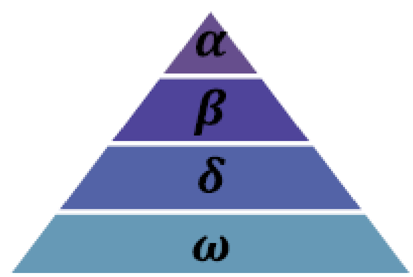

Figure 2. Social hierarchy.

The rest of the possible solutions are assumed to be omega (ω). Further hunting or optimization is guided by positions of α, β and δ and ω wolves follow these three wolves.

Encircling Prey: Grey wolves encircles a prey during the hunt. Following equations are proposed to mathematically model encircling behaviour of grey wolves:

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

where,

t - Current iteration

X_p - Position vector of the prey

X - Position vector of a grey wolf.

Vectors A and C are coefficient vectors calculated as follows

$$\vec{A} = 2a.\vec{r}_1 - a$$
$$\vec{C} = 2.\vec{r}_2$$

where, r1, r2 are random vectors in [0, 1].
a is linearly decreased from 2 to 0 over the course of iterations.

Hunting: Grey wolves recognizes the location of prey and encircle them. Alpha then guides other wolves for hunt. The beta and delta might also help in hunting. But in any optimization problems we don't know the exact solution or the location of prey and thus we take help of alpha (best known solution) beta and delta to estimate the position of prey and guide other wolves towards the same. Following equations are used for updating the position of search agents based on location of α, β and δ.

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

Attacking Prey (Exploitation): In order to mathematically model attacking behaviour we need to decrease the value of A, therefore the value of 'a' is decreased from [2 to 0], as the value of A will always be between [-a, a] if |A| < 1 then eq. 9 will force wolves to move towards the prey.

Search for Prey (Exploration): Grey wolves updates their position according to position of the alpha, beta, and delta. They diverge from each other or explore the search space to search for prey and converge or exploit to attack prey.

If |A|< 1 == Attacking prey – Exploitation
If |A|> 1 == Searching for prey – Exploration

Another parameter that favours exploration is vector C, its values is between [0, 2] and it can be considered as a hurdle for wolf to reach towards prey, if C>1 it emphasise or if C<1 it deemphasise the effect of distance D.

4. Hybridization of GWO

The simple grey wolf optimizer is also very flexible and convenient. It has given good results while tested on benchmark functions and other optimization problems in various fields. However, there is always room for improvement with these optimization tools. The operators like mutation and crossover are very popular population based operators in artificial intelligence. These operators are included in the simple grey wolf optimizer to improve its performance.

Crossover

The crossover operator of the Genetic Algorithm (GA) is introduced into the original GWO. By incorporating crossover operator in the HGWO, the global search ability is improved since every member of the pack gets chance to share information with each other. It helps in maintaining necessary exploration and exploitation. Thus, it alleviates the problem of diversity and avoids premature convergence. The probability of crossover P_C can be 0 to 1. According to this probability 100XP_C % of strings of total population is selected for crossover. While 100X (1-P_C)% of the population remains as it is.

Crossover is the first operator applied on population of Grey wolves in hybrid grey wolf optimizer. The crossover probability is defined first for selection of pair of population. From the population of grey wolves, according to probability crossover is executed. The cross site is selected randomly from size of population matrix and the values after cross site is interchanged. The process is repeated for each population pair.

Mutation

Mutation operator is used to further improve string/ array after crossover. Mutation operator can be used to compliment. The mutation probability *Pm is* decided first. In this algorithm P_m is set to 1%. 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.

5. Results and Discussions

The proposed HGWO based ORPD is tested on standard IEEE 30 bus power system. IEEE 30 power system consists of 41 transmission lines, 6 generator buses, and 24 load buses. There are five PV buses (i.e. Bus 2, Bus 5, Bus 8, Bus 11 and Bus 13). Bus 1 is selected as the slack bus. The others remaining buses are PQ buses. Four transmission lines 6-9, 6-10, 4-12 and 27-28 are under load tap setting transformers. The reactive power sources (i.e. capacitor/ inductor banks) are installed at Bus 3, Bus 10 and Bus 24.

The best optimal values of control parameters and objective function value (total real power transmission line loss) obtained by simple GWO, HGWO and other different methods are summarised in Table 1 These results show that the optimal dispatch solutions determined by the HGWO lead to least value of total real power transmission loss as compared to other methods, which confirms that the proposed HGWO is well capable to determine the global or near-global optimum dispatch solution All the simulations are carried out using MATLAB R2014a programming environment on Intel(R) Core(TM) i3-3110M, 2.40GHZ, 4.0 GB RAM computer system.

Optimal reactive dispatch values of generators are calculated and compared in Table 2 which shows encouraging results. Some statistical values obtained from 10 independent run, each run with 100 iterations is obtained and compared in Table 3, superior statistical results are obtained by HGWO compared to GWO

Table 1. Comparison optimal values of control parameters and objective function of HGWO with Other optimization techniques for IEEE-30 bus system

Control variables	HGWO	GWO	BBO[15]	PSO[16]	GPAC[16]	LPAC[16]	CA[16]
V1(p.u)	1.0266	1.069297	1.1	1.01775	1.02942	1.02342	1.02282
V2(p.u)	1.0059	1.060347	1.0943	1.02458	1.00645	0.99893	1.09093
V5(p.u)	0.9833	1.035578	1.0804	1.02466	1.01692	0.99469	1.03008
V8(p.u)	0.9871	1.027609	1.0939	1.01421	1.03952	1.01364	0.95
V11(p.u)	1.0283	1.00703	1.1	1.01717	1.03952	1.01647	1.04289
V13(p.u)	1.004	1.014764	1.1	0.99613	1.0487	1.01101	1.03921
TC6-9	0.9918	1.092684	1.1	1.09699	1.0425	1.04247	1.07894
TC6-10	1.0391	0.966694	0.9058	0.92509	0.99417	0.99432	0.94276
TC4-12	0.9999	0.964725	0.9521	1.00048	1.00218	1.00061	1.00064
TC27-28	0.9	0.955906	0.9638	1.00714	1.00751	1.00694	1.00693
Q10(MVAR)	9.1098	17.07352	28.91	15.365	17.267	17.737	15.32
Q24(MVAR)	14.65	6.992714	10.07	6.22	6.539	6.172	6.249
Losses (MW)	4.8126	4.9717	4.9650	5.09219	5.09226	5.09212	5.09209
computational time(s)	2.922	3.800	3.5680	3.72	3.434	1.262	1.365

Table 2. Reactive power dispatch value of each generator obtained using HGWO and GWO in IEEE 30 bus system

Bus no	Reactive power dispatch of each generator using HGWO (MVAR)	Reactive power dispatch of each generator using GWO (MVAR)
1	6.215537	6.335581
2	23.33853	32.21293
5	8.444262	27.76506
8	33.21169	32.80172
11	6.714723	11.16305
13	8.602718	0.222903
Total	**86.52746**	**110.5013**

Table 3. Statistical values of objective function obtained after 10 independent runs.

	BEST	AVG	STD DEV
HGWO	4.8126	5.1017	0.1248
GWO	4.9717	5.4985	0.4022

6. Conclusion

In this paper, HGWO technique is proposed by including mutation and crossover operator to improve the stochastic search capability of simple GWO method. Further the improved optimization technique, namely HGWO, has been successfully applied to solve the optimal reactive power dispatch problem. The proposed HGWO based ORPD is tested on IEEE 30 bus power systems. The simulation results prove the capability of the proposed approach to arrive at near global optimal solution as compared to other optimization techniques reported in literature.

7. References

1. Granville S. Optimal reactive dispatch through interior point methods. IEEE Transactions Power Systems. 1994; 9(1):136–46. https://doi.org/10.1109/59.317548
2. Momoh JA, Guo SX, Ogbuobiri EC, Adapa R. The quadratic interior point method solving power system optimization problems. IEEE Transactions Power Systems. 1994; 9(3):1327–36. https://doi.org/10.1109/59.336133
3. Momoh JA, El-Hawary ME, Adapa R. A review of selected optimal power flow literature to 1993. II. Newton, linear programming and interior point methods. IEEE Transactions. Power Systems. 1999; 14(1):105–11. https://doi.org/10.1109/59.744495
4. Zhao B, Guo CX, Cao YJ. A multiagent-based particle swarm optimization approach for optimal reactive power dispatch. IEEE Transactions Power Systems. 2005 May; 20(2):1070–8. https://doi.org/10.1109/TPWRS.2005.846064
5. Cai G, Ren Z, Yu T. Optimal reactive power dispatch based on modified particle swarm optimization considering voltage stability. 2007 IEEE Power Engineering Society General Meeting; 2007. p. 1–5. https://doi.org/10.1109/PES.2007.386101
6. Abbasy A, Hosseini SH. Ant colony optimization-based approach to optimal reactive power dispatch: A comparison of various ant systems. 2007 IEEE Power Engineering Society Conference and Exposition in Africa – PowerAfrica; 2007. p. 1–8. https://doi.org/10.1109/PESAFR.2007.4498067
7. Dai C, Chen W, Zhu Y, Zhang X. Seeker optimization algorithm for optimal reactive power dispatch. IEEE Transactions Power Systems. 2009 Aug; 24(3):1218–31. https://doi.org/10.1109/TPWRS.2009.2021226
8. Wu QH, Ma JT. Power system optimal reactive power dispatch using evolutionary programming. IEEE IEEE Transactions. Power Systems. 1995; 10(3):1243–9. https://doi.org/10.1109/59.466531
9. Lai LL, Ma JT. Application of evolutionary programming to reactive power planning-comparison with nonlinear programming approach. IEEE Transactions Power Systems. 1997; 12(1):198–206. https://doi.org/10.1109/59.574940
10. Yan W, Lu S, Yu DC. A novel optimal reactive power dispatch method based on an improved hybrid evolutionary programming technique. IEEE Transactions Power Systems. 2004 May; 19(2):913–18. https://doi.org/10.1109/TPWRS.2004.826716
11. Wu QH, Cao YJ, Wen JY. Optimal reactive power dispatch using an adaptive genetic algorithm. International Journal of Electrical Power and Energy Systems. 1998 Nov; 20(8):563–9. https://doi.org/10.1016/S0142-0615(98)00016-7
12. Wu QH, Cao YJ. Stochastic optimization of control parameters in genetic algorithms. Proceedings of 1997 IEEE International Conference on Evolutionary Computation (ICEC '97); 1997. p. 77–80.
13. Chen C–R, Lee C–Y, Hsu Y-F, Chao H–W. Optimal reactive power dispatch of power systems using a modified genetic algorithm. 2004 International Conference on Power System Technology, 2004. PowerCon. 2004; 2:1266–9.
14. Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. Advances in Engineering Software. 2014; 69:46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007
15. Roy PK, Ghoshal SP, Thakur SS. Optimal VAR control for improvements in voltage profiles and for real power loss minimization using Biogeography Based Optimization. International Journal of Electrical Power and Energy Systems. 2012 Dec; 43(1):830–8. https://doi.org/10.1016/j.ijepes.2012.05.032
16. Vlachogiannis JG, Lee KY. A comparative study on particle swarm optimization for optimal steady-state performance of power systems. IEEE Transactions Power Systems. 2006;21(4). https://doi.org/10.1109/TPWRS.2006.883687